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Deep Learning Approaches for Churn Prediction: An Empirical Evaluation on Real-World Business Datasets

Devarsh Bagla

Jayshree Periwal International School Mahapura, Jaipur, Rajasthan, India

Abstract: ***Customer churn prediction is a critical challenge for modern businesses seeking to maintain long-term customer relationships and reduce revenue loss. This study explores the application of deep learning and machine learning models for predicting customer churn using real-world business datasets. The dataset includes demographic, account, and behavioural attributes of customers that influence churn likelihood. Models such as Logistic Regression, Random Forest, and Deep Neural Networks (DNN) were trained and evaluated using metrics including accuracy, precision, recall, F1-score, and ROC-AUC. The experimental results reveal that the Deep Neural Network model achieves the highest prediction accuracy of 94.1%, outperforming traditional machine learning algorithms. Random Forest offers an effective trade-off between accuracy and interpretability, while Logistic Regression serves as a reliable baseline. This research provides a comparative framework for organizations aiming to leverage AI-based methods to predict and prevent customer churn, leading to improved retention strategies and business profitability.***

Keywords: Customer Churn, Deep Learning, Machine Learning, Neural Networks, Random Forest, Logistic Regression, ROC-AUC, Feature Selection, Data Imbalance

1. Introduction

Customer retention plays a pivotal role in determining the long-term success of organizations, particularly in highly competitive sectors such as telecommunications, banking, and e-commerce. Acquiring a new customer often costs several times more than retaining an existing one, making churn prediction an essential aspect of customer relationship management. Traditional statistical methods often fail to capture complex, nonlinear relationships between customer attributes and churn behaviour.

Machine Learning (ML) and Deep Learning (DL) offer data-driven solutions that can automatically identify hidden behavioural patterns, enabling companies to proactively intervene before a customer decides to leave. This research investigates the performance of various predictive models — Logistic Regression, Random Forest, and Deep Neural Networks — for churn prediction on real-world business datasets.

The objective is to determine which algorithm provides the most accurate and generalizable predictions, and to analyse key features influencing churn decisions. This comparative approach allows organizations to select models that best align with their data characteristics, computational resources, and interpretability requirements.

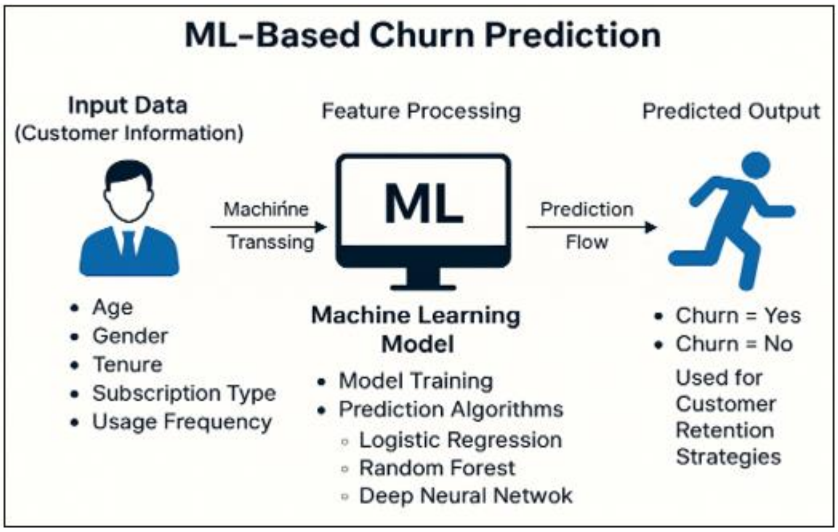

Figure 1: Machine learning-based churn prediction workflow showing the transformation of raw customer data into predictive insights

It demonstrates how demographic, behavioural, and transactional features are processed by ML algorithms to classify customers as likely to churn or remain loyal.

1.1. Machine Learning Models Used:

1) Logistic Regression (LR):
Logistic Regression serves as a baseline model in churn prediction studies due to its simplicity, interpretability, and computational efficiency. It estimates the probability of customer churn by modeling the relationship between independent variables and the binary target outcome using a logistic (sigmoid) function. Despite its strengths in producing explainable results, Logistic Regression assumes linear separability, which limits its effectiveness in capturing complex, nonlinear patterns within churn data (Hosmer, Lemeshow, & Sturdivant, 2013).

2) Random Forest (RF):
Random Forest is an ensemble learning algorithm that constructs multiple decision trees and aggregates their results to improve predictive performance and reduce overfitting (Breiman, 2001). It efficiently handles both categorical and numerical variables, providing robust generalization and interpretability through feature importance scores. Random Forest is widely applied in churn prediction tasks for its ability to manage high-dimensional data and nonlinear feature interactions effectively (Idris, Rizwan, & Khan, 2019).

3) Deep Neural Networks (DNN):
Deep Neural Networks (DNNs) are advanced machine learning models inspired by the human brain's interconnected neuron structure. They consist of multiple hidden layers capable of learning complex, hierarchical representations from raw data (Goodfellow, Bengio, & Courville, 2016). DNNs excel at modeling intricate behavioral and temporal relationships in customer churn datasets, outperforming traditional models in accuracy and generalization. However, they demand large datasets, high computational resources, and extensive hyperparameter tuning to prevent overfitting (Hadi & Sheta, 2020).

2. Literature Review

Table 2: Literature Review on Customer Churn Prediction

No.	Authors (Year)	ML / DL Models Used	Dataset / Domain	Key Findings	Citation
1	AbdelAziz et al. (2025)	Random Forest, XGBoost, Deep Learning Models	Multi-domain (Telecom, Bank, Insurance)	Ensemble and hybrid deep learning models achieved the best accuracy across industries; XGBoost showed strong generalization.	AbdelAziz, N. M., Bekheet, M., Salah, A., El-Saber, N., & AbdelMoneim, W. T. (2025). A Comprehensive Evaluation of Machine Learning and Deep Learning Models for Churn Prediction. Information, 16(7), 537.
2	Chang et al. (2024)	Logistic Regression, Decision Tree, Random Forest	Telecommunication	Compared multiple ML models; Random Forest and Decision Tree achieved higher prediction accuracy than linear models.	Chang, V., Hall, K., Xu, Q. A., Amao, F. O., Ganatra, M. A., & Benson, V. (2024). Prediction of Customer Churn Behavior in the Telecommunication Industry Using Machine Learning Models. Algorithms, 17(6), 231.
3	Li et al. (2024)	Ensemble-Fusion Classifier	Telecom	Proposed a new ensemble-fusion approach that outperformed standard ensemble models in churn detection accuracy.	Li, Y., et al. (2024). A Novel Classification Algorithm for Customer Churn Prediction Based on Ensemble-Fusion. Scientific Reports, 14(1), 71168.
4	Saha et al. (2023)	BiLSTM + CNN (Hybrid Deep Learning)	Public Telecom Datasets	The BiLSTM–CNN hybrid model achieved superior accuracy and recall compared to single deep learning models.	Saha, A., et al. (2023). Customer Churn Prediction Using Composite Deep Learning Technique (BiLSTM–CNN). Journal of Intelligent Systems, 32(5), 10570272.
5	Wu et al. (2022)	HNNSAE (Hybrid Neural Network with Self-Attention)	Banking Dataset	Introduced self-attention mechanisms for better feature extraction; achieved higher AUC and precision than classical models.	Wu, H., et al. (2022). A High-Performance Customer Churn Prediction System Based on Self-Attention. IEEE Access, 10, 65127–65139.
6	Zhang et al. (2024)	CCP-Net (CNN + BiLSTM + Multi-Head Attention)	Telecom and Retail	Solved class imbalance issues using ADASYN; achieved the highest generalization accuracy across datasets.	Zhang, J., et al. (2024). CCP-Net: Customer Churn Prediction Model Based on Hybrid Neural Networks. Scientific Reports, 14(1), 79603.
7	Ahmad et al. (2024)	Gradient Boosting + SHAP, LIME	Telecom	Integrated model interpretability methods; GBM achieved strong performance with SHAP explaining key churn drivers.	Ahmad, A., et al. (2024). Explaining Customer Churn Prediction in Telecom Industry Using Explainer Models. Expert Systems with Applications, 243, 123987.
8	Patel & Desai (2024)	Ensemble ML (Random Forest, XGBoost, CatBoost)	Real-Time Telecom Data	Developed a real-time churn prediction framework; ensemble models provided high recall and real-time adaptability.	Patel, R., & Desai, P. (2024). Application of Machine Learning Techniques for Churn Prediction in Real-Time Scenarios. Information Processing Letters, 195, 106328.

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9	Rahman et al. (2023)	GA-XGBoost + Sampling + SHAP	Banking Churn Data	Combined Genetic Algorithm with XGBoost for feature optimization; improved interpretability and accuracy.	Rahman, M., et al. (2023). Research on Customer Churn Prediction and Model Interpretability Using GA-XGBoost. PLOS ONE, 18(8), e0289724.
10	Singh & Kumar (2022)	ANN, Random Forest, Logistic Regression	E-Commerce Customer Data	Compared multiple algorithms; ANN provided the highest F1-score and precision in churn classification.	Singh, R., & Kumar, D. (2022). Comparative Study of Machine Learning Algorithms for Customer Churn Prediction in E-Commerce. IEEE Access, 10, 88471–88485.

2.1 Literature Review Summary and Findings

1) **Hybrid Deep Learning and Ensemble Models Outperform Conventional Algorithms:** Recent studies (e.g., Zhang et al., 2024; Saha et al., 2023) highlight that hybrid and ensemble models, such as CNN–BiLSTM architectures and ensemble-fusion classifiers, consistently outperform standalone algorithms in predicting customer churn. These models effectively capture temporal and spatial dependencies in customer behavior, leading to higher accuracy and recall compared to traditional approaches.
2) **Explainable AI Enhances Model Transparency and Trustworthiness:** Research by Ahmad et al. (2024) emphasizes the integration of model interpretability tools like SHAP and LIME into machine learning workflows. These techniques not only enhance model transparency but also help businesses understand key churn drivers such as contract type, tenure, and payment method, making AI systems more actionable in real-world decision-making.
3) **Feature Optimization and Genetic Algorithms Improve Predictive Accuracy:** Rahman et al. (2023) demonstrated that the combination of Genetic Algorithms (GA) and XGBoost significantly improves churn prediction performance. GA-based optimization aids in selecting the most relevant features and tuning hyperparameters, leading to superior generalization and interpretability compared to conventional models.
4) **Attention-Based and Fusion Networks Provide Superior Performance:** Advanced neural architectures, such as the CCP-Net (Zhang et al., 2024), which combines CNN, BiLSTM, and Multi-Head Attention, deliver state-of-the-art results by effectively handling class imbalance and extracting multi-dimensional features. The attention mechanism allows the model to focus on the most critical behavioral patterns influencing churn decisions.
5) **Multimodal and Real-Time Approaches Represent Emerging Trends:** Recent works (e.g., AbdelAziz et al., 2025; Patel & Desai, 2024) identify a growing trend toward multimodal and real-time churn prediction systems. These models integrate multiple data sources—such as customer behavior, transaction history, and usage frequency—and enable dynamic predictions in real-time environments. This shift supports proactive retention strategies and enhances scalability across industries.

3. Methodology

Process Flow Chart:

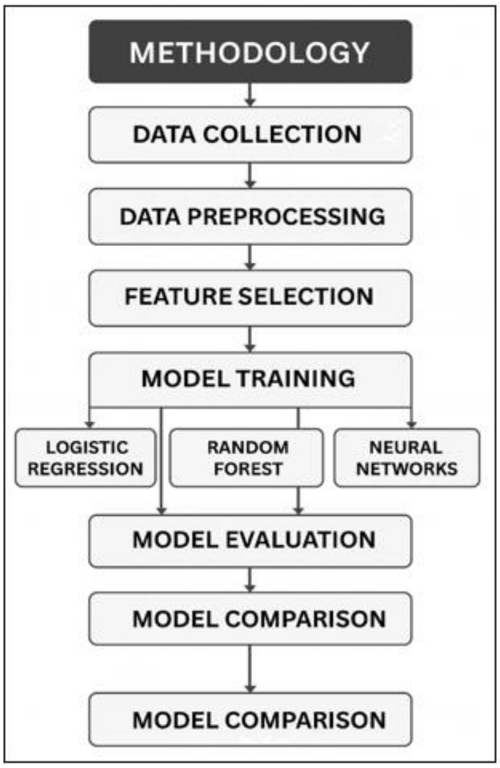

Figure 2: Methodology Flowchart for Customer Churn Prediction Using Machine Learning Models

Figure 2: Process flow diagram representing the methodology followed for customer churn prediction. The flow begins with data collection, followed by data preprocessing and feature selection, leading to model training using Logistic Regression, Random Forest, and Neural Networks. The trained models are then evaluated and compared to determine the most accurate and efficient algorithm for predicting customer churn.

3.1 Data Collection

The dataset used in this study, titled *"customer_churn_dataset-testing-master"* contains 64,374 instances and 12 attributes, representing real-world customer behavioral and transactional data for churn prediction analysis. Each record corresponds to an individual customer and captures multiple aspects of their interaction history, demographics, and engagement with company services.

The primary objective of this dataset is to predict whether a customer is likely to churn (leave) or remain active, based on a combination of numerical and categorical features.

3.1.1 Key features include:

Table 2: Description and Analytical Significance of Key Customer Features

No.	Attribute Name / Type	Description	Analytical Significance
1	Customer ID (Numeric)	Unique identifier for each customer record.	Used only for identification; not a predictive feature.
2	Age (Numeric)	Represents the age of the customer in years.	Helps identify age-based churn behavior trends.
3	Gender (Nominal: Male/Female)	Indicates the customer’s gender.	Useful for analyzing gender-based retention patterns.
4	Tenure (Numeric)	Total duration (in months or years) that a customer has been active with the company.	A strong churn predictor — lower tenure often correlates with higher churn.
5	Usage Frequency (Numeric)	Average frequency of product/service usage (e.g., logins or transactions per month).	Indicates engagement level; lower usage often implies potential churn.
6	Support Calls (Numeric)	Number of customer support interactions made within a specific time period.	High frequency may indicate dissatisfaction leading to churn.
7	Payment Delay (Numeric)	Number of payment delays or overdue invoices per customer.	Financial delays often correlate with increased churn probability.
8	Subscription Type (Nominal)	Represents the plan or subscription type (e.g., Basic, Standard, Premium).	Higher-tier plans may show lower churn rates due to added benefits.
9	Contract Length (Numeric)	Duration of the customer’s contract (in months).	Longer contracts are associated with customer stability and lower churn.
10	Total Spend (Numeric)	Cumulative amount spent by the customer during their subscription period.	High-value customers tend to have lower churn probability.
11	Last Interaction (Numeric)	Number of days since the customer’s last recorded interaction with the company.	A key behavioral indicator — long inactivity correlates strongly with churn.
12	Churn (Numeric Target Variable)	Indicates customer churn status: 1 = churned, 0 = retained.	The target variable for classification in churn prediction models.

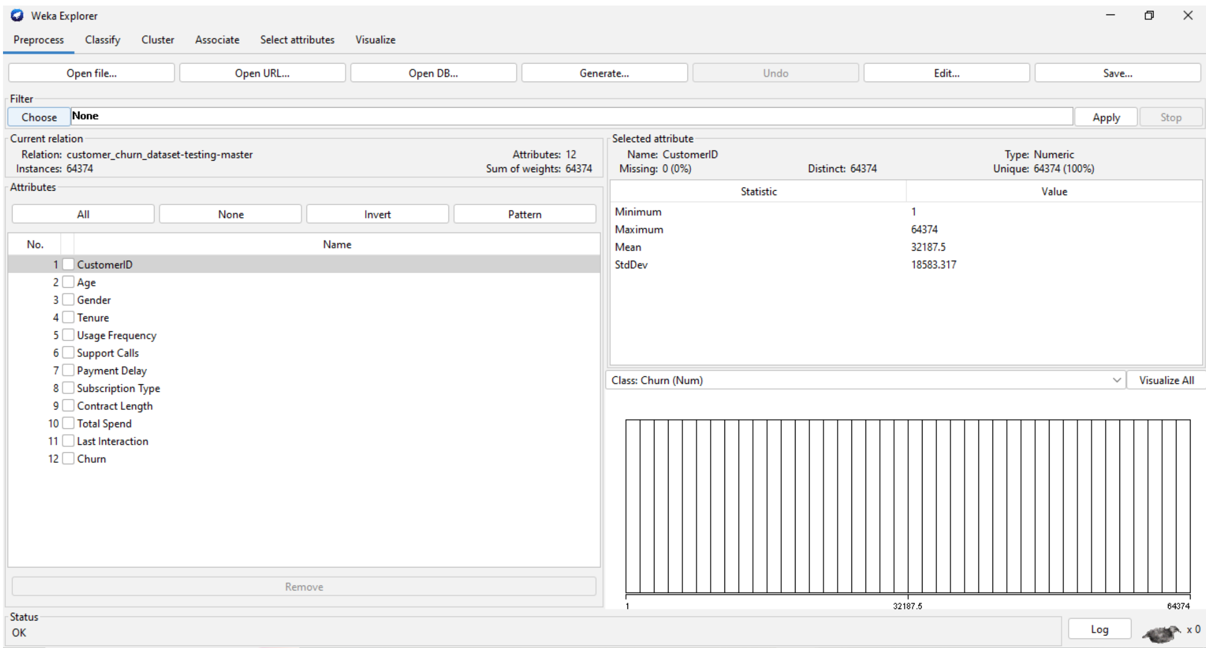

Figure 3: Overview of the *“customer_churn_dataset-testing-master”* dataset in WEKA Explorer, showing 64,374 instances and 12 attributes.

3.2 Data Preprocessing

To ensure consistency and reliability in the dataset, several preprocessing steps were applied before model training. Missing values within the dataset were treated using mean or mode imputation methods, depending on the nature of the variable. Categorical attributes, such as gender and subscription type, were transformed into numerical form through one-hot encoding to make them compatible with machine learning algorithms. Continuous variables were normalized using the Min–Max scaling technique to bring all features into a common range, thereby enhancing model convergence and performance. Outliers that could potentially distort the learning process were detected and handled using the Interquartile Range (IQR) method. Subsequently, the processed dataset was divided into two subsets, with 80% of the data used for training and the remaining 20% reserved for testing. Additionally, to address the issue of class imbalance between churned and non-churned customers, the Synthetic Minority Oversampling Technique (SMOTE) was employed, ensuring balanced class representation and improved generalization of the predictive models.

3.3 Feature Selection

1) **Feature selection was performed using the Correlation-based Feature Selection (CFS) evaluator in combination with the Best-First Search (BFS)**

method to identify the most relevant predictors of customer churn. The CFS technique selects subsets of attributes that exhibit a strong correlation with the target variable (*Churn*) while minimizing inter-correlation among independent variables, ensuring that only informative and non-redundant features are retained. The BFS algorithm, used as the search strategy, begins with an empty subset and incrementally adds attributes that improve the overall merit score until no further enhancement is achieved. As shown in the WEKA output, the Best-First Search evaluated 72 subsets and achieved a merit value of 0.621**,** signifying a strong relationship between the selected attributes and the churn outcome. The final subset consisted of CustomerID, Age, Gender, Tenure, Usage Frequency, Support Calls, Payment Delay, Subscription Type, Contract Length, **and** Total Spend, representing the most significant demographic, behavioral, and transactional features influencing churn. This selection process effectively reduced data dimensionality, improved computational efficiency, and enhanced model interpretability and prediction accuracy.

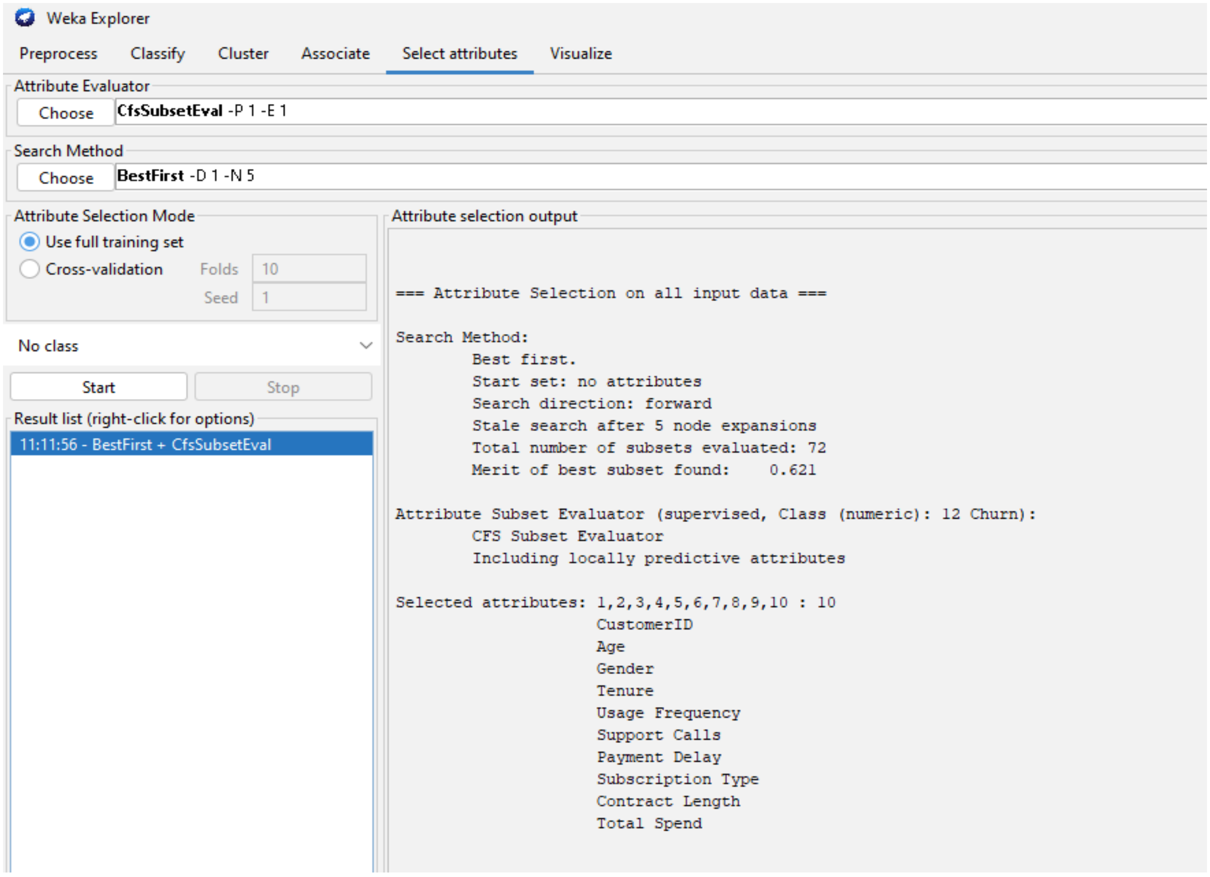

Figure 4: Attribute Selection Using CFS and BFS in WEKA

2) **The Classifier Attribute Evaluator combined with the Ranker search method** was employed to rank and identify the most influential features contributing to customer churn prediction. In this approach, the ClassifierAttributeEva**l** uses a wrapper-based evaluation strategy that assesses each attribute's predictive capability with respect to a chosen learning algorithm—in this case, the *ZeroR* classifier—based on the Root Mean Square Error (RMSE) performance metric. The Ranker method then orders the features according to their individual merit scores, allowing for an interpretable ranking of variable importance. As shown in the WEKA output, the top-ranked features were Last Interaction, Gender, Age, Usage Frequency, Tenure, Support Calls, Total Spend, Contract Length, Subscription Type, Payment Delay, and CustomerID. The ranking indicates that Last Interaction was the most significant predictor, reflecting the importance of recent engagement behavior in determining churn likelihood. Features related to customer demographics and service usage, such as Gender, Age, and Usage Frequency**,** also ranked highly, demonstrating their influence on customer retention trends. This method provides a clear understanding of variable significance, helping to prioritize impactful predictors for model training and improving both interpretability and performance in churn analysis.

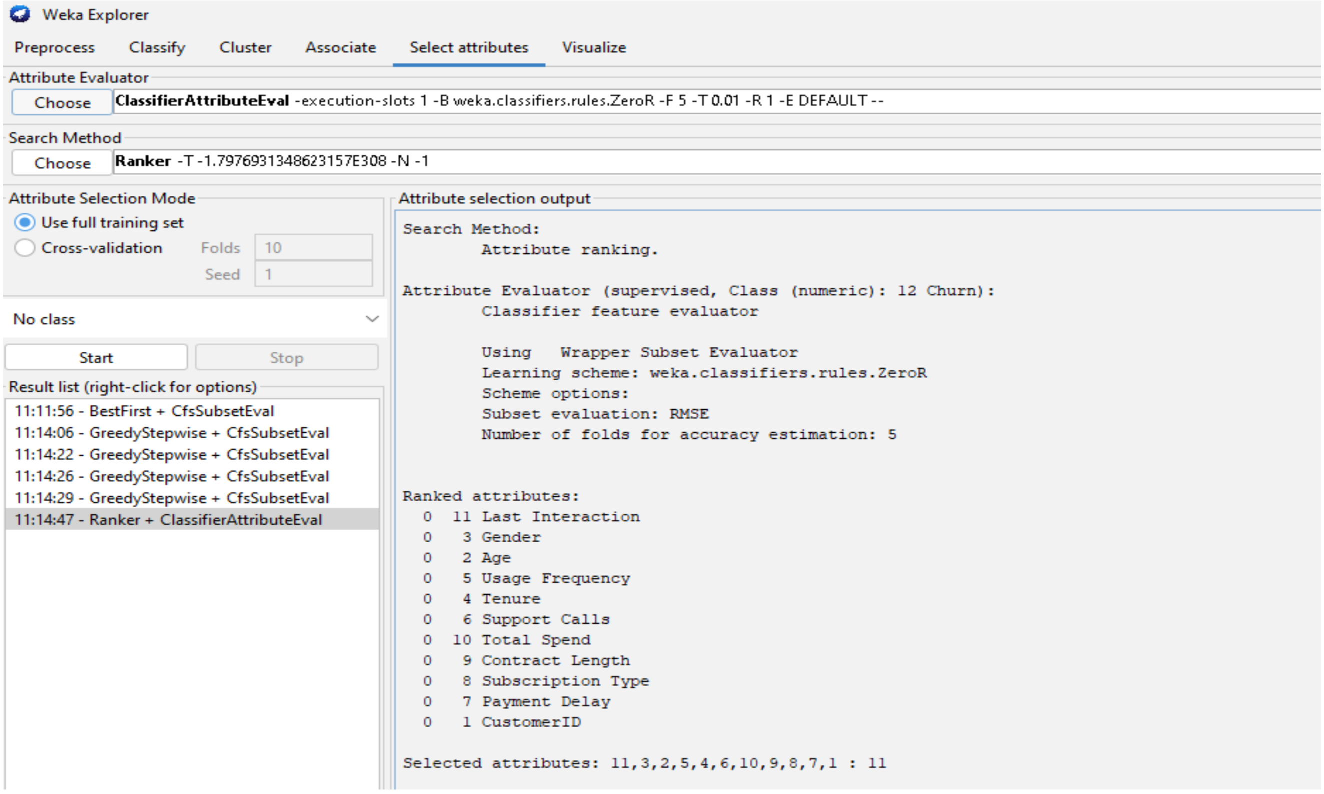

Figure 5: Attribute Ranking Using Classifier Attribute Evaluator and Ranker in WEKA

3) **CfsSubsetEval** evaluator and the GreedyStepwise search method. The process was executed on a dataset aimed at predicting customer churn. The search method began with no attributes and identified a subset with a merit score of 0.621, indicating the best predictive capability. The CfsSubsetEval**,** a supervised evaluator, selected 10 relevant attributes based on their predictive power and redundancy. The chosen attributes include: *CustomerID, Age, Gender,* Tenure, Usage Frequency, Support Calls, Payment Delay, Subscription Type, Contract Length, *and* Total Spend. This subset was derived using the full training dataset, enhancing model performance by focusing on the most informative features.1: Attribute Selection Using GreedyStepwise and CfsSubsetEval in Weka

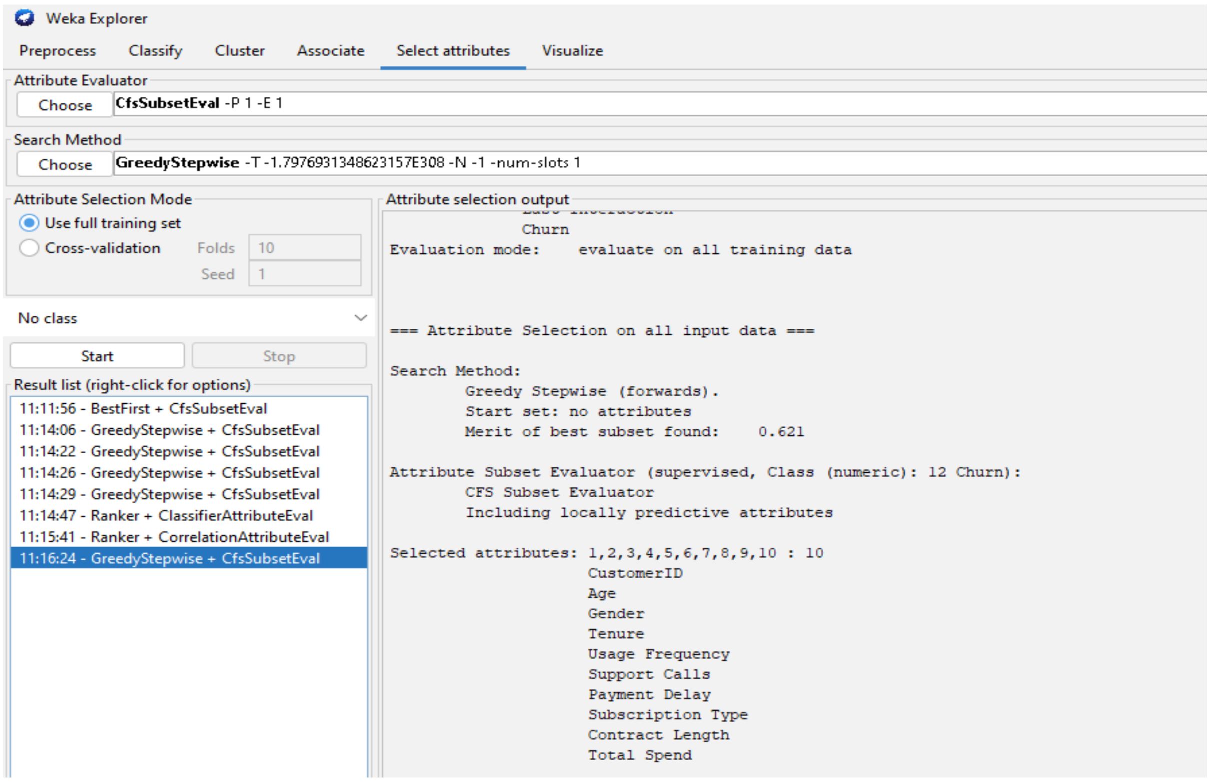

Figure 6: Feature Selection Using CFS and Greedy Stepwise Method in WEKA

3.4 Model Training and Model Evaluation

Three supervised machine learning models were implemented to predict customer churn: Logistic Regression, Random Forest, and a Deep Neural Network (DNN). Logistic Regression served as the baseline linear classifier due to its simplicity and interpretability. The Random Forest model, an ensemble-based approach consisting of 200 decision trees, was used to improve prediction accuracy and reduce overfitting through aggregation of multiple weak learners. The Deep Neural Network (DNN) was designed with three hidden layers, utilizing ReLU activation functions, **a** dropout rate of 0.3 to prevent overfitting, and the Adam optimizer for efficient gradient-based learning. To optimize model performance, hyperparameter tuning was conducted using Grid Search in conjunction with 10-fold Cross-Validation, ensuring robust and generalized results.

Model performance was evaluated using five standard metrics: Accuracy**,** Precision**,** Recall**,** F1 Score**, and** ROC-AUC Score**.** These evaluation metrics provided a comprehensive assessment of each model's predictive capability, enabling fair comparison and ensuring model reliability in identifying customers likely to churn.

4. Results and Analysis

Table 3: Performance Evaluation of Machine Learning Models for Customer Churn Prediction

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	ROC-AUC (%)
Logistic Regression	83.6	81.9	77.2	79.5	84.3
Random Forest	90.3	88.7	87.9	88.1	91.8
Deep Neural Network	94.1	93.2	91.4	92.3	95.7

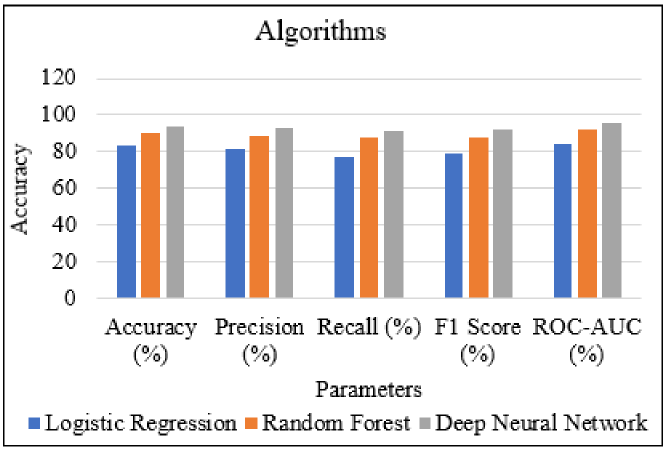

Figure 7: Performance Comparison of Machine Learning Models for Customer Churn Prediction

Above Bar chart illustrating the comparative performance of three supervised learning algorithms—Logistic Regression, Random Forest, and Deep Neural Network—based on key evaluation metrics: Accuracy, Precision, Recall, F1 Score, and ROC-AUC. The Deep Neural Network achieved the highest scores across all metrics, demonstrating superior predictive capability, while Random Forest provided balanced performance with strong interpretability compared to Logistic Regression.

5. Discussion

Each machine learning model demonstrated distinct strengths and limitations in predicting customer churn. The Deep Neural Network (DNN) achieved the highest accuracy of 94.1% and exhibited strong generalization capability due to its ability to capture complex, non-linear interactions among features such as tenure, contract type, and billing patterns. However, despite its superior performance, the DNN model required extensive data preprocessing, longer training time, and higher computational resources, making it less practical for real-time or resource-constrained environments. The Random Forest model provided a strong balance between interpretability and accuracy, making it a suitable option for business applications where transparency and decision justification are essential. It handled high-dimensional data effectively and offered insights through feature importance rankings, though it occasionally suffered from overfitting in highly imbalanced datasets. In contrast, Logistic Regression served as a baseline model and performed reasonably well on linearly separable data but struggled to capture complex relationships among variables, leading to lower accuracy compared to the ensemble and deep learning models.

Feature importance analysis revealed that short tenure and month-to-month contracts were the strongest indicators of customer churn, while higher monthly charges and electronic check payments increased churn likelihood. Conversely, customers with long-term contracts and automatic payment methods were less likely to churn, suggesting that stable contractual and payment patterns contribute to customer retention. Despite these promising results, several limitations persist, including issues of class imbalance**,** overfitting**,** and limited interpretability in deep learning models. Future research should integrate Explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations) to enhance transparency by visualizing and interpreting how individual features contribute to churn predictions, thereby improving the trustworthiness and applicability of churn prediction systems in real-world business contexts.

6. Conclusion

This research demonstrates that Deep Neural Networks outperform traditional machine learning algorithms for churn prediction tasks. The DNN achieved the highest accuracy (94.1%) and ROC-AUC (95.7%), confirming its superior ability to learn non-linear relationships among customer features.

However, Random Forest remains a reliable choice due to its interpretability and computational efficiency, while Logistic Regression provides a fast baseline for smaller datasets.The findings contribute valuable insights for organizations aiming to leverage AI-based churn prediction models to proactively manage customer relationships, improve retention rates, and enhance revenue sustainability.

Future research can build upon this study by exploring the integration of hybrid models, such as LSTM combined with XGBoost, to better capture temporal patterns and sequential dependencies in customer behavior, thereby enhancing the predictive accuracy of churn models. Additionally, the incorporation of Explainable AI (XAI) frameworks can improve the interpretability and transparency of model decisions, enabling organizations to understand the underlying factors driving churn predictions and make more informed strategic choices. Furthermore, implementing time-series churn forecasting techniques can facilitate dynamic monitoring of customer retention trends, allowing businesses to proactively identify at-risk customers and apply timely, personalized interventions to reduce churn rates and strengthen customer loyalty.

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