



Bangladesh Army University of Science and Technology (BAUST) Saidpur Cantonment, Nilphamari

Department of Computer Science and Engineering (CSE)

Course Code: CSE 4140

**Course Title: Machine Learning Sessional
Customer Churn Prediction using Machine Learning**

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Introduction

- Customer churn refers to the loss of existing customers over a given period.
- Telecom industries face significant revenue loss due to high churn rates.
- Machine Learning enables data-driven identification of customers likely to churn.

Key Focus

- Identify churn vs. non-churn customers
- Support decision-making using data-driven insights



Objectives

- To detect customers who are likely to churn.
- To analyze key features that influence churn.
- To apply machine learning algorithms for churn prediction.
- To evaluate model performance using standard ML metrics.

Related Works

In [1], **Ahmad et al., 2019** proposed a “Customer Churn Prediction Framework Using Machine Learning in Big Data Platform.”

Shortcomings:

- Features were not easy to interpret.
- Did not evaluate using ROC curves or thresholds.
- Did not fully handle class imbalance in the data.

Related Works (Cont.)

In [2], Vafeiadis et al., 2015

conducted “A Comparison of Machine Learning Techniques for Customer Churn Prediction.”

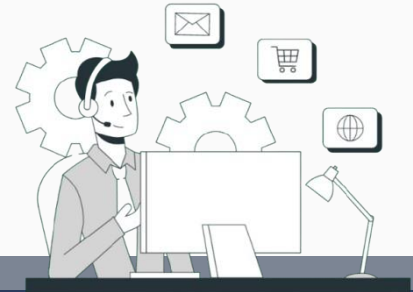
Shortcomings:

- Focused mainly on accuracy, ignoring other important metrics.
- Did not analyze performance per class (no confusion matrix).
- Limited handling of noisy or imbalanced data.

Dataset

[3] Kaggle Customer Churn Dataset

- 7043 customers
- Features: Tenure, Monthly Charges, Internet Service, Contract Type, etc.
- Target Variable: Churn (Yes/No)
- Highly imbalanced dataset (more Non-Churn than Churn)



Methodology

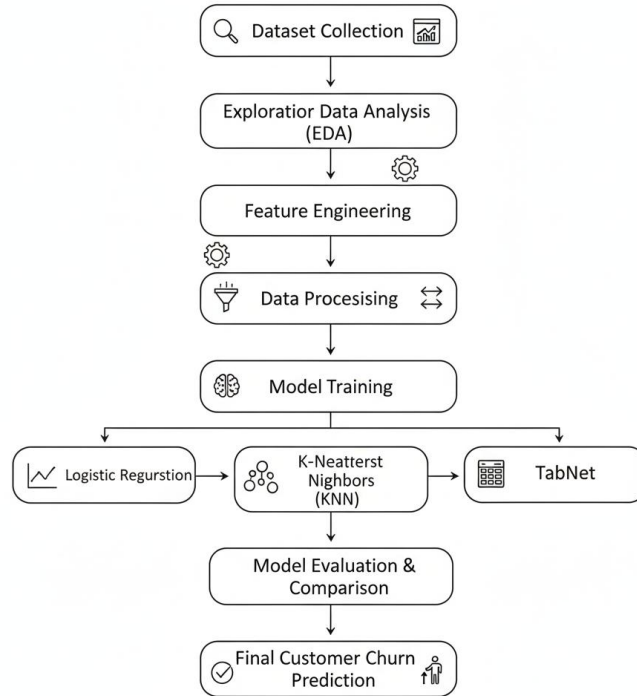


Figure-01: Methodology



Models Used

- Logistic Regression
- K-Nearest Neighbors
- Decision Tree (Tebnet)

Models Used (Cont.)

Logistic Regression Results: Accuracy: 79%

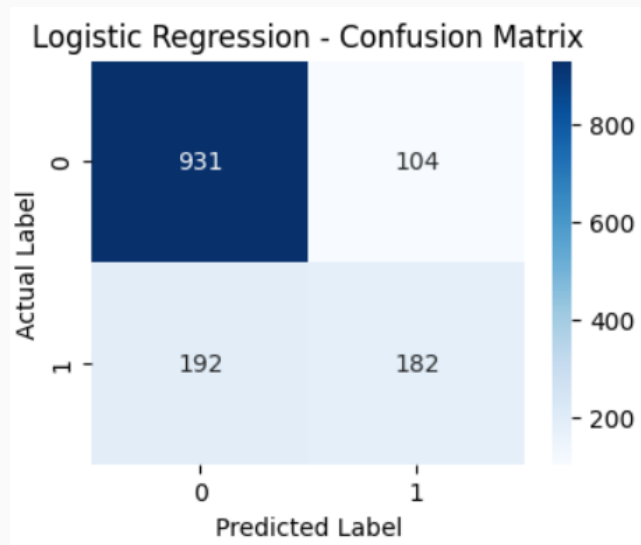


Figure-02: Confusion matrix for Logistic Regression Model

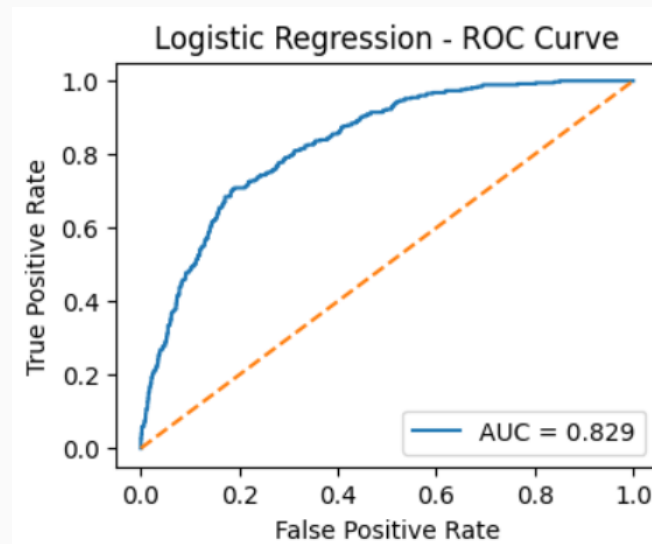


Figure-03: ROC Curve for Logistic Regression Model

Model Used (Cont.)

KNN Model Results: Accuracy: 78%

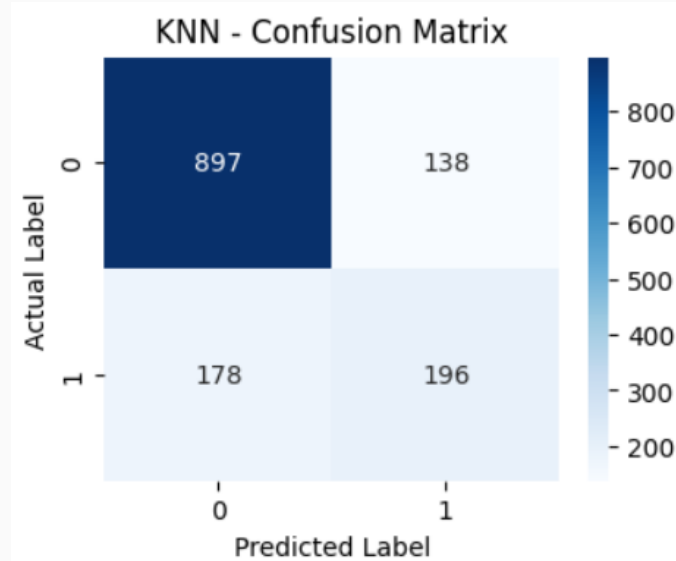


Figure-04: Confusion matrix for KNN Model

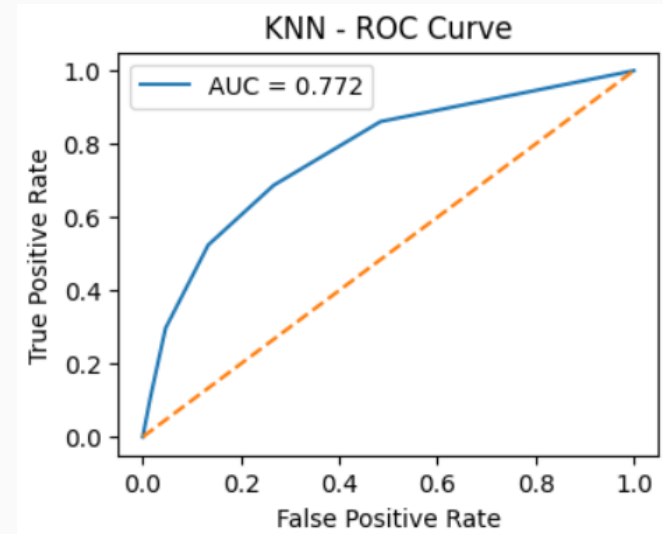


Figure-05: ROC Curve for KNN Model

Model Used (Cont.)

Decision Tree (Tebnet) Results: Accuracy: 72%

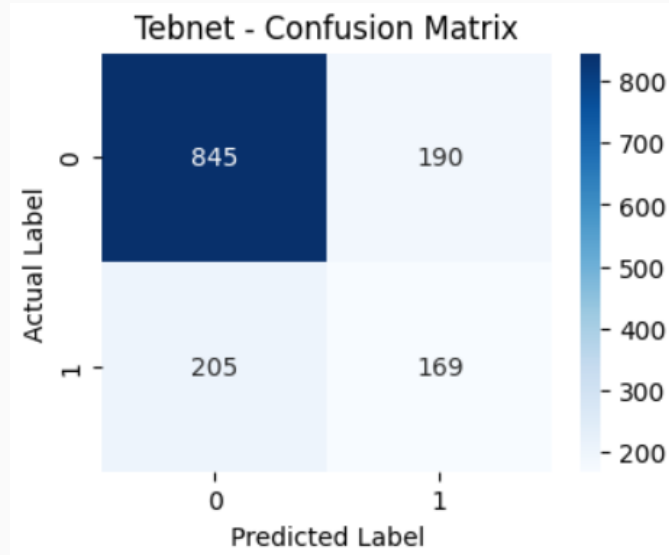


Figure-06: Confusion matrix for Tebnet Model

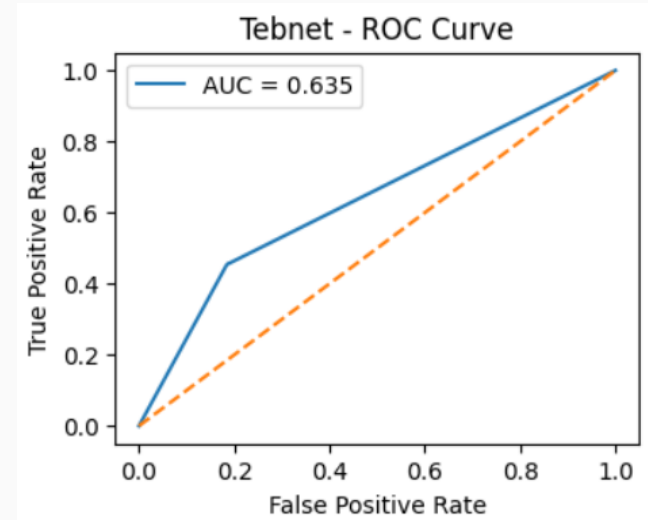


Figure-07: ROC Curve for Tebnet Model

Comparison Table

| Model | Precision | Recall | F1-Score | Accuracy |
|---------------------|-----------|--------|----------|----------|
| Logistic Regression | 0.78 | 0.79 | 0.78 | 0.79 |
| KNN | 0.77 | 0.78 | 0.77 | 0.78 |
| Decision Tree | 0.72 | 0.72 | 0.72 | 0.72 |

Our Improvements

| Paper | Shortcomings | How Our Model Improves |
|------------------------|--|--|
| Ahmad et al., 2019 | No ROC | Includes ROC curves |
| Vafeiadis et al., 2015 | Focused only on accuracy; No class-level evaluation | Uses multiple metrics (precision, recall, F1); Confusion matrix for per-class performance |

Conclusion

- Logistic Regression showed best performance.
- KNN provided balanced results but still struggled with churn class.
- Decision Tree overfitted and performed worst.

References

- [1] A. K. Ahmad, A. Jafar, and K. Aljoumaa, *Journal of Big Data*, vol. 6, no. 28, 2019.
- [2] S. Vafeiadis et al., *International Journal of Computer Applications*, vol. 127, no. 8, 2015.
- [3] Kaggle, “Customer Churn Dataset,” Kaggle, 2018. [Online]. Available: <https://www.kaggle.com/datasets/rashadrmammadov/customer-churn-dataset>.



Thanks

Any Questions?