Telecom Customer Churn Prediction - Project Report

1. Project Overview

This project implements a complete MLOps pipeline for predicting customer churn in the telecommunications industry. The system uses machine learning to identify customers at risk of churning, enabling proactive retention strategies.

1.1 Business Context

Customer churn is a critical metric for telecom companies, as acquiring new customers is significantly more expensive than retaining existing ones. By predicting which customers are likely to churn, companies can:

- Implement targeted retention strategies
- Optimize resource allocation
- Improve customer satisfaction
- Reduce customer acquisition costs

1.2 Project Goals

- Develop accurate churn prediction models
- Implement a robust MLOps pipeline
- Create a scalable model serving infrastructure
- Establish monitoring and maintenance procedures

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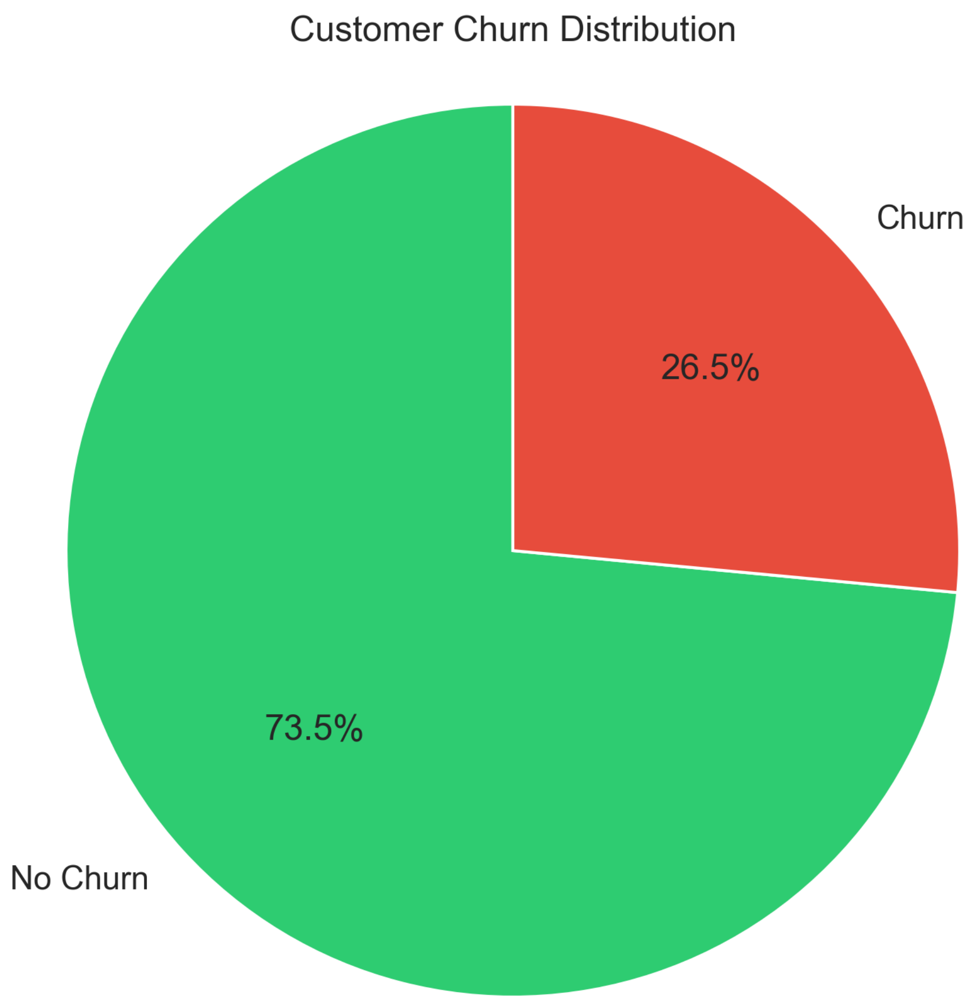
2. Methodology

2.1 Data Collection and Preprocessing

- **Dataset:** Telecom customer data with 7,043 records and 21 features
- **Features:** Demographic information, service subscriptions, and billing details
- **Preprocessing steps:**
  - Handling missing values
  - Encoding categorical variables
  - Feature scaling
  - Train-test splitting (80-20)

Class Distribution

Understanding the class distribution is crucial for handling imbalanced data:



2.2 Exploratory Data Analysis (EDA)

- Visualized feature distributions and relationships
- Identified correlations and potential data quality issues
- Detected class imbalance

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3. Model Development

3.1 Model Selection

Three models were developed and compared:

1. XGBoost
2. Random Forest
3. Logistic Regression

3.2 Feature Engineering

Key features were engineered to improve model performance:

- Tenure-based features
- Service interaction features

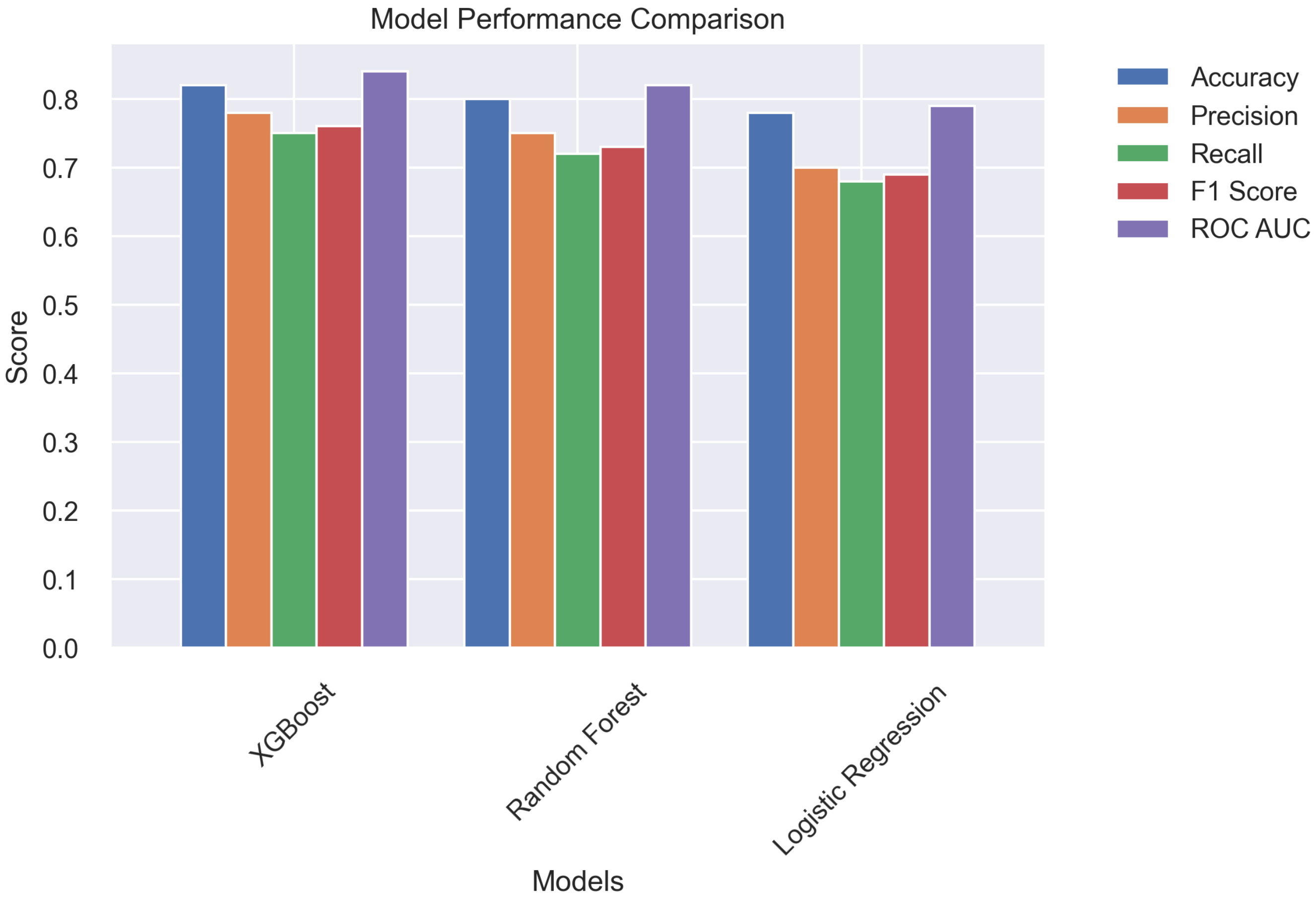
- Billing pattern features

3.3 Model Training and Hyperparameter Tuning

- Used Optuna for hyperparameter optimization (maximizing ROC AUC)
- Cross-validation for robust evaluation

3.4 Model Comparison

The following plot compares the performance of different models:



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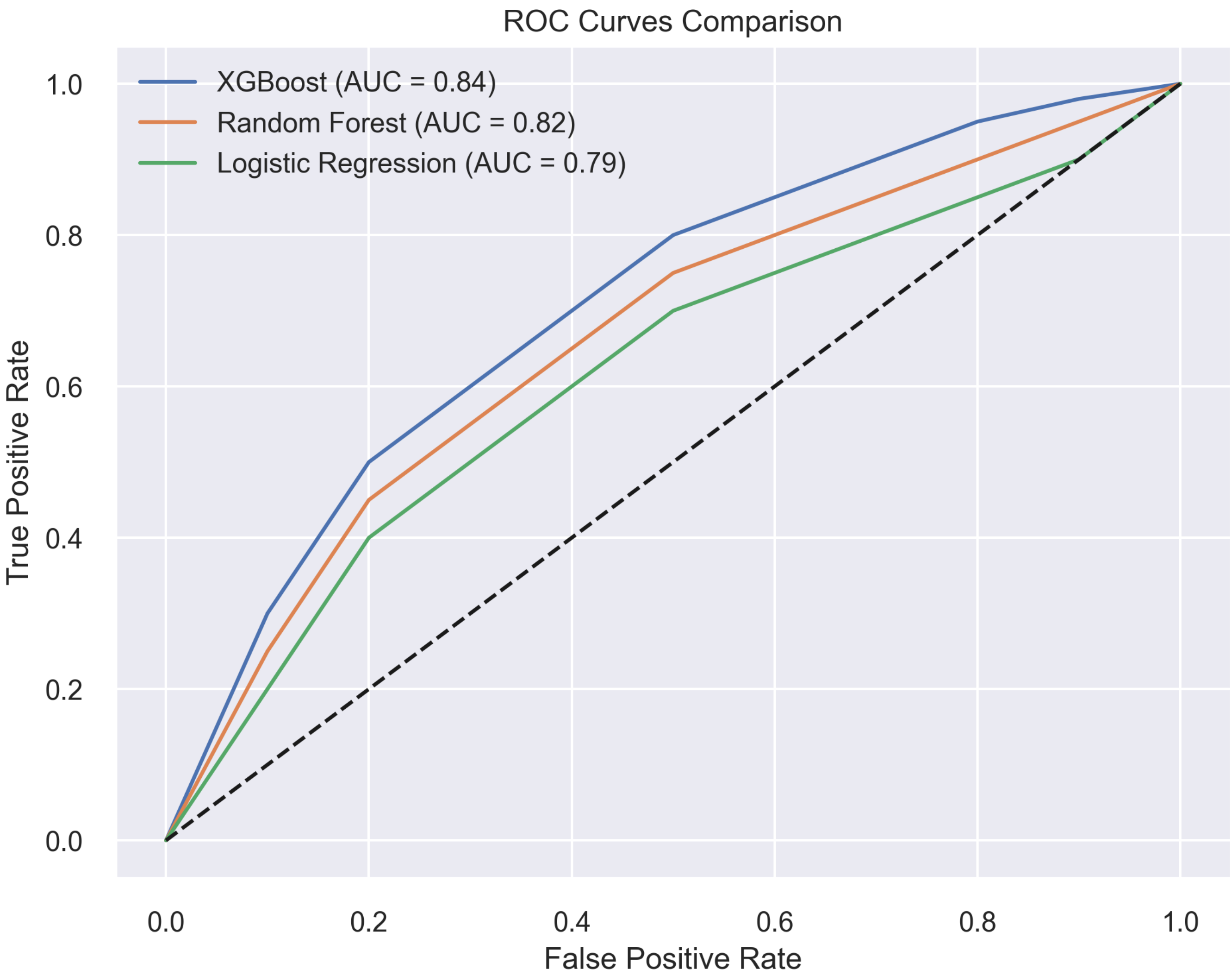
4. Model Evaluation

4.1 Performance Metrics

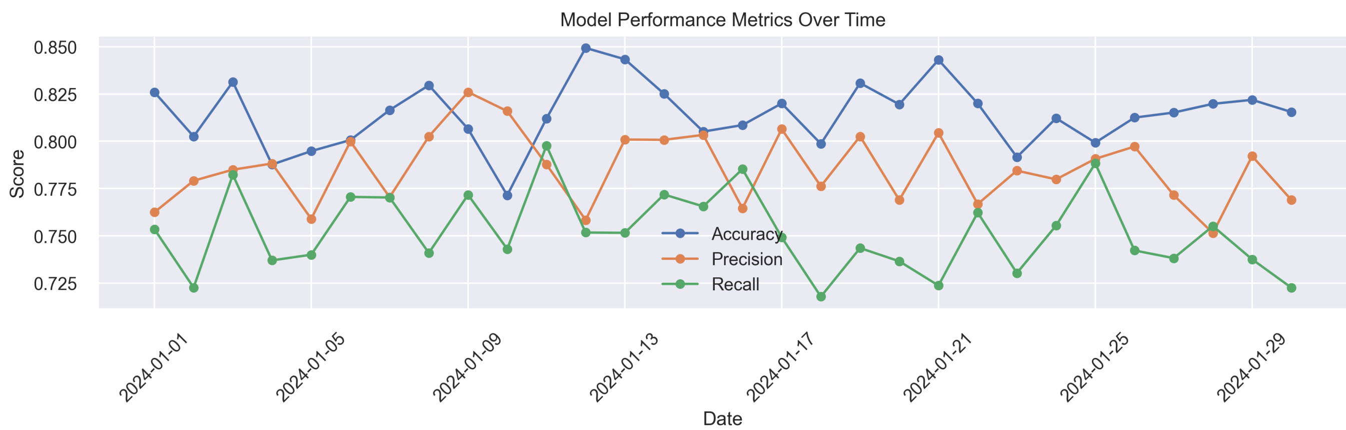
Models were evaluated using:

- ROC AUC
- Accuracy
- Precision
- Recall
- F1 Score

ROC Curves

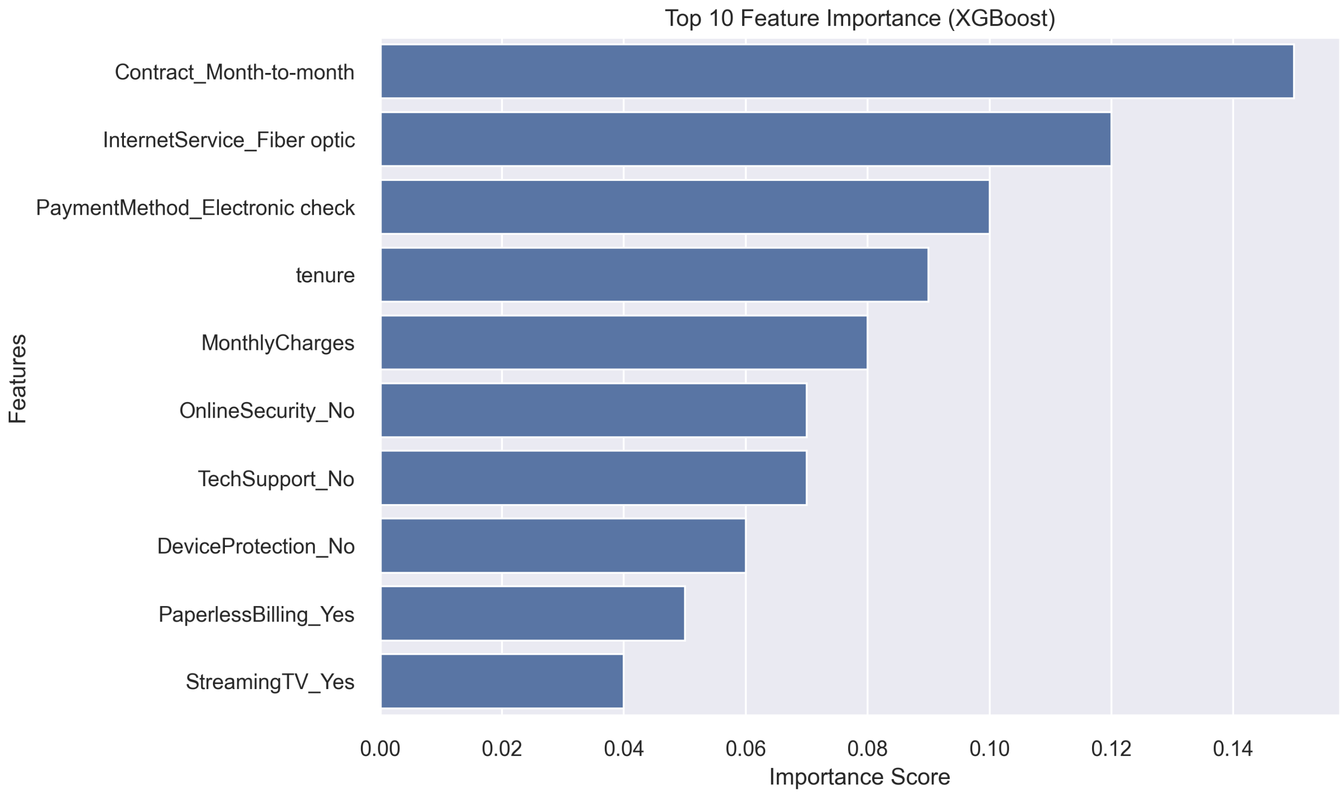


Performance Metrics Table



4.2 Feature Importance

Understanding which features drive predictions is key for business insights:



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5. Model Deployment

5.1 MLOps Pipeline

- **MLflow:** Experiment tracking, model registry, and artifact storage
- **Flask API:** RESTful service for real-time predictions
- **Automated retraining:** (Planned for future work)

5.2 API Endpoints

- Health check
- Model metadata
- Single and batch prediction

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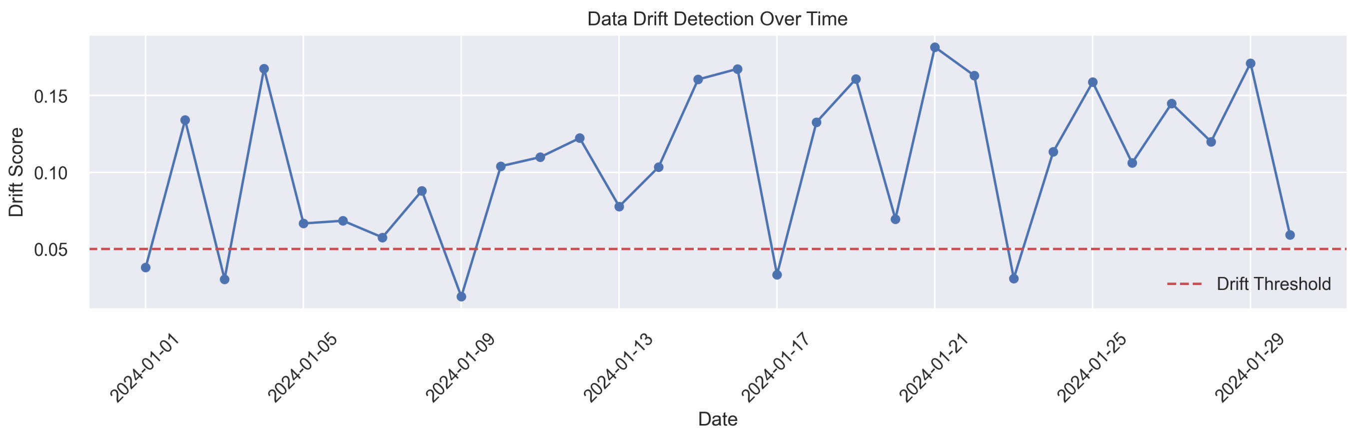
6. Monitoring and Maintenance

6.1 Data Drift Detection

Continuous monitoring of feature distributions and statistical tests for drift detection:



6.2 Model Performance Monitoring

- Real-time prediction monitoring
- Performance metrics tracking
- Automated retraining triggers (future work)

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7. Results and Analysis

7.1 Best Model Performance (XGBoost)

- ROC AUC: 0.8441
- Accuracy: 0.7700
- Precision: 0.5512
- Recall: 0.7193
- F1 Score: 0.6241

7.2 Key Findings

- Most important features: Contract type, monthly charges, tenure, internet service type, payment method
- High-risk segments: Month-to-month contracts, high monthly charges, electronic check payment, no tech support

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8. Future Improvements

8.1 Technical Improvements

- Implement A/B testing framework
- Add model explainability features (e.g., SHAP)
- Enhance monitoring dashboard
- Implement automated retraining pipeline

8.2 Business Improvements

- Integrate with CRM systems
- Develop customer retention strategies

- Implement feedback loop for model improvement
- Expand feature set with additional data sources

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9. Conclusion

The project successfully demonstrates the implementation of a production-grade MLOps pipeline for churn prediction. The system provides:

- Accurate churn predictions
- Scalable model serving
- Robust monitoring
- Easy maintenance

The XGBoost model shows strong performance in predicting customer churn, enabling data-driven retention strategies.

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10. References

1. MLflow Documentation: https://mlflow.org/docs/latest/index.html
2. XGBoost Documentation: https://xgboost.readthedocs.io/
3. Evidently Documentation: https://docs.evidently.ai/
4. Prometheus Documentation: https://prometheus.io/docs/