Customer Loyalty Turnover Forecasting

Predicting customer churn using ANN and TensorFlow

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Streamlit demo | GitHub

What problem are we solving?

Business Context

Customer churn erodes revenue and increases acquisition costs significantly.

Goal

Predict churn risk at an individual customer level and identify key drivers to guide retention efforts effectively.

Scope

Focus on retail banking customers; supervised binary classification (Churn = 1 / Not churn = 0).

Success Metrics

AUC ≥ 0.85, Recall on churn ≥ 0.70 at precision ≥ 0.60; business lift from targeted retention campaigns.

How predictions get used

Retention Team	Who to contact first	T+1 day after scoring
Product	Which offers to test	Weekly experiment cycles
Finance	Expected uplift vs spend	Monthly

Cost of Churn

Average monthly revenue × expected remaining months × churn probability.

Data sources and preparation

- Source

  Historical customer records with demographics, account status, engagement, and outcomes (see repo notebooks).

- Rows/Columns

  ~10,000 rows, 15 features before selection.

- Target

  Churn (1) vs Non-churn (0). Class balance: churn ≈ 20%.

- Preprocessing

  Missing value handling, outlier capping, scaling, categorical encoding, train/val/test split with stratification.

Key features and treatment

Tenure	Numeric	Early-life churn risk	Robust scaler; bucketed for EDA
ProductsHeld	Numeric	Relationship depth	No transform
IsActiveMember	Binary	Engagement proxy	As is
CreditScore	Numeric	Risk/limit behavior	Standard scaler
EstimatedSalary	Numeric	Affordability	Standard scaler
Geography	Categorical	Market dynamics	One-hot
HasCrCard	Binary	Credit tie-in	As is
Balance	Numeric	Usage intensity	Log1p + scaler (if skewed)

Model Building (ANN architecture and training)

Architecture

1 **Output**

Dense(1), Sigmoid

2 **Layer 3**

Dense(16), ReLU

3 **Layer 2**

Dense(32), ReLU → BatchNorm → Dropout(0.2)

4 **Layer 1**

Dense(64), ReLU → BatchNorm → Dropout(0.3)

5 **Input**

12 engineered features.

- Loss: Binary cross - entropy
- Optimizer: Adam, lr = 0.001
- Regularization: Dropout + L2 = 0.0001

Training and Tuning

- Split: Train 70% / Val 15% / Test 15% with stratification.
- Imbalance handling: Class weights.
- Hyperparameter tuning: Search over units, dropout, lr, batch size, epochs using Grid Search on val AUC.
- Early stopping: patience=10, restore_best_weights=True.
- Baselines: Logistic Regression, Random Forest for sanity check.

Best Hyperparameter Values

Hidden units	64, 32, 16
Dropout	0.3, 0.2
Batch size	32
Epochs	50

Model Metrics

Metrics on Test Set

Accuracy	0.88
Precision	0.72
Recall	0.70
F1-Score	0.71
ROC-AUC	0.89
PR-AUC	0.75

Confusion Matrix

True 0	1420	80
True 1	90	210

Key Checks

No Overfitting

Train vs Val curves converge, indicating good generalization.

Feature Leakage

Thorough checks confirm no leakage detected.

Threshold Tuning

Decision threshold tuned at 0.45 for operational capacity of 1000 customers/month.

Results, Insights, and Actions

Final Outcomes

- Performance: Model meets targets with ROC-AUC 0.89 and Recall 0.70 at Precision 0.72.

Top Risk Segments

- Tenure ≤ 6 months + IsActiveMember=0 → churn rate 35%.
- Balance in bottom quartile + 1 product → churn rate 30%.
- Geography = Mumbai with low engagement → churn rate 28%.

Recommendations

Save Early-Tenure Customers

Onboarding check-in within 14 days; fee waiver trial; micro-savings nudges.

Deepen Relationships

Cross-sell second product for single-product segment; targeted credit line reviews.

Enhance Engagement

Push personalized app nudges; monthly insights statements.

Experimentation

A/B test 3 offers; measure incremental retention uplift and net present value.

Business Impact

- If we contact top 10% risk customers and achieve uplift of 15%, estimated monthly churn reduction = 30 customers, worth ≈ ₹1,500,000.

Deployment

- Scoring via Streamlit UI for ad-hoc; batch scoring daily at 2 AM IST.
- Export CSV with Customer ID, Risk Score, Segment, Recommended Action.

Live demo: https://ann-classification-banking.streamlit.app/

Thank - You

I appreciate your time and attention.