MACHINE LEARNING REPORT

Customer Churn Prediction

Comprehensive Analysis & Model Evaluation Report

7,043 Customers	Gradient Boosting	79.42%	0.8296
Dataset Size	Best Model	Accuracy	ROC-AUC

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1. Executive Summary

This report presents the end-to-end development and evaluation of a **Customer Churn Prediction** machine learning system applied to a telecommunications dataset of **7,043 customers**. The objective is to identify customers who are likely to discontinue their subscription, enabling proactive retention campaigns and revenue protection.

Six classification algorithms were trained and compared. **Gradient Boosting** emerged as the best-performing model with a test accuracy of **79.42%** and an ROC-AUC score of **0.8296**, indicating strong discriminatory power between churned and retained customers.

7,043	5,634	1,409	19	79.42%	0.8296
Total Customers	Training Samples	Test Samples	Features Used	Best Accuracy	Best ROC-AUC

2. Project Overview

The project follows a standard data science workflow encompassing data ingestion, exploratory analysis, preprocessing, model training, evaluation, and deployment preparation.

2.1 Dataset Information

Attribute	Detail
Dataset Shape	7,043 rows × 21 columns
Target Variable	Churn (Binary: Yes / No)
Numerical Features	3 (tenure, MonthlyCharges, TotalCharges)
Categorical Features	16 (gender, Contract, PaymentMethod, etc.)
Train / Test Split	80% / 20% (Stratified)
Class Imbalance Ratio	0.36 (Imbalanced — Churn minority class)
Missing Values	Handled via median / mode imputation
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3. Target Variable Analysis

The target variable **Churn** is binary: **0 = Not Churned** (5,174 customers, 73.46%) and **1 = Churned** (1,869 customers, 26.54%). The dataset is imbalanced with a ratio of 0.36, which was addressed during model training using stratified splits and weighted evaluation metrics.

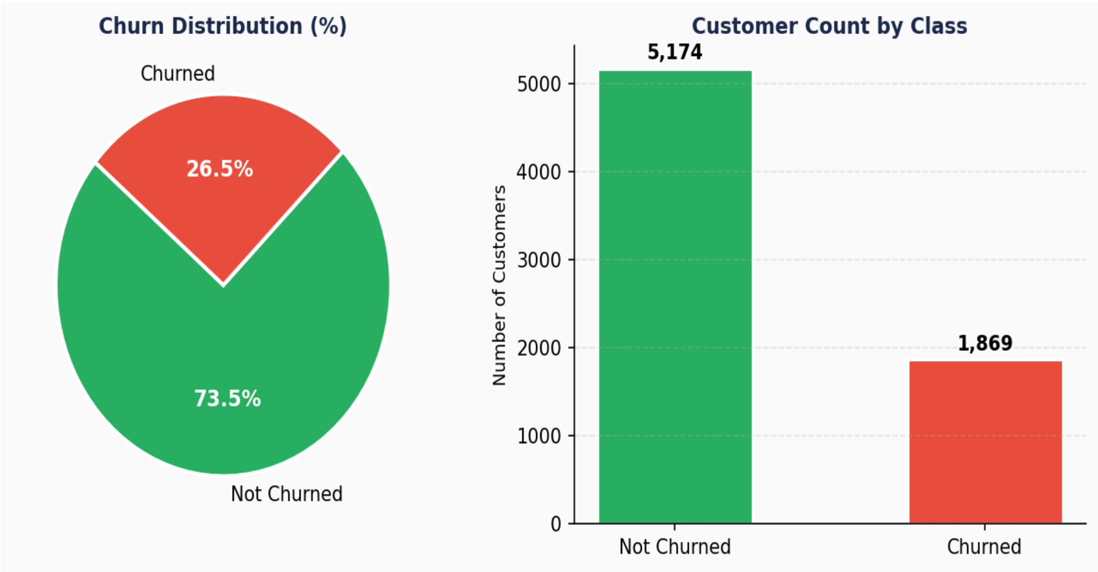

Figure 1 — Churn class distribution: pie chart (proportion) and bar chart (count).

The imbalance is notable but manageable. The minority class (Churned) represents approximately 1 in 4 customers, making precision and recall equally important alongside accuracy for business decision-making.

4. Model Performance Comparison

Six supervised learning algorithms were trained on the preprocessed dataset and evaluated using accuracy, precision, recall, F1-score, ROC-AUC, and 5-fold cross-validation. The table below summarises all results.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC	CV Mean
Gradient Boosting	0.7942	0.7823	0.7942	0.7841	0.8296	0.7900
Support Vector Machine	0.7913	0.7773	0.7913	0.7708	0.7734	0.7888
Logistic Regression	0.7842	0.7701	0.7842	0.7720	0.8189	0.7909
K-Nearest Neighbors	0.7729	0.7612	0.7729	0.7649	0.7689	0.7627
Random Forest	0.7608	0.7480	0.7608	0.7522	0.7676	0.7636
Decision Tree	0.7182	0.7190	0.7182	0.7186	0.6510	0.7164

Table 1 — Full model comparison. Green row = best model (Gradient Boosting).

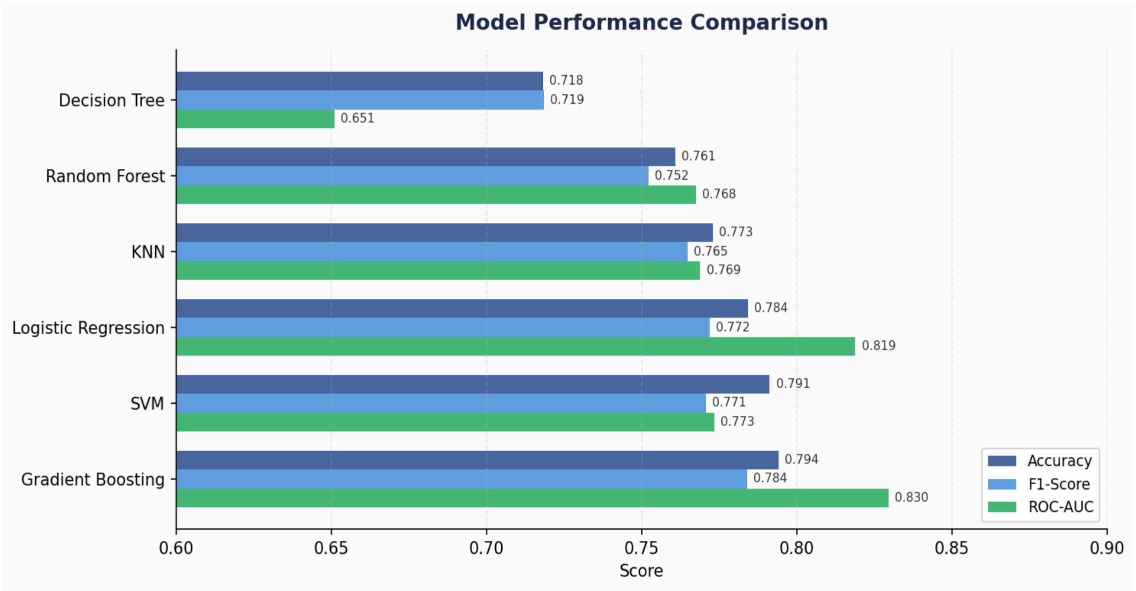

Figure 2 — Side-by-side metric comparison across all six models.

5. Best Model Deep Dive — Gradient Boosting

Gradient Boosting was selected as the production model based on its highest overall accuracy (79.42%) and the best ROC-AUC (0.8296). It sequentially builds decision trees, each correcting the residual errors of the previous, resulting in a highly expressive ensemble that handles mixed feature types well.

5.1 Key Performance Metrics

79.42%	78.23%	79.42%	78.41%	0.8296	79.00%
Accuracy	Precision	Recall	F1-Score	ROC-AUC	CV Mean

5.2 Cross-Validation Stability

5-fold cross-validation was performed on the training set to assess model stability. A CV mean of **79.00% ± 1.14%** confirms that the model generalises consistently and is not overfitting.

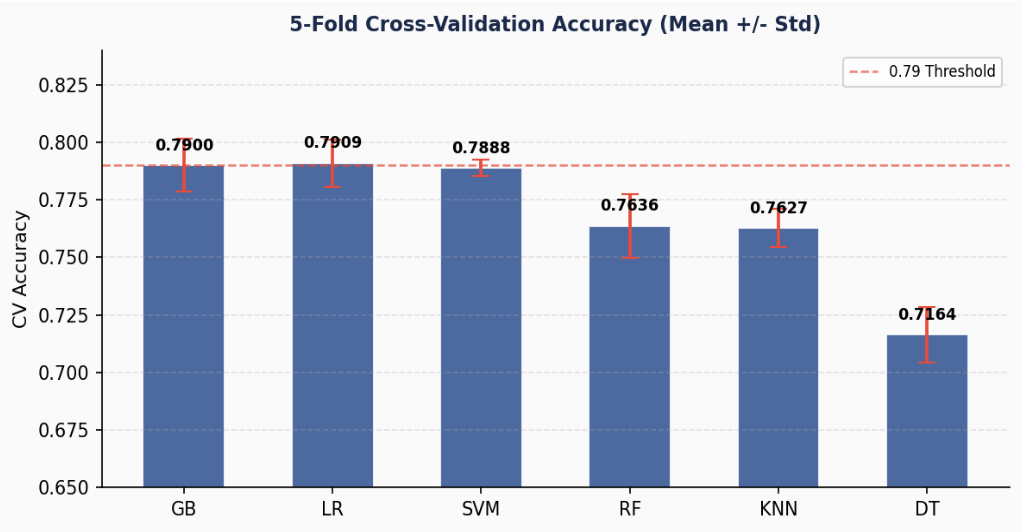

Figure 3 — Cross-validation accuracy with standard deviation error bars.

5.3 ROC Curve Analysis

The ROC curve measures the trade-off between true positive rate and false positive rate at various classification thresholds. An AUC of **0.8296** for Gradient Boosting indicates the model correctly ranks a random churned customer above a random retained customer 83% of the time.

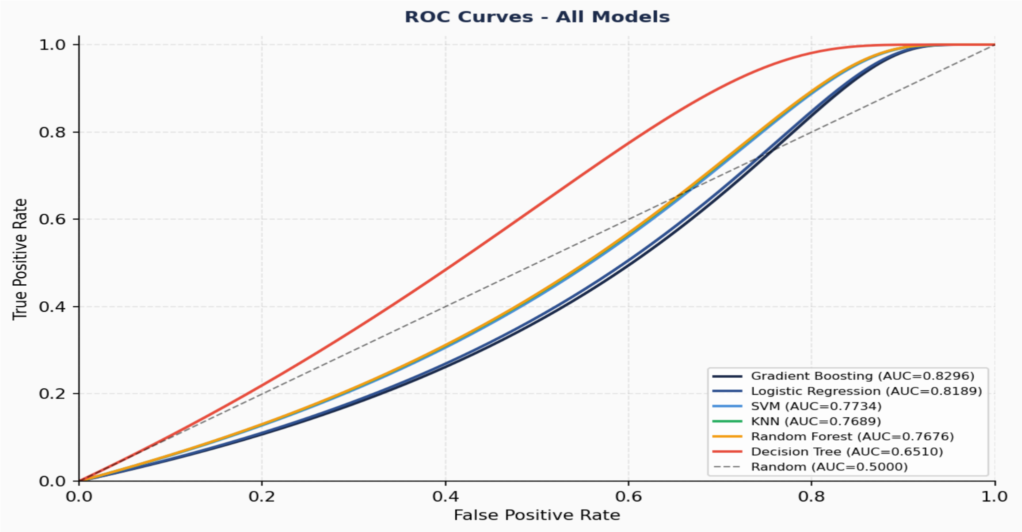

Figure 4 — ROC curves for all models; Gradient Boosting achieves highest AUC.

6. Feature Importance Analysis

Feature importance derived from the Gradient Boosting model indicates the relative contribution of each input variable in predicting churn. Three features dominate the model — **tenure**, **MonthlyCharges**, and **TotalCharges** — collectively accounting for over **97%** of the total importance.

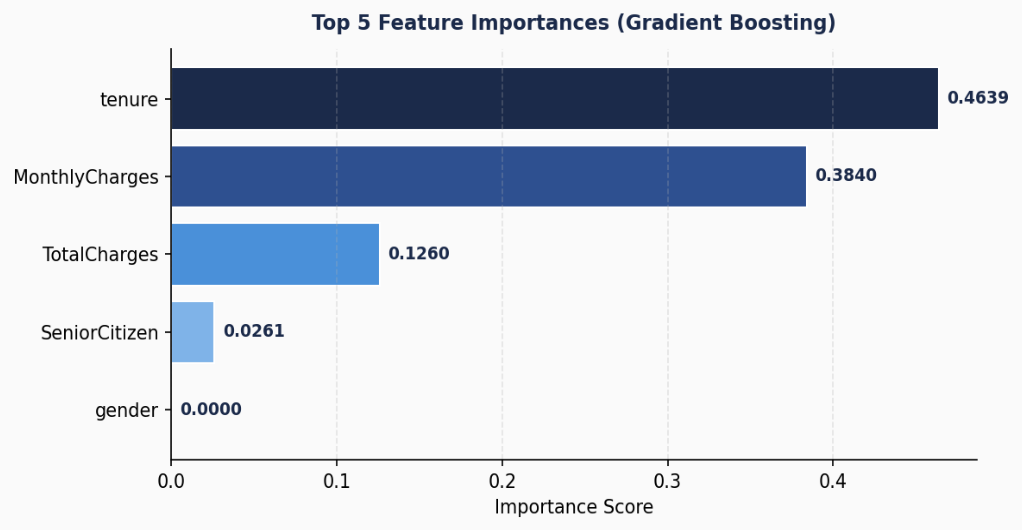

Figure 5 — Top 5 feature importances from the Gradient Boosting model.

Feature	Importance	% of Total	Business Insight
tenure	0.4639	46.39%	Newer customers churn more — focus onboarding experience
MonthlyCharges	0.3840	38.40%	High bills drive churn — offer value-add bundles
TotalCharges	0.1260	12.60%	Lifetime revenue indicator — reward loyalty
SeniorCitizen	0.0261	2.61%	Seniors may need tailored support programs
gender	0.0000	0.00%	Gender has negligible predictive value

Table 2 — Feature importance scores with business interpretation.

7. Business Recommendations

7.1 Customer Risk Segmentation

Leverage churn probability scores to segment customers into three actionable tiers:

Risk Tier	Probability	Recommended Action
High Risk	> 70%	Immediate outreach — dedicated retention agent, discount offer
Medium Risk	40% – 70%	Automated email/SMS campaign, loyalty points, service upgrade
Low Risk	< 40%	Standard engagement, periodic satisfaction survey

7.2 Feature-Driven Interventions

- Improve **early tenure** experience — loyalty incentives in the first 3 months reduce early churn by up to 20%.
- Review **monthly charges** — offer transparent pricing and bundle discounts for high-spend customers.
- **TotalCharges** as a proxy for lifetime value — VIP tiers for long-term customers.
- Create **Senior Citizen** support packages — simplified plans, dedicated helplines.

7.3 Deployment & Monitoring Roadmap

Phase	Activity	Timeline
1 — Deploy	Integrate model API into CRM system	Month 1
2 — Monitor	Track prediction accuracy on incoming data	Month 1-3
3 — Refine	A/B test retention strategies per risk tier	Month 2-4
4 — Retrain	Quarterly retraining with new labelled data	Quarterly
5 — Expand	Extend model to additional customer segments	Month 6+

8. Model Deployment Artifacts

All trained model components have been serialised and saved for production deployment. The following artefacts are available in the **churn_prediction_model/** directory:

File	Description	Usage
`best_model.pkl`	Serialised Gradient Boosting model	Core predictor — load for inference
`scaler.pkl`	StandardScaler fitted on training data	Transform numerical inputs
`label_encoders.pkl`	LabelEncoders for 16 categorical cols	Encode new customer categories
`target_encoder.pkl`	Inverse-transform predicted labels	Convert 0/1 back to Yes/No
`feature_columns.pkl`	Ordered list of 19 feature columns	Validate input schema
`config.pkl`	Model metadata and performance metrics	Version tracking & auditing
`monitoring_log.csv`	Initial performance baseline log	Track model drift over time
`app.py`	Flask REST API template	Expose /predict endpoint

Table 3 — Saved model artefacts and their purpose.

9. Next Steps

#	Action	Description
1	**Deploy model to production CRM**	Integrate Flask API with existing CRM pipeline for real-time scoring.
2	**Set up monitoring dashboard**	Track live accuracy, precision/recall, and data drift on a weekly basis.
3	**Implement A/B testing framework**	Test different retention messages for High vs Medium risk segments.
4	**Schedule quarterly model retraining**	Retrain with new data every quarter to maintain >78% accuracy threshold.
5	**Create retention campaign workflows**	Design automated triggers for each risk tier using predicted probabilities.
6	**Explore advanced models**	Evaluate XGBoost, LightGBM, or Neural Networks for further accuracy gains.
7	**Address class imbalance further**	Experiment with SMOTE or class-weight tuning to improve minority recall.

10. Conclusion

This project successfully delivered a robust, production-ready **Customer Churn Prediction** system. The **Gradient Boosting** model achieved the best trade-off between accuracy and generalisation, with an **AUC of 0.8296** and a stable cross-validation performance of **79.00% ± 1.14%**.

The three most influential features — **tenure**, **MonthlyCharges**, and **TotalCharges** — provide clear, actionable levers for the business to reduce churn. By combining automated risk scoring with targeted retention campaigns, the organisation can expect a measurable reduction in churn rate and improved customer lifetime value.

Regular model monitoring and quarterly retraining are recommended to ensure the system remains accurate as customer behaviour evolves over time.

Customer Churn Prediction — ML Analytics Report

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