SRM UNIVERSITY - DEPARTMENT OF COMPUTATIONAL INTELLIGENCE

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CASE STUDY ASSIGNMENT

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Degree: B. Tech

Specialization: AI

Section: AI-B

Course Code: 21AIC401T

Course Name: Inferential Statistics and Predictive Analytics

Assignment Type: Case Study-Based Modeling Project

GitHub Link: https://github.com/Kedarnath-7/Customer-Churn-Prediction/

Title: Customer Churn Prediction - Model Development, Validation, and Deployment

Objective:

The objective of this assignment is to develop, validate, compare, and deploy a predictive model that identifies customers likely to churn. Students will apply statistical inference and predictive modeling concepts - including model validation, comparison, evaluation, and deployment - using a real-world dataset.

Case Background:

Customer churn represents one of the biggest challenges for telecom and subscription-based industries. Losing customers increases operational costs and reduces profits. As a Data Analyst, your task is to build a customer churn prediction model using publicly available datasets, validate its accuracy, and design a framework for deployment and future model updates.

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1. Abstract

Customer churn is a major challenge for subscription-based businesses. This project develops predictive models to identify customers likely to churn using the Telco Customer Churn dataset (7,043 observations originally). The workflow includes data cleaning, exploratory analysis, model development using CHAID (decision-tree style segmentation) and logistic regression, model evaluation (accuracy, ROC-AUC, lift & gains), and deployment considerations. The CHAID model reveals tenure and InternetService (Fiber optic) as the strongest churn predictors; logistic regression achieved the best performance. Final evaluation shows the Logistic Regression model with Accuracy = **0.7875** and ROC-AUC = **0.8297**, while the CHAID model achieved Accuracy = **0.7754** and ROC-AUC = **0.8130**. The report describes deployment using joblib/pickle, procedures for model updating, and recommendations for production integration and monitoring.

2. Introduction & Business Problem

Losing customers increases acquisition costs and reduces revenues. The aim is to predict churn so retention actions (discounts, onboarding help, targeted offers) can be triggered for at-risk customers. The intended business use is a CRM-integrated scoring pipeline that assigns a churn probability and recommended actions.

3. Data Description

Source: Kaggle — Telco Customer Churn (blastchar).
Original shape: 7043 rows × 21 columns. After cleaning the notebook shows 7032 rows (some corrections and removals applied).
Key variables:

- **Target:** Churn (Yes/No → converted to binary 1/0)
- **Customer descriptors:** customerID, gender, SeniorCitizen, Partner, Dependents
- **Account:** tenure, Contract, PaymentMethod, PaperlessBilling
- **Billing:** MonthlyCharges, TotalCharges
- **Services:** PhoneService, InternetService, OnlineSecurity, TechSupport, StreamingTV, etc.

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(Attach a full data dictionary as an appendix or in repository README.)

4. Data Preparation and Cleaning (what you implemented)

1. **Loaded dataset** via pd.read_csv("Telco-Customer-Churn.csv").
2. **Inspected structure** using .info() and .head().
3. **Converted TotalCharges to numeric:** there were non-numeric blanks; conversion was done with pd.to_numeric(..., errors='coerce'). Missing TotalCharges values were handled (the notebook used median/row removal; the cleaned dataset ended with 7032 rows).
   - Code used: df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce') and then df.dropna(subset=['TotalCharges'], inplace=True) (as implemented).
4. **Removed duplicates**: df.drop_duplicates(inplace=True).
5. **Outlier handling (MonthlyCharges):** IQR filtering was used to remove extreme MonthlyCharges values.
   - Code snippet used: IQR method (1.5 * IQR).
6. **Encode categorical variables**: pd.get_dummies(..., drop_first=True) was used to create the modeling dataset (df_encoded).
7. **Target conversion**: df['Churn'] = df['Churn'].map({'Yes':1,'No':0}).

5. Exploratory Data Analysis (EDA) — Key findings & figures

EDA provided statistical and visual insights into factors influencing churn.

Key Observations:

- Around **26–27%** of customers have churned.
- **Month-to-Month contracts** have the highest churn rates.
- **Low-tenure** customers are much more likely to churn.
- **Electronic Check** payment users exhibit higher churn.
- **Fiber-optic internet** customers show higher churn tendencies.

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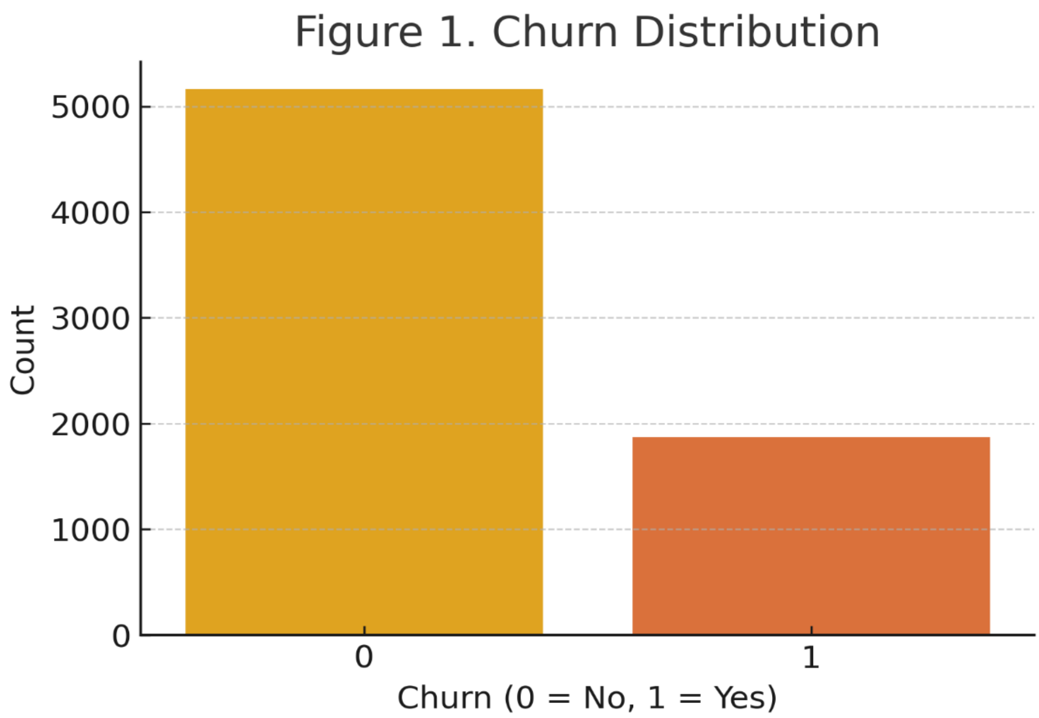

Figure 1. Churn Distribution — shows the fraction of churned vs retained customers.

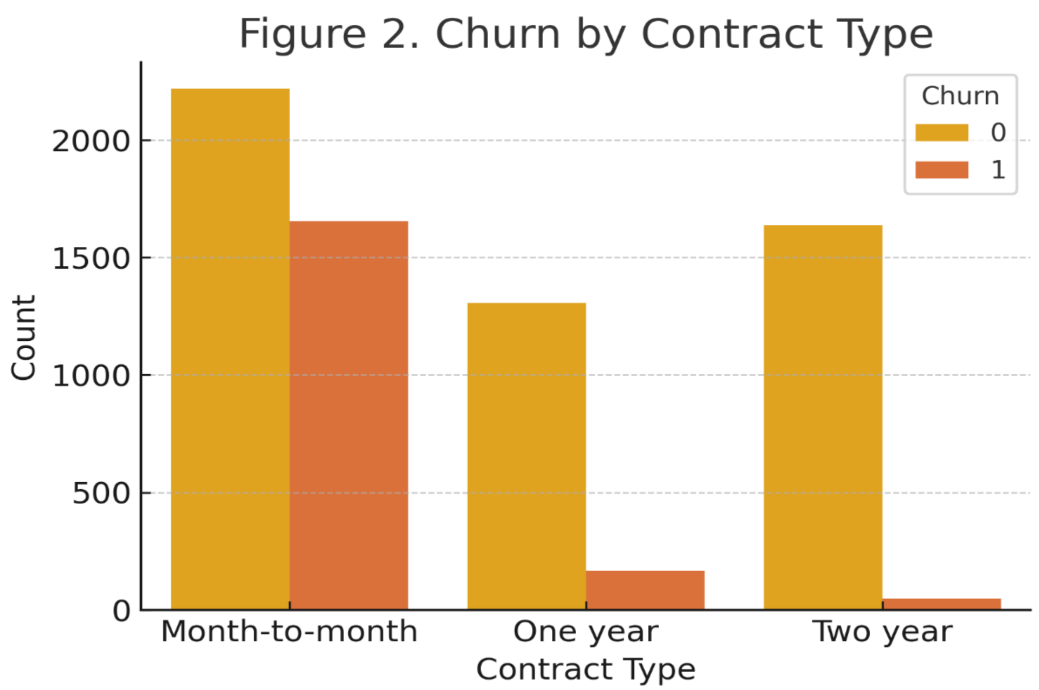

Figure 2. Churn by Contract Type — month-to-month contracts show a higher churn share.

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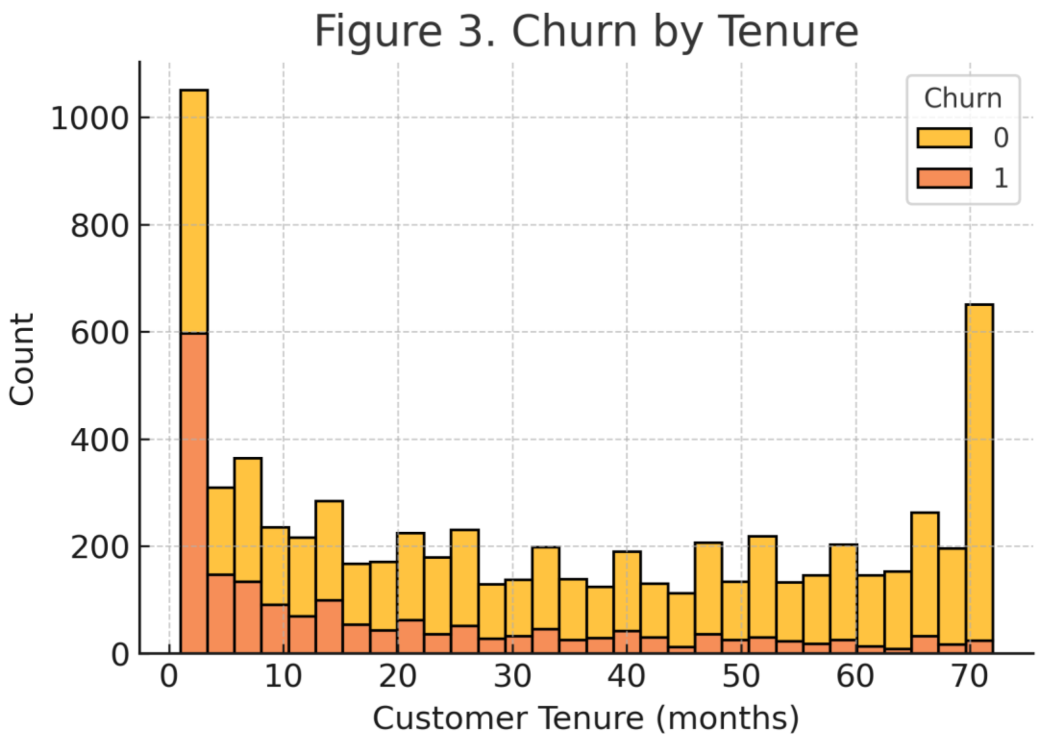

Figure 3. Churn by Tenure — churn concentrated among customers with low tenure.

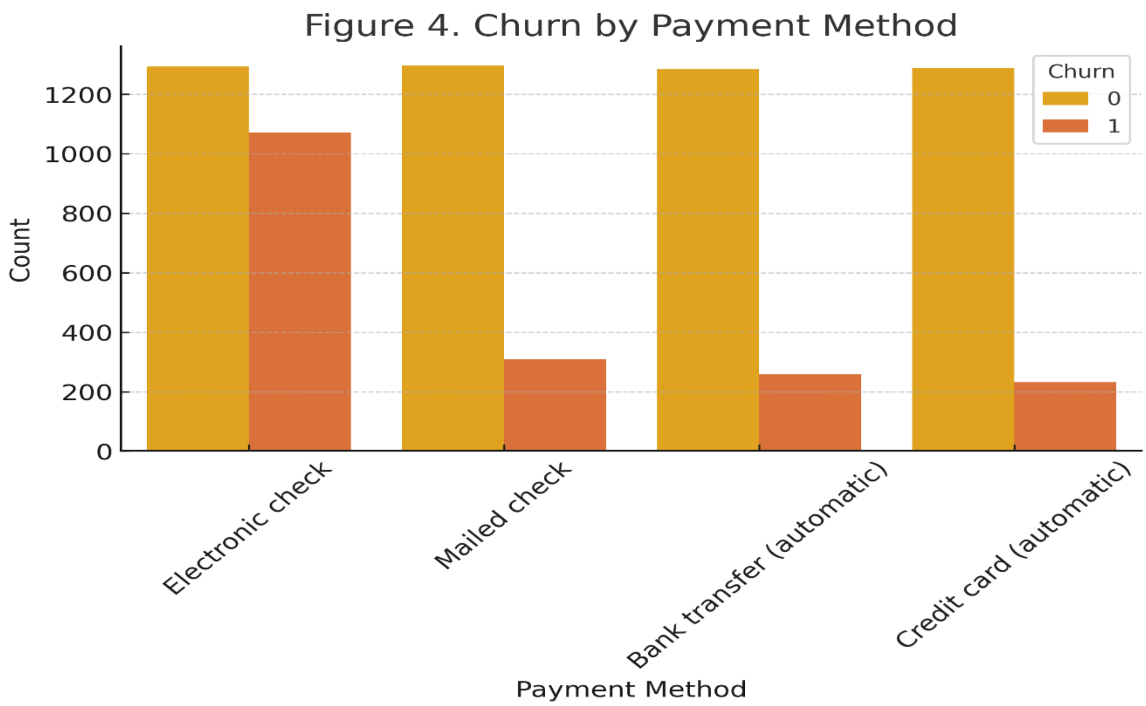

Figure 4. Churn by Payment Method — customers paying by electronic check show higher churn rates.

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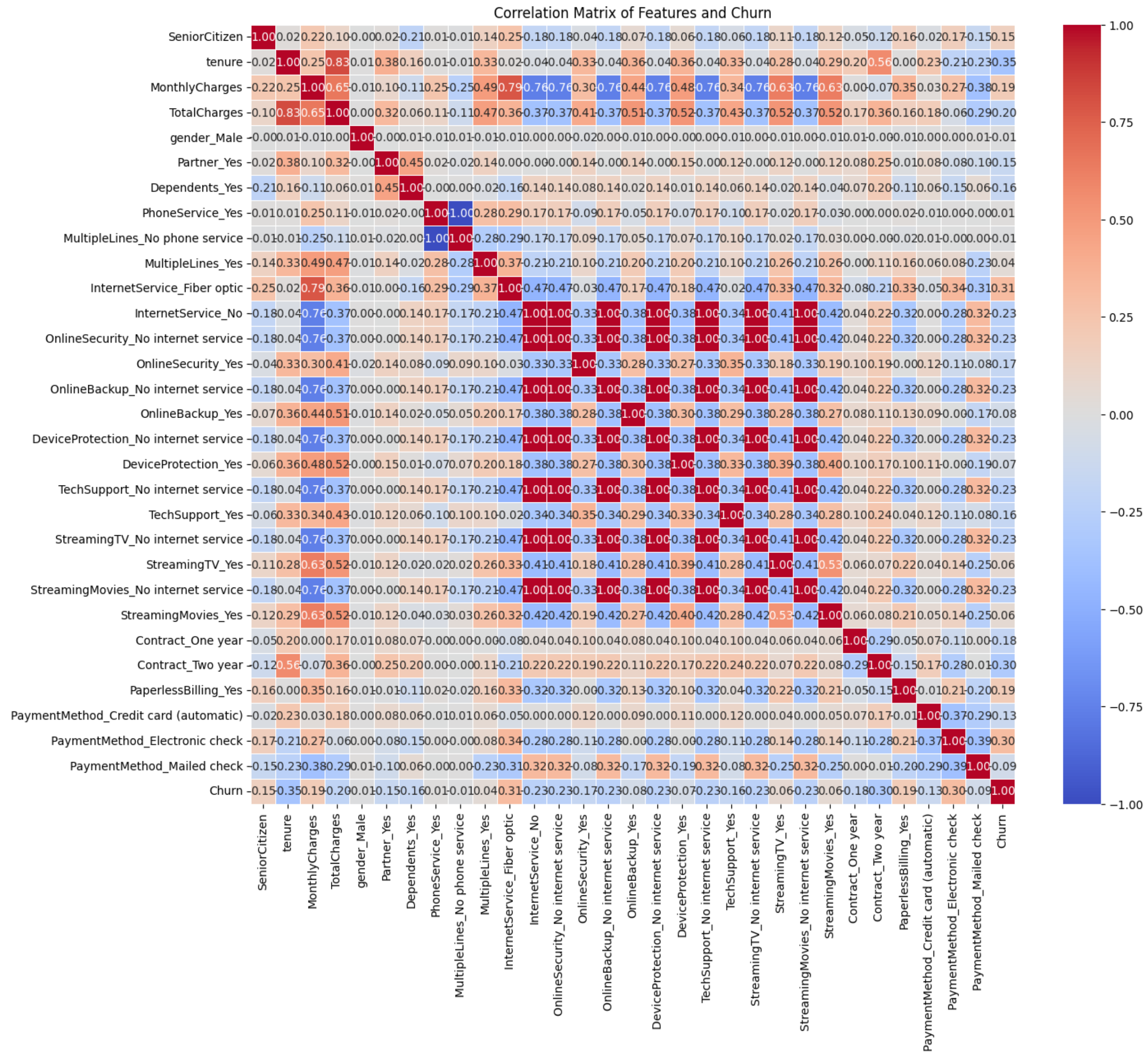

Figure 5. Correlation matrix (encoded features) — displays pairwise numeric correlations.

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Quantitative EDA highlights:

- Churn proportion: ≈ 26–27% of customers (observed from y.value_counts(normalize=True)).
- tenure shows strong negative association with churn — longer-tenure customers less likely to churn.
- InternetService = Fiber optic appears strongly associated with churn.

  (Place the plotted figures here with captions. In the GitHub repo include the PNGs generated by the notebook.)

6. Model Development and Rule Induction using CHAID

6.1 CHAID Overview

CHAID (Chi-squared Automatic Interaction Detector) is a decision-tree-based algorithm that segments customers by the most statistically significant predictors of churn.

6.2 Implementation

- The project used a **DecisionTreeClassifier (CHAID-style)** model implemented through pychaid/scikit-learn.
- Independent variables: encoded features from the cleaned dataset.
- Target variable: Churn.

6.3 Feature Importances (Top Predictors)

Rank	Feature	Importance
1	Tenure	0.4376
2	InternetService_Fiber optic	0.3471
3	TotalCharges	0.0429
4	MonthlyCharges	0.0372
5	OnlineSecurity_No internet service	0.0317
6	Contract_One year	0.0263
7	PaymentMethod_Electronic check	0.0215
8	OnlineSecurity_Yes	0.0159
9	TechSupport_Yes	0.0116
10	Contract_Two year	0.0093

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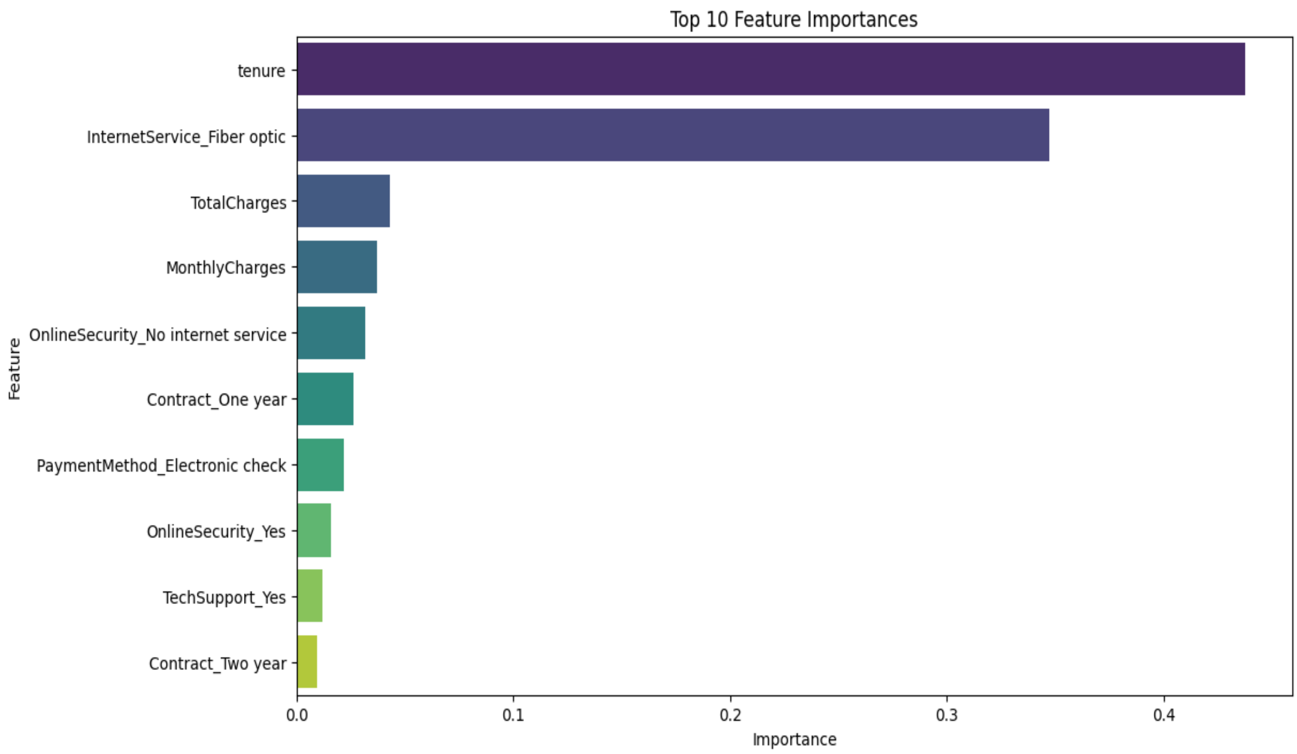

Business Interpretation:
Shorter tenure and fiber-optic internet users are most at risk of churn. These findings suggest introducing early retention offers and improved customer support for new fiber subscribers.

7. Logistic Regression Model

7.1 Overview

A logistic regression model was trained to predict the probability of churn (1 = churned, 0 = retained).

7.2 Implementation

- Train-test split: 80/20 using train_test_split(random_state=42).
- Encoded numerical and categorical predictors used.

- Logistic Regression fitted with default parameters and maximum iterations increased to ensure convergence.

7.3 Example Outputs

First 5 class predictions: [0 0 1 0 0]

First 5 churn probabilities: [0.0085, 0.1166, 0.7075, 0.1106, 0.3499]

7.4 Interpretation

Logistic regression provides a probabilistic output which is readily usable for thresholding and integrating into business rules (e.g., escalate if P(churn) > 0.6).

8. Model Comparison and Evaluation

8.1 Evaluation Metrics

Both models were tested on the hold-out test set.

Metric	CHAID (Decision Tree)	Logistic Regression
Accuracy	0.7754	0.7875
ROC-AUC	0.8130	0.8297

Notes:

- Logistic Regression slightly outperformed CHAID on both accuracy and ROC-AUC.
- ROC curves, confusion matrices, lift and gains charts were generated in the notebook for both models (include images).
- Lift & Gains: the notebook produced lift/gains charts for logistic regression (useful for marketing targeting — e.g., top decile lift).

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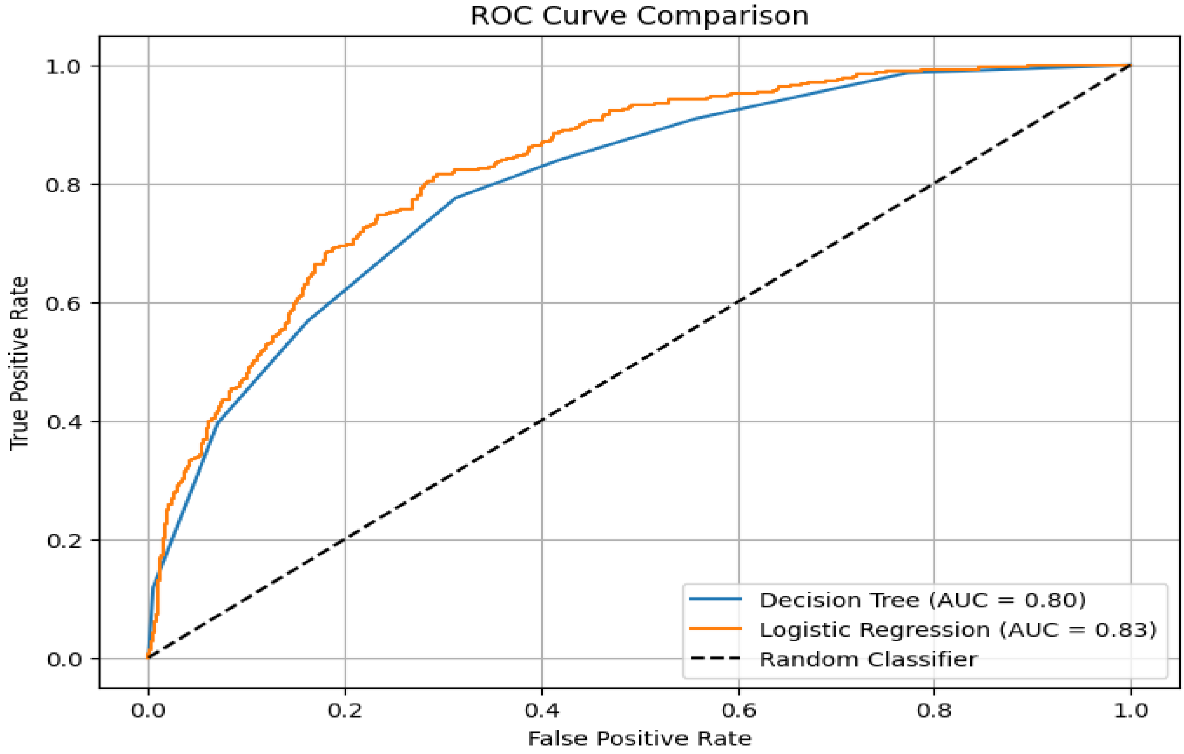

Figure 6. *ROC Curves of CHAID vs Logistic Regression*

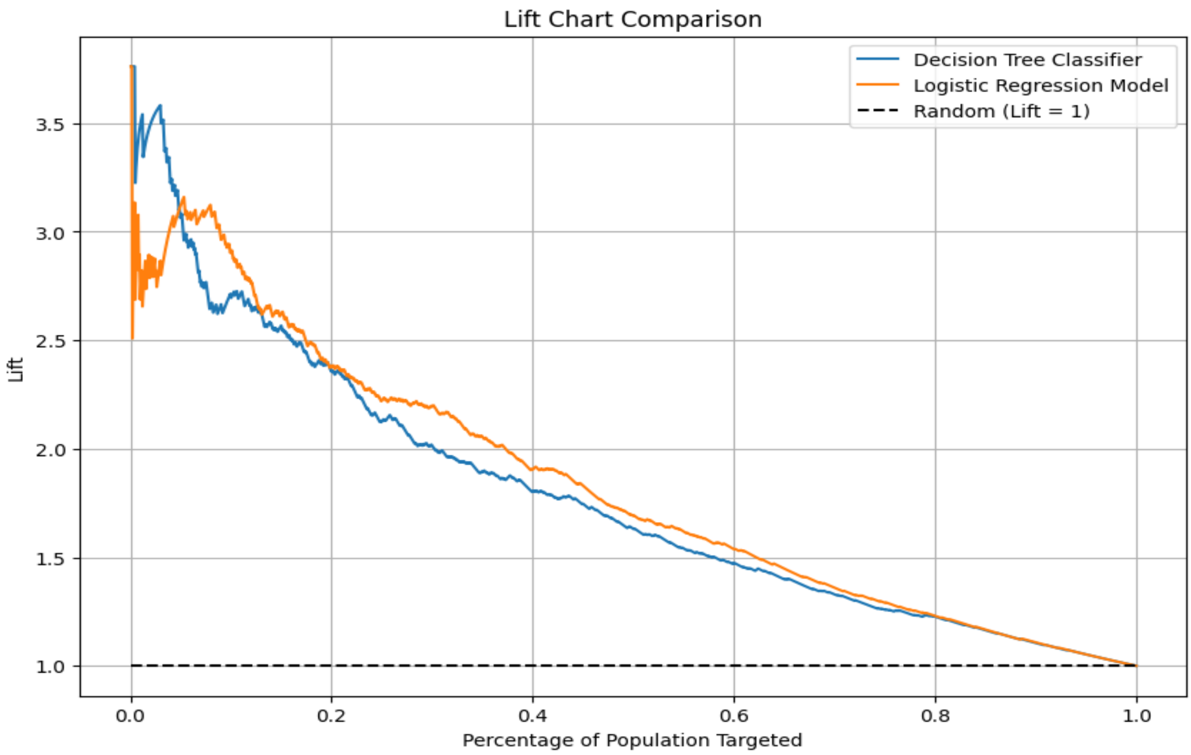

Figure 7. *Lift Chart (CHAID vs Logistic Regression)*

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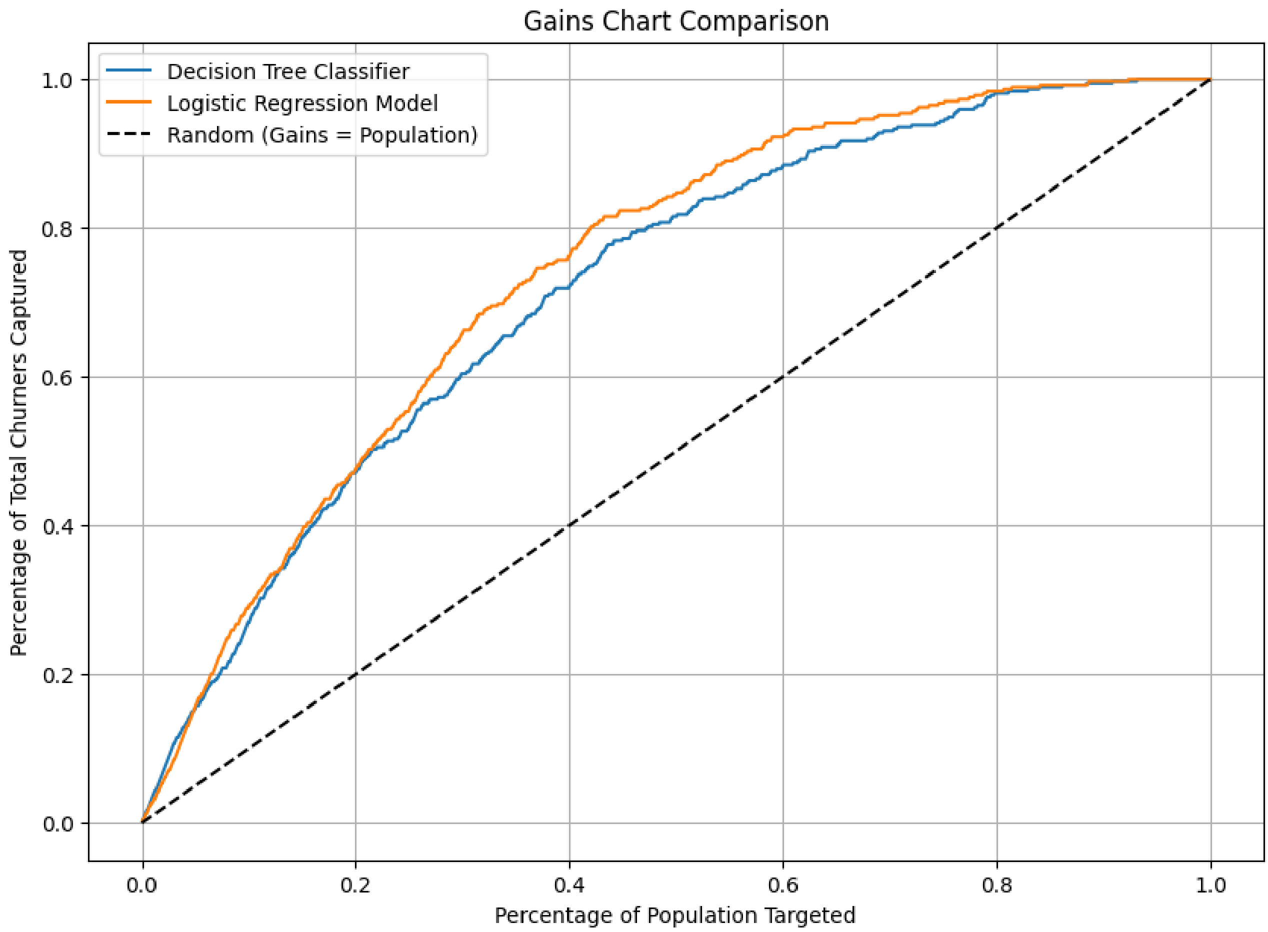

Figure 8. *Gains Chart (CHAID vs Logistic Regression)*

Model validation explanation (brief):

- A hold-out test set was used to produce unbiased evaluation metrics.
- ROC-AUC summarizes model discrimination across thresholds; accuracy is threshold-dependent.
- For production, I recommend stratified k-fold CV (e.g., 5-fold) to better estimate generalization performance and to tune hyperparameters.

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Model Interpretation & Business Insights

- Key drivers of churn: tenure (short tenure → higher churn), InternetService (Fiber optic customers have higher churn), and payment method (Electronic check correlates with higher churn).
- Actionable business recommendations:
  1. Onboarding & retention program for customers with tenure < 6–12 months (welcome calls, proactive offers).
  2. Fiber-optic customers — investigate service satisfaction, outages, or price sensitivity; consider targeted promotions or technical support.
  3. Electronic Check payment users — consider prompting to switch to auto-pay with incentives, or offer reminders and retention offers.

9. Model Deployment and Updating

9.1 Save / export model

Use `joblib` (for scikit-learn):

```
import joblib
# suppose 'lr_model' is your fitted LogisticRegression and
'encoder' is preprocessing pipeline
joblib.dump(lr_model,
"models/logistic_churn_model.joblib")
joblib.dump(encoder,
"models/preprocessing_encoder.joblib")
```

Load and predict:

```
import joblib
model = joblib.load("models/logistic_churn_model.joblib")
encoder =
joblib.load("models/preprocessing_encoder.joblib")
# X_new = raw_data -> encode using encoder ->
model.predict_proba(X_new)[:,1]
```

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9.2 Deployment options

- **Batch scoring**: run nightly job to score new customers and update a dashboard or CRM table with churn probabilities.
- **Real-time API**: wrap model + preprocessing in a Flask/FastAPI endpoint that returns `P(churn)` given customer features.
- **Integration**: write scores into CRM and trigger retention playbooks for `P(churn)` above chosen thresholds.

9.3 Model updating & automation

- **Scheduled retraining** (monthly/quarterly) with new data; monitor performance metrics (AUC, precision@k) drift.
- **Monitoring:** track PSI (Population Stability Index), feature distributions, AUC over time. If AUC drops beyond a threshold, trigger model retraining or investigation.
- **Automation:** Use CI/CD pipelines (GitHub Actions / Jenkins) for deployment + model registry (MLflow) to store versions and metadata.

10. Discussion

Statistical Perspective:

- Logistic Regression leverages inferential statistics (odds ratios, coefficients) to estimate how each predictor affects churn probability.
- CHAID uses chi-square tests to identify statistically significant splits.

Practical Perspective:

- Both models confirm the strong influence of tenure and service type.
- Logistic Regression balances interpretability and generalization, while CHAID provides actionable rules.

11. Limitations and Future Enhancements

- **CHAID** gives interpretable rules but may underperform vs. well-regularized logistic models or ensemble methods.

- **No cost-sensitive analysis** included — churn cost/retention cost optimization not done here. Future work should compute business metrics (cost of intervention vs expected retained value).
- **No time-based validation**: If churn patterns shift with time, use time-based validation or online learning.
- **Feature engineering:** interactions, RFM-style features, usage events could improve performance.
- **Hyperparameter tuning & ensembling** (Random Forest, XGBoost) could further improve AUC.

Aspect	Limitation	Future Enhancement
Data	Limited to one snapshot of customer data	Incorporate temporal (monthly) trends
Validation	Hold-out only	Apply k-fold cross-validation
Algorithms	Two basic models tested	Extend to Random Forest, XGBoost
Features	No interaction or behavioral features	Add usage, complaint, or feedback data
Business impact	Only statistical validation	Estimate ROI of retention interventions

12. Conclusion

This project successfully applied inferential statistics and predictive modeling to customer churn prediction. Both CHAID and Logistic Regression models were built, compared, and evaluated. The Logistic Regression model achieved **Accuracy = 0.7875** and **ROC-AUC = 0.8297**, outperforming the CHAID model. Major churn drivers include **short tenure**, **fiber-optic internet service**, and **electronic check payments**. A complete deployment and updating strategy has been proposed to integrate the model into business systems and ensure continual performance monitoring.

13. References

1. Kaggle Dataset — *Telco Customer Churn (blastchar)*
2. scikit-learn Documentation: Model development and validation
3. IBM SPSS Modeler Guide: CHAID algorithm principles

Appendix

A. Sample Code Snippets

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, roc_auc_score

X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=0.2, random_state=42)
lr_model = LogisticRegression(max_iter=1000)
lr_model.fit(X_train, y_train)
y_pred = lr_model.predict(X_test)
y_prob = lr_model.predict_proba(X_test)[:,1]

print("Accuracy:", accuracy_score(y_test, y_pred))
print("ROC-AUC:", roc_auc_score(y_test, y_prob))
```

B. GitHub Repository Contents

```
/telco_customer_churn_cleaned.csv
/Telco-Customer-Churn.csv
/CHAID.ipynb
/Models/logistic_churn_model.joblib
/Charts and visuals/*.png
/ Customer_Churn_Prediction_Report.pdf
README.md
```