CHURN RADAR

Predicting who stays and who goes

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OR...

The story of how we built a crystal ball for customer behavior – and it's 98% accurate.

WHAT'S INSIDE THIS STORY?

01 ONCE UPON A CHURN...

Meet Kolo*, an online store selling tech gadgets—from laptops to smartphones.
But behind the scenes, there was a problem: customers were disappearing.

Could we figure out who’s likely to leave before they actually do?
This became our mission: predict churn and help keep customers.

*ficticious company

02

THE VILLAIN: CUSTOMER CHURN

WHY?

Because every lost customer = lost revenue, lost trust, lost growth.

HOW TO SOLVE?

With Machine Learning that spots which customers are at risk, so the business can act before it's too late.

03 THE EVIDENCE: DATA

We had data on 5,630 customers—their preferences, complaints, time with us, and more.
Here's what we did:

01 Filled in missing info

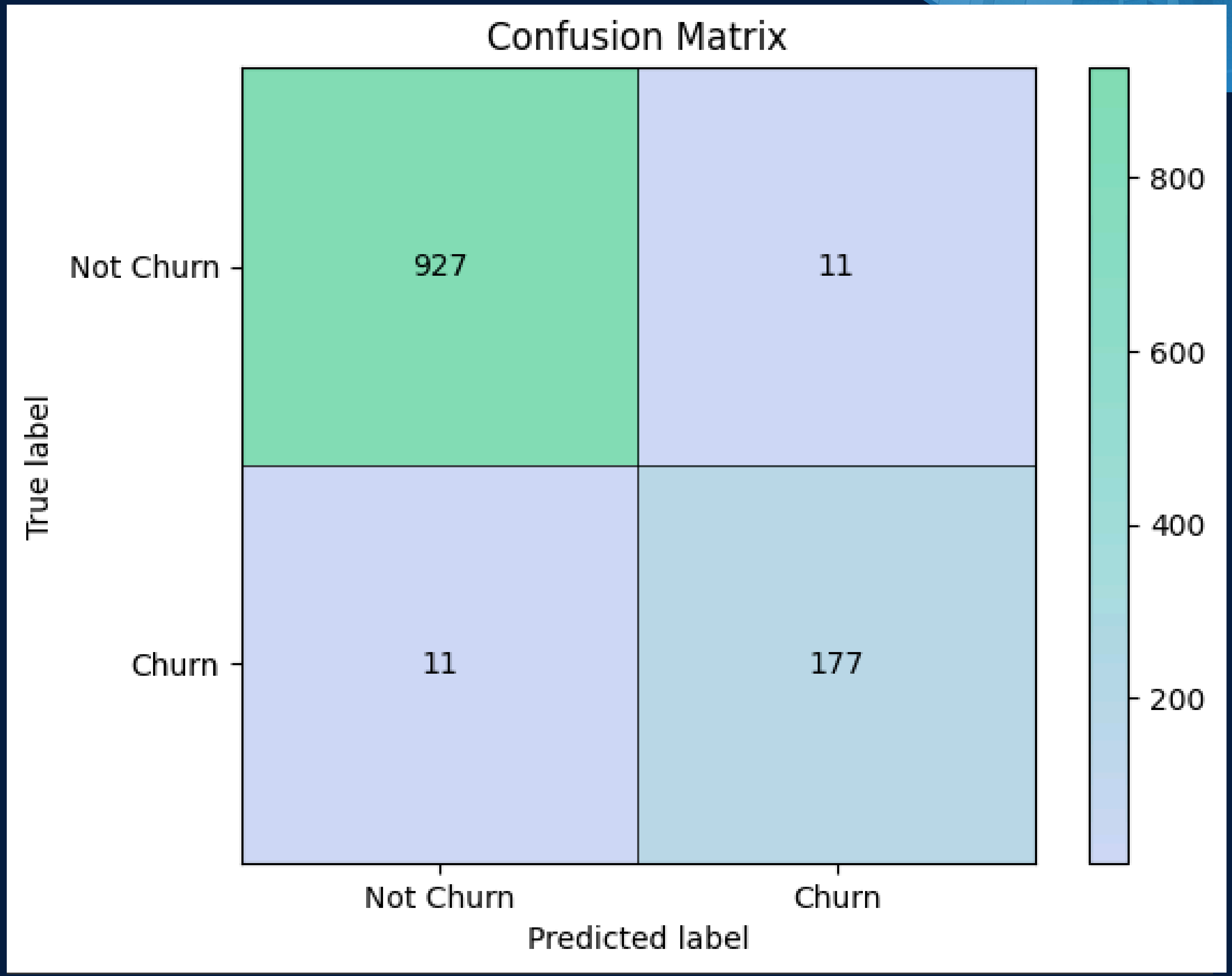
02 Translated messy labels into clear insights

03 Got the data model-ready: scaled, cleaned, and sorted
Each row told a tiny part of the churn story.

04 THE MAGIC OF THE MODEL

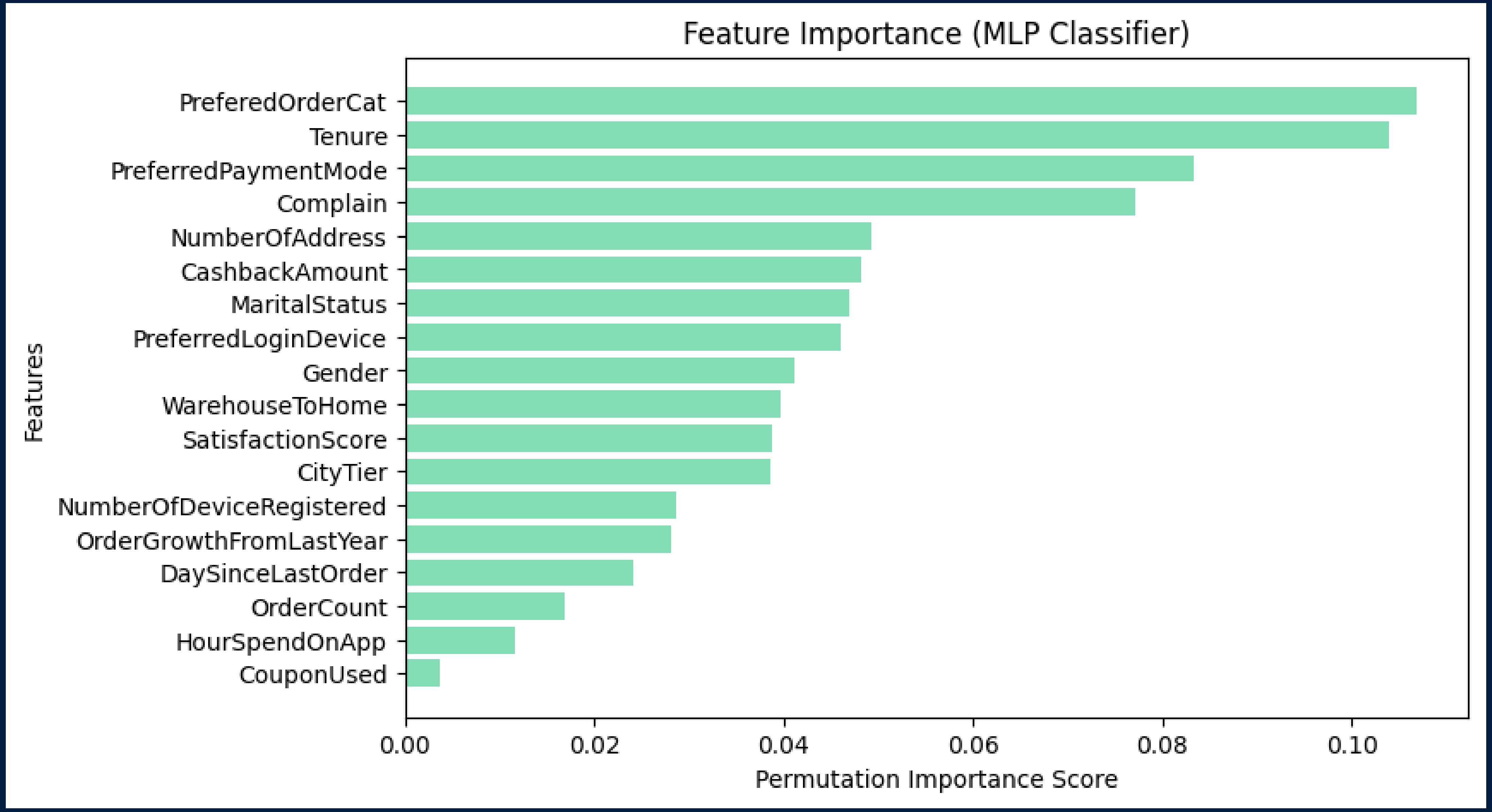
All models outperformed the 83% Dummy model, with MLP Classifier leading. The Confusion Matrix also shows few false positives and negatives.

		Accuracy score
1	KNN	0.913
2	Logistic Regression	0.887
3	Random Forest	0.960
4	Support vector machine	0.912
5	**MLP Classifier**	**0.980**
6	XGBoost	0.970
7	Decision Tree	0.913



*performance was calculated on test dataset

WHAT THE MODEL FOUND IMPORTANT



No single feature could predict churn.

But certain combinations—like preferred category + tenure + complaints + certain payment methods—formed powerful signals.

It's not just about what the customer does, but how all those things fit together.

05

FROM LAB TO LIFE: DEPLOYMENT

STEP 1

Predict churn probability, not just a yes/no

STEP 2

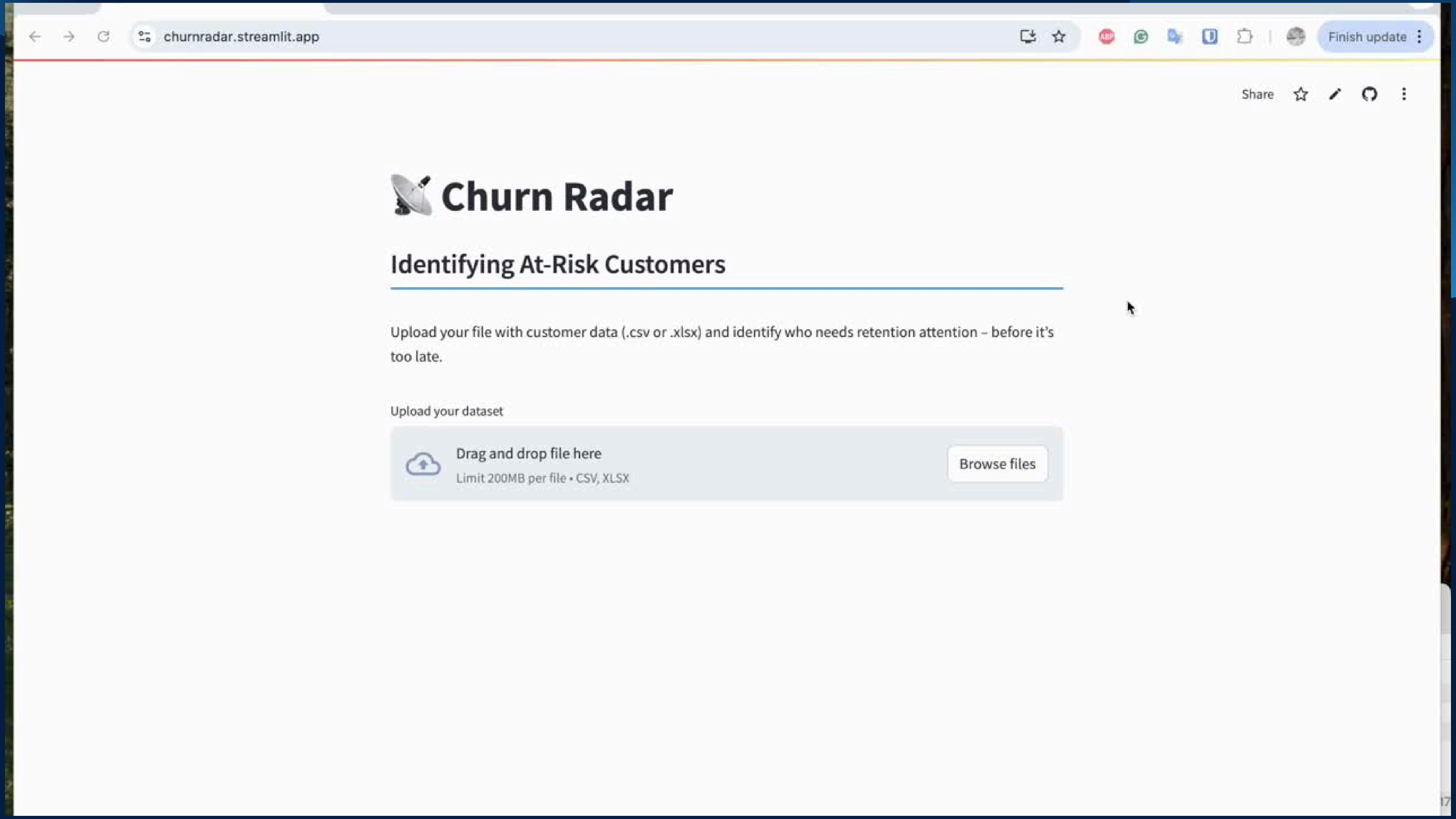
Saved the trained model to use again and again

STEP 3

Built a web app so anyone can use it—no code needed.

You can check it here: ChurnRadar Streamlit App

WATCH IT IN ACTION



[Link to the video](#)

06 THE HAPPY ENDING: BUSINESS IMPACT

Knowing who might leave lets companies:

- Talk to the right customers at the right time
- Reduce wasted ad spend
- Increase loyalty and lifetime value
- Make smarter marketing decisions

WHAT'S NEXT?

We will integrate our model with a cloud-based database (such as GCP) to consolidate and continuously update customer data.

This integration will enable further exploratory data analysis (EDA) on high-risk customers, helping us uncover insights into why they may be at risk of leaving.

07 OUR TEAM

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Data Scientist

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Data Scientist

THANK YOU!

ANY QUESTIONS? WE’RE HAPPY TO SHARE MORE!

LET’S KEEP CUSTOMERS HAPPY—TOGETHER

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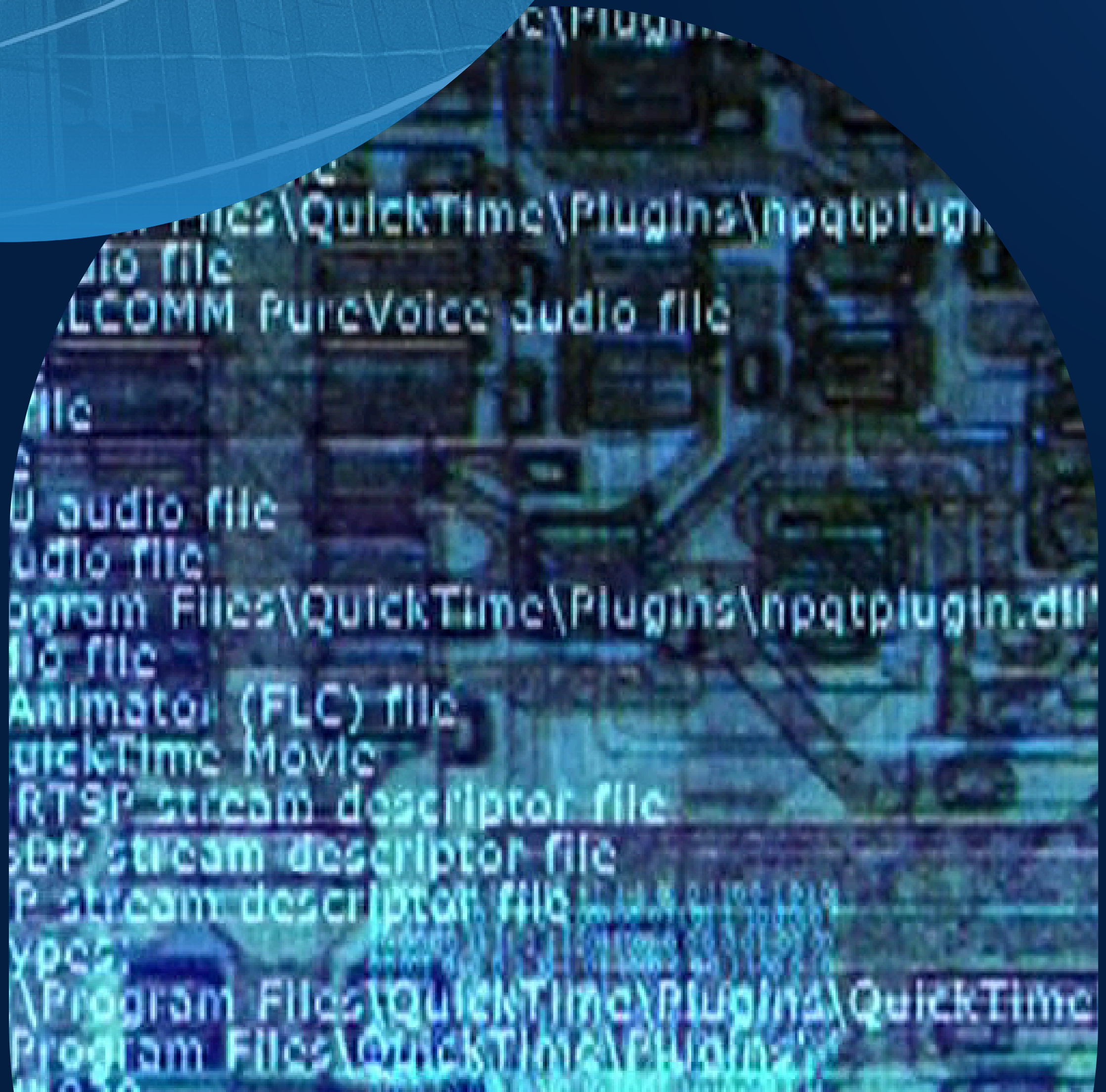
APPENDIX


PureVoice audio file
audio file
Animator (FLC) file
RTSP stream descriptor file
stream descriptor file

CHURN RISK DRIVERS

Complaints = High Churn Risk

- "Complain = 1" → high churn:
- Mobile Phone + Credit Card → 72%
- Mobile Phone + COD → 75%
- Mobile Phone + Debit Card → 69.6%

✅ Complaints = strongest signal of churn

Risky Payment Modes

- COD → 75%, UPI → 46%
- Debit Card + Complain → up to 69.6%

✅ Alternative payment modes = less loyal users

Tenure = 1.0

- New customers (Tenure 1.0) often churn early
- Especially when paired with complaint or risky payments

✅ Short tenure = early dropout

SUMMARY TABLE

Feature_Combo ("PreferedOrderCat", "Tenure", "PreferredPaymentMode", "Complain", "NumberOfAddress")	Count	ChurnRate
Mobile Phone_0.0_CC_1_2	17	58.8%
Mobile Phone_0.0_Debit Card_1_2	34	64.7%
Mobile Phone_1.0_COD_0_3	12	66.7%
Mobile Phone_1.0_COD_1_3	16	75.0%
Mobile Phone_1.0_Credit Card_1_3	25	72.0%
Mobile Phone_1.0_Debit Card_0_3	63	41.3%
Mobile Phone_1.0_Debit Card_1_2	11	54.5%
Mobile Phone_1.0_Debit Card_1_3	46	69.6%
Mobile Phone_1.0_UPI_0_3	13	46.2%
Mobile Phone_9.0_Debit Card_1_2	18	55.6%

🔎 Churn Driver	📉 Impact
❗ Complain = 1	Strongest churn signal
💳 COD / UPI / Debit Card	Risky payment methods
🕐 Tenure = 1.0	New customers = higher churn
📱 Mobile Phone category	Most represented in high-churn segments