Vodafone Customer Churn Prediction

This project demonstrates advanced machine learning techniques to predict customer churn for Vodafone subscribers. The goal is to identify customers who are likely to leave the service, enabling proactive retention strategies with measurable business impact.

Key Objectives:

- Build a robust churn prediction model using CatBoost
- Handle class imbalance (6.4% churn rate)
- Provide actionable business insights
- Demonstrate ROI potential for retention campaigns

Project Structure:

1. Data Preparation and Exploration
2. Feature Engineering and Selection
3. Model Training and Optimization
4. Evaluation and Business Insights
5. Recommendations and ROI Analysis

1. Data Preparation and Exploration

In [1]:

```
# Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pickle
import seaborn as sns
from datetime import datetime
from sklearn.metrics import (
    classification_report, confusion_matrix, f1_score,
    precision_score, recall_score, roc_auc_score, make_scorer,
)

from sklearn.model_selection import train_test_split, cross_val_score, St
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustSca
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from catboost import CatBoostClassifier

import warnings
warnings.filterwarnings('ignore')

# Import custom functions
```

```python
from my_functions import (
    load_data,
    save_model,
    evaluate_classification_model,
    plotting_confusion_matrix,
    drop_highly_correlated,
    get_features,
    calculate_optimal_threshold,
    plot_learning_curve,
    plot_probabilities_hist,
    plot_roc_pr_curves,
)

print("Libraries imported successfully!")
print(f"Analysis started at: {datetime.now().strftime('%Y-%m-%d %H:%M:%S'
```

```
Libraries imported successfully!
Analysis started at: 2025-06-23 11:30:10
```

In [2]:

```python
# Load the dataset
df_train = load_data('churn_train_data.pcl')

print("Sample data structure:")
print(f"Dataset shape: {df_train.shape}")
print(f"Memory usage: {df_train.memory_usage().sum() / 1024**2:.2f} MB")
print("Target variable: 0 = active, 1 = churned")
df_train.target
```

```
Sample data structure:
Dataset shape: (150000, 817)
Memory usage: 238.90 MB
Target variable: 0 = active, 1 = churned
```

Out[2]:

```
0         0.0
1         0.0
2         0.0
3         0.0
4         0.0
         ...
149995    0.0
149996    0.0
149997    0.0
149998    0.0
149999    0.0
Name: target, Length: 150000, dtype: float16
```

In [3]:

```python
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150000 entries, 0 to 149999
Columns: 817 entries, Ama_rchrgmnt_sum_max_mnt1 to abon_id
dtypes: float16(773), float32(1), float64(11), int8(32)
memory usage: 238.9 MB
```

In [4]:

```python
df_train.describe()
```

Out [4]:

	Ama_rchrgmnt_sum_max_mnt1	content_clc_mea_mnt1	content_cnt_max_m
count	150000.0	150000.000000	150000.000
mean	0.0	0.000000	N
std	0.0	0.396484	0.0000
min	0.0	0.000000	0.0000
25%	0.0	0.000000	9.6718
50%	0.0	0.000000	11.617
75%	0.0	0.000000	13.6406
max	0.0	22.843750	64.0625

8 rows × 817 columns

In [5]:
```
df_train[df_train.duplicated()]
```

Out [5]:

Ama_rchrgmnt_sum_max_mnt1	content_clc_mea_mnt1	content_cnt_max_mnt1	v

0 rows × 817 columns

In [6]:
```
# Missing values
missing_values = df_train.isnull().sum()
missing_values_percentage = 100 * df_train.isnull().sum() / len(df_train)

missing_values_df = pd.DataFrame({'missing_values': missing_values,
                                  'percentage': missing_values_percentage
missing_values_df.sort_values('missing_values', ascending=False).head(20)
```

Out[6]:

	missing_values	percentage
bs_of_recall_m1	150000	100.000000
bs_of_succ_m1	150000	100.000000
bs_of_succ_but_drop_m1	150000	100.000000
bs_of_unsucc_attemp_equip_m1	150000	100.000000
bs_recall_rate	150000	100.000000
bs_of_unsucc_low_balance_m1	150000	100.000000
bs_of_attemps_all_m1	150000	100.000000
bs_drop_rate	150000	100.000000
bs_succ_rate	150000	100.000000
bs_drop_call_rate	150000	100.000000
device_has_gprs	150000	100.000000
MV_FRAUD_BLOCK	149998	99.998667
entertainment	149994	99.996000
Food	149989	99.992667
tsoa_mail_cnt	149977	99.984667
MV_SERV_RLH	149967	99.978000
Cars	149934	99.956000
MV_DOU_Neg_Bal	149887	99.924667
Fax	149845	99.896667
Shops	149475	99.650000

In [7]:

```
threshold = 90.0
cols_to_drop = missing_values_df[missing_values_df['percentage'] > thresh
df_train = df_train.drop(columns=cols_to_drop)
print("Dropped columns:", cols_to_drop)
print(f"{len(cols_to_drop)} columns were dropped")
print(f"The size of our train dataset is: {df_train.shape}")
```

```
Dropped columns: ['DNZ_MEAN_days_closed_loan_year2', 'DNZ_MIN_days_closed_loan_year2', 'DNZ_DAYS_from_last_year2', 'DNZ_MAX_days_closed_loan_year2', 'DNZ_STD_days_closed_loan_year5', 'DNZ_COUNT_open_loan_year2', 'DNZ_MEAN_days_open_loan_year5', 'DNZ_COUNT_closed_loan_year2', 'DNZ_MEAN_days_open_loan_year2', 'Fax', 'tsoa_direct_cnt', 'tsoa_mail_cnt', 'SMS', 'tsoa_chat_cnt', 'device_has_gprs', 'device_ios_version', 'bs_delte_omo_change_tp', 'bs_delte_mb_change_tp', 'bs_delte_ppm_change_tp', 'bs_delte_ppd_change_tp', 'bs_direct_change_tp', 'bs_arpu_change_tp', 'bs_day_of_change_tp', 'bs_count_change_tp', 'entertainment', 'Food', 'Shops', 'Cars', 'Good_deed', 'Minutes', 'AMA', 'day_end_gba', 'active_gba', 'bs_of_succ_m1', 'bs_drop_call_rate', 'bs_succ_rate', 'bs_drop_rate', 'bs_of_recall_m1', 'bs_of_attemps_all_m1', 'bs_of_unsucc_low_balance_m1', 'bs_recall_rate', 'bs_of_unsucc_attemp_equip_m1', 'bs_of_succ_but_drop_m1', 'MV_VLR_Guest', 'MV_FRAUD_BLOCK', 'MV_SERV_Y_WO_AF', 'MV_SERV_RLH', 'MV_DOU_Neg_Bal']
48 columns were dropped
The size of our train dataset is: (150000, 769)
```

In [8]:
```python
df_train.isna().sum()
```

Out[8]:
```
Ama_rchrgmnt_sum_max_mnt1           0
content_clc_mea_mnt1                0
content_cnt_max_mnt1                0
voice_out_short_part_max_mnt1       0
voice_mts_in_nrest_part_std_mnt1    0
                                ...
MV_Migr_To                         91
MV_DOU_PPM_VF                   72366
MV_ot_total                     41450
target                              0
abon_id                             0
Length: 769, dtype: int64
```

In [9]:
```python
df_train = df_train.fillna(-1)
df_train.isna().sum().any()
```

Out[9]:
```
False
```

In [10]:
```python
df_train.head()
```

Out[10]:

	Ama_rchrgmnt_sum_max_mnt1	content_clc_mea_mnt1	content_cnt_max_mnt1
0	0	0.0	13.843750
1	0	0.0	11.359375
2	0	0.0	10.265625
3	0	0.0	9.976562
4	0	0.0	6.750000

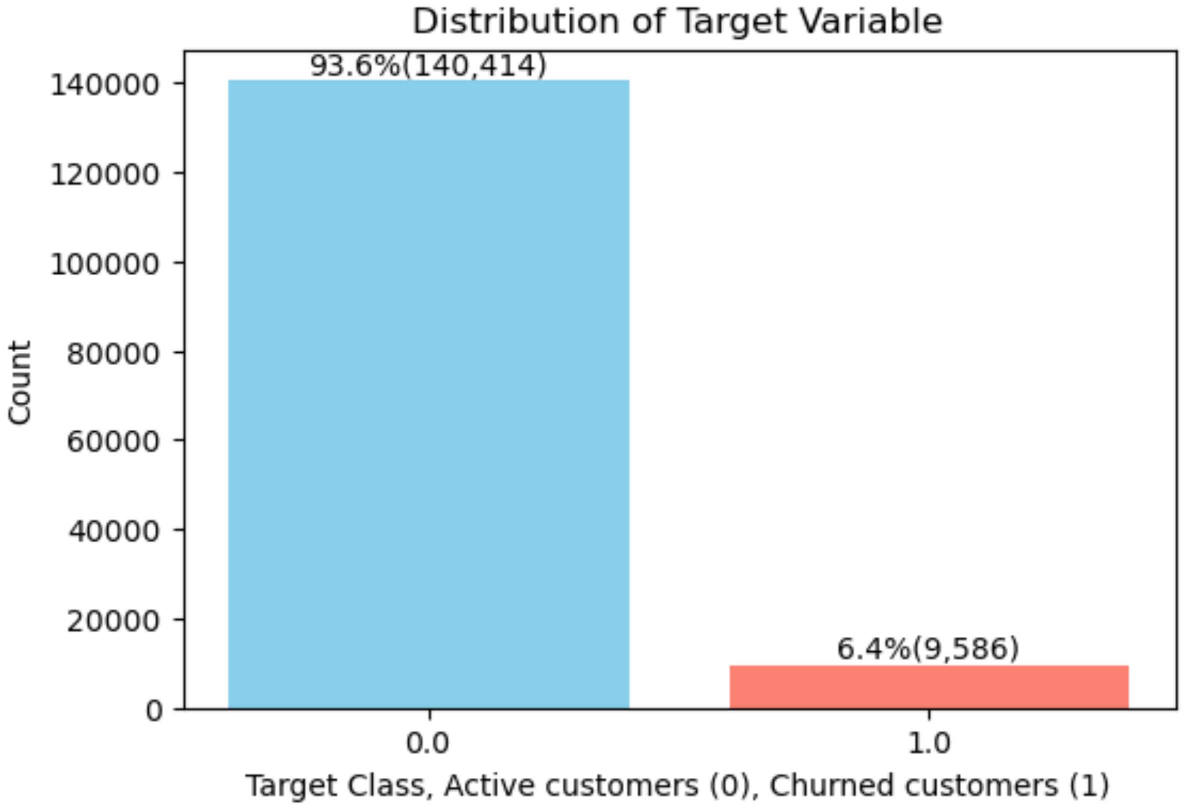
5 rows × 769 columns

Vizualize target distribution

In [11]:
```python
target_col = 'target'
```

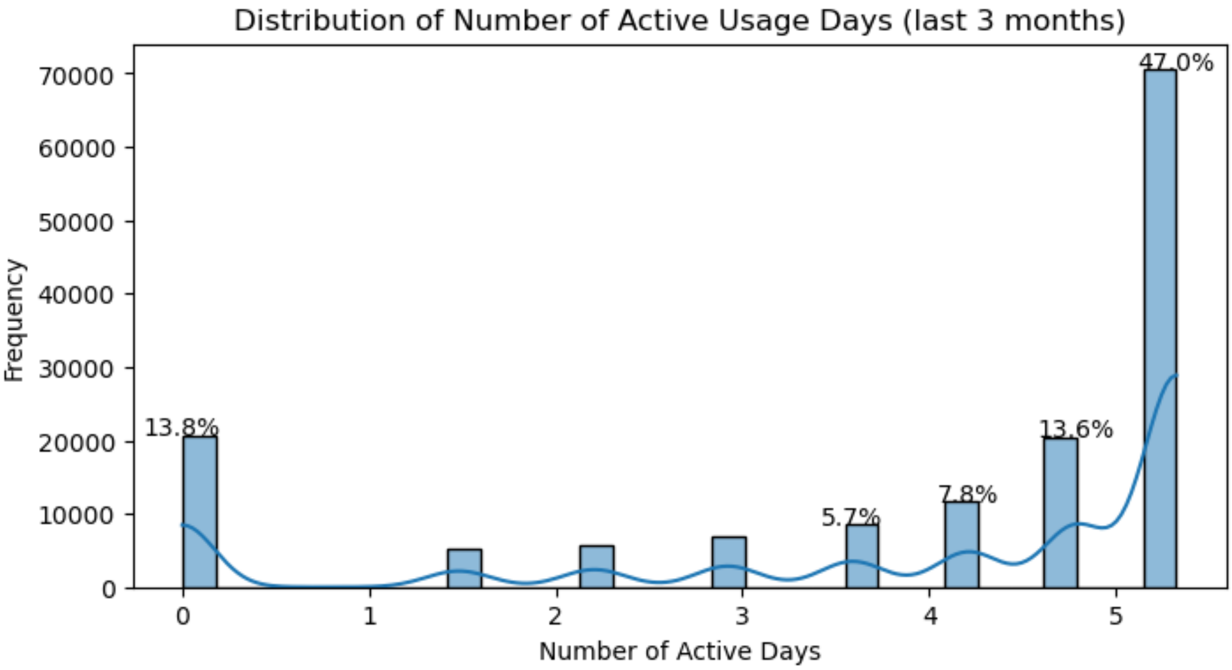
```
# Calculate value counts and ratios
counts = df_train[target_col].value_counts()
ratios = df_train[target_col].value_counts(normalize=True)

print("Target Variable Distribution:")

plt.figure(figsize=(6,4))
bars = plt.bar(counts.index.astype(str), counts.values, color=['skyblue',
plt.title('Distribution of Target Variable')
plt.xlabel('Target Class, Active customers (0), Churned customers (1)')
plt.ylabel('Count')

# bars with percentage and counts
for idx, value in enumerate(counts.index):
    plt.text(
        idx,
        counts[value] + max(counts.values)*0.01,
        f"{ratios[value]*100:.1f}%({counts[value]:,})",
        ha='center',
        fontsize=10
    )

plt.show()
```

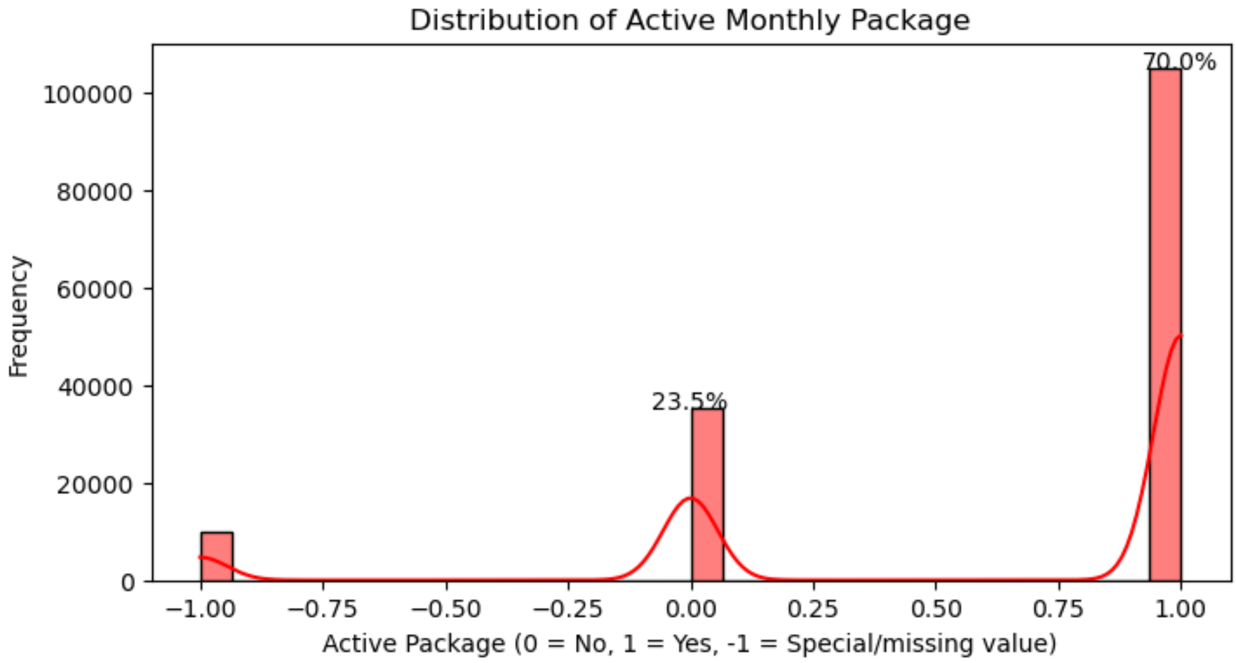
```
Target Variable Distribution:
```



In [12]:
```
col = 'num_act_days_min_mnt3'
plt.figure(figsize=(8, 4))
sns.histplot(df_train[col], kde=True, bins=30)
plt.title('Distribution of Number of Active Usage Days (last 3 months)')
plt.xlabel('Number of Active Days')
plt.ylabel('Frequency')
```

```
# Calculate value ratios for labeling
value_counts = df_train[col].value_counts(normalize=True)
for value, ratio in value_counts.items():
    if ratio > 0.05:  # Only label values with more than 5% frequency
        plt.text(value, df_train[col].value_counts()[value], f'{ratio*100

plt.show()

# For 'active_ppm'
col = 'active_ppm'
plt.figure(figsize=(8, 4))
sns.histplot(df_train[col], kde=True, bins=30, color='red')
plt.title('Distribution of Active Monthly Package')
plt.xlabel('Active Package (0 = No, 1 = Yes, -1 = Special/missing value)'
plt.ylabel('Frequency')

# Calculate and add ratios for 0 and 1
counts = df_train[col].value_counts(normalize=True)
for value in [0, 1]:
    if value in counts:
        plt.text(value, df_train[col].value_counts()[value], f'{counts[va

plt.show()
```





2. Feature engineering and primary selection

In [13]:

```
print("Removing highly correlated features...")
df_uncorr, dropped_cols = drop_highly_correlated(df_train, threshold=0.98

print(f"\nFeatures before correlation removal: {df_train.shape[1]}")
print(f"Features after correlation removal: {df_uncorr.shape[1]}")
print(f"Dropped {len(dropped_cols)} highly correlated features")
```

```
Removing highly correlated features...
Droped columns: 164 nr ['pay_avg_max_mnt1', 'content_clc_max_mnt3', 'pay_p
2p_in_sum_mea_mnt3', 'DNZ_COUNT_open_loan_year5', 'non_accum_internet_vol_
max_mnt1', 'sms_out_cnt_std_mnt1', 'data_3g_tv_cnt_min_mnt3', 'BS_OVERBUND
LE_MB_CNT_M1', 'all_roam_clc_std_mnt3', 'voice_mts_out_nrest_partstd_mnt
1', 'MV_ARPU_innet_inc_v_Traf', 'voice_out_cmpttrs_td_cntstd_mnt3', 'MV_ap
_Roam_d', 'MV_ot_innet_out_v', 'block_all_dur_max_mnt3', 'voice_out_td_cnt
_max_mnt1', 'voice_out_fix_tar_dur_std_mnt3', 'data_3g_dou_mea_mnt1', 'voi
ce_in_fix_tar_dur_max_mnt3', 'ama_volume_max_mnt1', 'sms_out_cnt_mea_mnt
3', 'MV_ot_Unkn', 'conn_in_uniq_cnt_mea_mnt1', 'MV_ARPU_Other_out_v_Traf',
'voice_in_kievstar_part_max_mnt3', 'voice_in_short_part_std_mnt1', 'voice_
in_life_part_max_mnt1', 'pay_max_mea_mnt1', 'sms_clc_max_mnt3', 'MV_ap_Oth
er', 'gprs_tar_vol_mea_mnt1', 'sms_out_cnt_max_mnt3', 'all_clc_std_mnt1',
'all_clc_max_mnt1', 'pay_avg_min_mnt1', 'vas_clc_mea_mnt3', 'all_roam_clc_
max_mnt3', 'all_home_clc_max_mnt1', 'data_3g_tv_cnt_max_mnt3', 'DNZ_MEAN_d
ays_closed_loan_year5', 'clc_no_vas_roam_std_mnt1', 'block_all_dur_min_mnt
3', 'gprs_clc_std_mnt3', 'vas_clc_std_mnt3', 'pay_max_std_mnt3', 'conn_com
_part_min_mnt3', 'voice_in_tar_dur_max_mnt1', 'MV_dou_omo_out_v', 'block_a
ll_dur_mea_mnt1', 'BS_OVERBUNDLE_MB_CNT_M2', 'pay_max_max_mnt3', 'voice_in
_roam_clc_max_mnt1', 'voice_out_tar_dur_mea_mnt1', 'MV_ot_inc_v', 'gprs_ta
r_vol_max_mnt1', 'voice_in_cmpttrs_td_cnt_std_mnt3', 'sms_roam_clc_std_mnt
3', 'gprs_clc_max_mnt1', 'pay_avg_std_mnt1', 'pay_p2p_out_sum_min_mnt3', '
MV_ot_R_v', 'ama_volume_std_mnt3', 'all_roam_clc_std_mnt1', 'MV_Traf_mn_ou
t_v_Min', 'voice_mts_in_nrest_part_std_mnt3', 'all_roam_clc_max_mnt1', 'gp
rs_tar_vol_mea_mnt3', 'MV_ot_pstn_out_v', 'voice_in_roam_clc_mea_mnt1', 'b
lock_all_dur_mea_wk1', 'MV_Traf_Other_inc_v_Min', 'pay_p2p_out_sum_min_mnt
1', 'data_3g_tv_cnt_min_mnt1', 'voice_in_fix_tar_dur_std_mnt1', 'voice_in_
```

```
fix_tar_dur_mea_mnt1', 'voice_out_fix_tar_dur_std_mnt1', 'vas_clc_max_mnt
1', 'gprs_clc_max_mnt3', 'data_3g_tar_vol_max_mnt3', 'non_accum_internet_v
ol_max_mnt3', 'MV_dou', 'pay_max_max_mnt1', 'pay_max_min_mnt1', 'abon_part
_std_mnt1', 'all_home_clc_std_mnt3', 'pay_p2p_in_sum_std_mnt3', 'data_3g_t
ar_vol_std_mnt3', 'ama_volume_mea_mnt1', 'pay_p2p_out_sum_mea_mnt1', 'cont
ent_clc_std_mnt1', 'voice_out_fix_tar_dur_mea_mnt1', 'clc_no_vas_roam_max_
mnt1', 'voice_in_cmpttrs_avg_durstd_mnt3', 'ama_volume_mea_mnt3', 'MV_ap_2
G_d', 'voice_mts_in_nwork_part_std_mnt3', 'abon_part_max_mnt1', 'vas_clc_s
td_mnt1', 'pay_p2p_in_sum_max_mnt1', 'MV_ap_inc_v', 'voice_in_fix_tar_dur_
std_mnt3', 'abon_part_mea_mnt3', 'voice_mts_out_nrest_partmax_mnt3', 'data
_3g_tar_vol_max_mnt1', 'MV_ot_4G_d', 'MV_DOU_AP', 'MV_ARPU_Other_inc_v_Tra
f', 'data_3g_tv_cnt_max_mnt1', 'all_home_clc_max_mnt3', 'voice_in_roam_clc
_max_mnt3', 'MV_Traf_Cont_inc_v_Min', 'pay_sum_mea_mnt3', 'accum_oth_dur_m
ax_mnt1', 'all_home_clc_std_mnt1', 'num_act_days_min_mnt3', 'MV_ot_R_sm',
'voice_in_cmpttrs_td_cnt_mea_mnt1', 'pay_avg_mea_wk1', 'gprs_tar_vol_max_m
nt3', 'pay_p2p_in_sum_mea_mnt1', 'pay_sum_max_mnt1', 'DNZ_MAX_days_closed_
loan_year5', 'data_3g_tar_vol_std_mnt1', 'voice_out_short_part_std_mnt1',
'voice_mts_out_nwork_partmax_mnt1', 'MV_ap_pstn_out_v', 'voice_mts_in_nres
t_part_max_mnt1', 'pay_avg_mea_mnt3', 'MV_ot_Other', 'voice_out_fix_tar_du
r_mea_mnt3', 'voice_in_roam_clc_std_mnt3', 'voice_out_cmpttrs_avg_dumax_mn
t3', 'abon_part_std_mnt3', 'sms_clc_max_mnt1', 'pay_sum_mea_wk1', 'voice_m
ts_out_nwork_partstd_mnt3', 'pay_max_std_mnt1', 'voice_out_cmpttrs_td_cntm
ax_mnt1', 'voice_in_life_part_max_mnt3', 'sms_out_cnt_max_mnt1', 'voice_mt
s_out_nrest_partmea_mnt1', 'MV_ot_Cont_v', 'voice_in_td_cnt_max_mnt1', 'ac
cum_oth_dur_max_mnt3', 'gprs_clc_std_mnt1', 'device_type_rus_other', 'sms_
roam_clc_mea_mnt3', 'MV_ot_total', 'block_all_dur_max_mnt1', 'sms_in_cnt_s
td_mnt3', 'DNZ_COUNT_closed_loan_year5', 'BS_OVERBUNDLE_MB_SUM_M3', 'num_a
ct_days_min_mnt1', 'sms_clc_mea_mnt3', 'MV_ap_4G_d', 'content_clc_max_mnt
1', 'content_clc_std_mnt3', 'sms_clc_mea_mnt1', 'pay_sum_mea_mnt1', 'MV_ot
_Roam_d', 'MV_Traf_Roam_d_Mb', 'MV_ARPU_inc_s_Traf', 'pay_p2p_out_sum_std_
mnt3', 'MV_ap_Cont_v']

Features before correlation removal: 769
Features after correlation removal: 605
Dropped 164 highly correlated features
```

In [14]:
```python
#df_uncorr = df_train.drop(columns=['voice_in_fix_tar_dur_mea_mnt1', 'voi
#df_uncorr.shape[1]
```

In [15]:
```python
# Prepare features and target
df = df_uncorr.copy()
X = df.drop(['target', 'abon_id'], axis=1, errors='ignore')
y = df['target']

print(f"Final feature matrix shape: {X.shape}")
print(f"Target shape: {y.shape}")
```

```
Final feature matrix shape: (150000, 603)
Target shape: (150000,)
```

In [16]:
```python
# lets use the StandardScaler
#scaler = StandardScaler()
#df_train_scaled = scaler.fit_transform(df_train)
#df_train_scaled = pd.DataFrame(df_train_scaled, index=df_train.index, co
```

FIRST TRAIN

In [17]:
```
# Split the data into training and testing sets
print("Splitting data into training and testing sets...")
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,

print(f"Training set shape: {X_train.shape}")
print(f"Testing set shape: {X_test.shape}")
print(f"Training set target distribution: {y_train.value_counts().to_dict
print(f"Testing set target distribution: {y_test.value_counts().to_dict()
```

```
Splitting data into training and testing sets...
Training set shape: (120000, 603)
Testing set shape: (30000, 603)
Training set target distribution: {0.0: 112331, 1.0: 7669}
Testing set target distribution: {0.0: 28083, 1.0: 1917}
```

In [18]:
```
# Count classes in your train set
neg = y_train.value_counts()[0]
pos = y_train.value_counts()[1]
scale_pos_weight = neg / pos
scale_pos_weight

# Dictionary of models to train
models = {
    "Random Forest": RandomForestClassifier(class_weight='balanced', rand
    "XGBoost": XGBClassifier(scale_pos_weight=scale_pos_weight, random_st
    "CatBoost": CatBoostClassifier(auto_class_weights='Balanced', verbose
    "Logistic Regression": LogisticRegression(class_weight='balanced', ra
    "LightGBM": LGBMClassifier(is_unbalance=True, random_state=42)
}

# Train each model and evaluate
results = []

for name, model in models.items():
    # Train the model
    model.fit(X_train, y_train)

    # Predict probabilities and binary outcomes
    prob_pred = model.predict_proba(X_test)[:, 1]
    binary_pred = model.predict(X_test)

    # Calculate metrics
    auc_score = roc_auc_score(y_test, prob_pred)
    recall = recall_score(y_test, binary_pred)
    precision = precision_score(y_test, binary_pred)
    f1 = f1_score(y_test, binary_pred)

    # Append results
    results.append({
    "Model": name,
    "AUC-ROC": auc_score,
    "F1": f1,
    "Recall": recall,
    "Precision": precision
```

```
    })

# Convert results to DataFrame
results_df = pd.DataFrame(results)
results_sorted_df = results_df.sort_values(['AUC-ROC', 'F1', 'Recall'], a
results_sorted_df
```

```
[LightGBM] [Info] Number of positive: 7669, number of negative: 112331
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.176425 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 92346
[LightGBM] [Info] Number of data points in the train set: 120000, number o
f used features: 559
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.063908 -> initscore=-2.6
84264
[LightGBM] [Info] Start training from score -2.684264
```

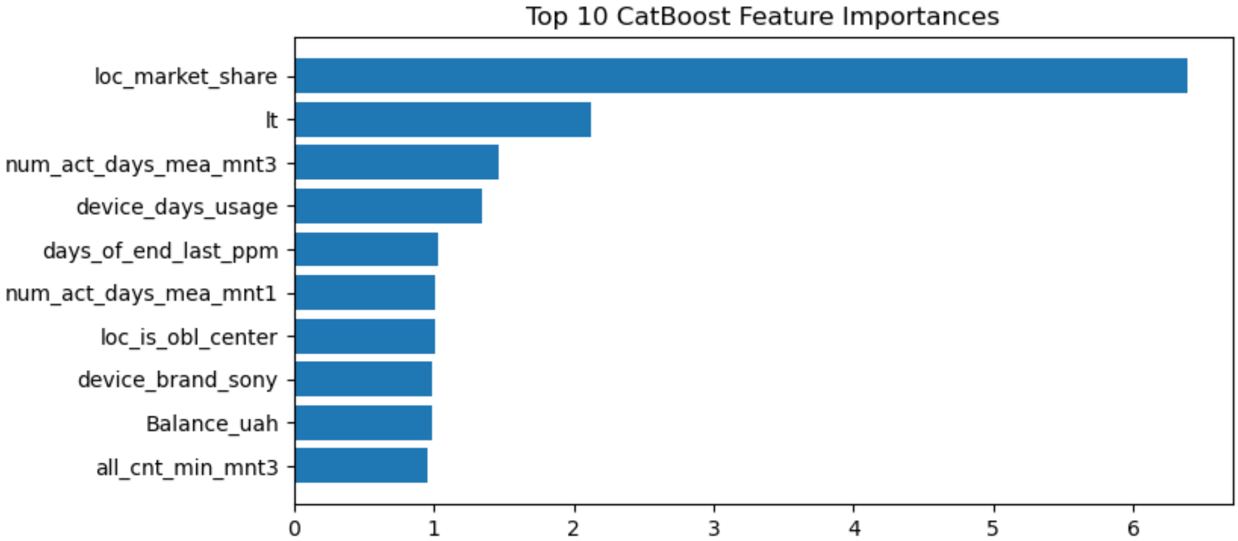
Out[18]:

	Model	AUC-ROC	F1	Recall	Precision
4	LightGBM	0.901252	0.415447	0.777256	0.283486
2	CatBoost	0.899300	0.466816	0.706312	0.348610
1	XGBoost	0.886481	0.450729	0.677621	0.337666
0	Random Forest	0.878825	0.327532	0.215962	0.677578
3	Logistic Regression	0.864833	0.326526	0.775691	0.206786

Feature importance

In [19]:

```
# After training:
catboost_model = models["CatBoost"]

# Feature importance: CatBoost
catboost_importance = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': catboost_model.get_feature_importance()
}).sort_values('Importance', ascending=False)

plt.figure(figsize=(8, 4))
plt.barh(catboost_importance['Feature'].head(10), catboost_importance['Im
plt.gca().invert_yaxis()
plt.title('Top 10 CatBoost Feature Importances')
plt.show()
```



In [20]:
```
print("\nCatBoost Feature Importance (less important):")
print(catboost_importance[catboost_importance['Importance'] <= 0.1])
```

```
CatBoost Feature Importance (less important):
                           Feature  Importance
104      conn_out_uniq_cnt_mea_mnt3    0.099827
244  voice_out_short_part_max_mnt3    0.099726
123   voice_in_short_part_max_mnt3    0.099634
235        clc_no_vas_roam_min_mnt1    0.099282
175      conn_out_uniq_cnt_mea_mnt1    0.098061
..                             ...         ...
434      conn_out_uniq_cnt_max_mnt1    0.000000
102       Ama_rchrgmnt_sum_min_mnt3    0.000000
440       Ama_rchrgmnt_sum_min_mnt1    0.000000
101            content_clc_mea_mnt3    0.000000
0         Ama_rchrgmnt_sum_max_mnt1    0.000000

[288 rows x 2 columns]
```

In [21]:
```
print("Feature Importance (less important):")
col_to_drop = catboost_importance[catboost_importance['Importance'] <= 0.
df_reduced = df.drop(columns=col_to_drop)
print(f"Dropped {len(col_to_drop)} columns. New shape: {df_reduced.shape}
```

```
Feature Importance (less important):
Dropped 288 columns. New shape: (150000, 317)
```

In [22]:
```
X = df_reduced.drop(['target', 'abon_id'], axis=1, errors='ignore')
y = df_reduced['target']

# SNew split
print("Splitting data into training and testing sets...")
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,

print(f"Training set shape: {X_train.shape}")
print(f"Testing set shape: {X_test.shape}")
print(f"Training set target distribution: {y_train.value_counts().to_dict
print(f"Testing set target distribution: {y_test.value_counts().to_dict()
```

```
Splitting data into training and testing sets...
Training set shape: (120000, 315)
Testing set shape: (30000, 315)
Training set target distribution: {0.0: 112331, 1.0: 7669}
Testing set target distribution: {0.0: 28083, 1.0: 1917}
```

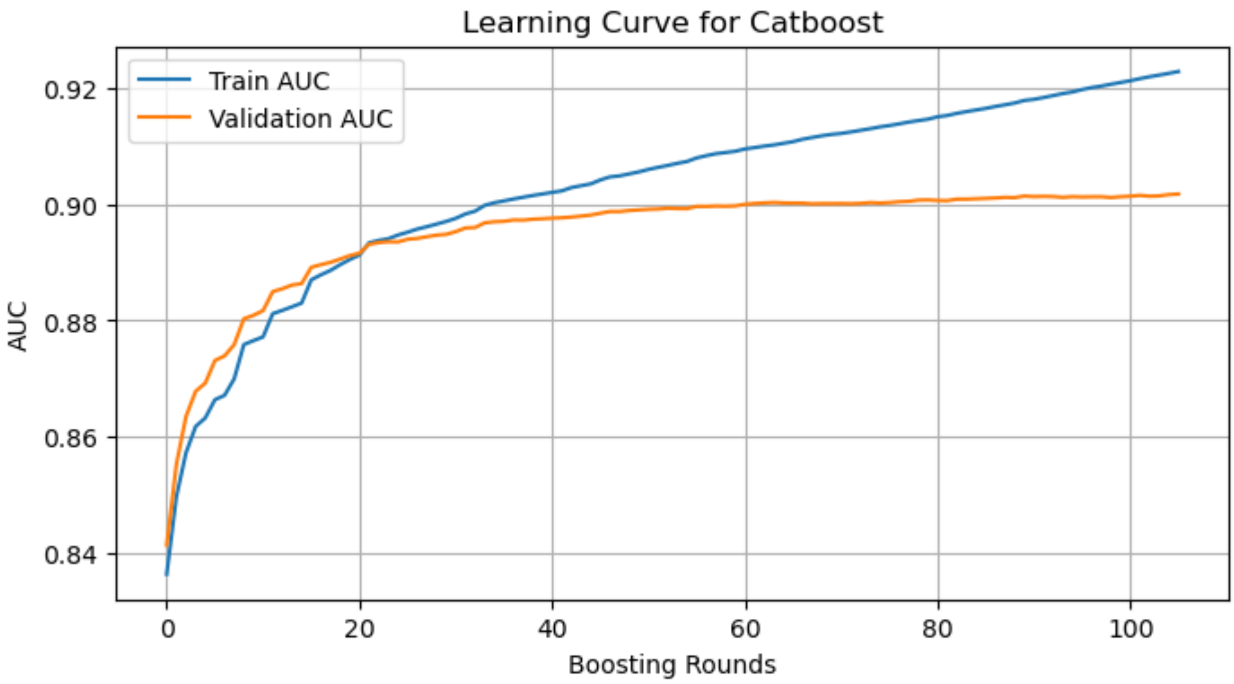
Train again on important features

In [ ]:

```
#Train again
model = CatBoostClassifier(auto_class_weights='Balanced', eval_metric='AU

model.fit(X_train, y_train, eval_set=(X_test, y_test), use_best_model=Tru

# Predict probabilities and binary outcomes
prob_pred = model.predict_proba(X_test)[:, 1]
binary_pred = model.predict(X_test)

results_df = evaluate_classification_model(
    y_true=y_test,
    y_pred_binary=binary_pred,
    y_pred_proba=prob_pred,
    model_name='catboost'
)
```

```
Learning rate set to 0.13977
0:      test: 0.8413138 best: 0.8413138 (0)     total: 31.8ms   remaining:
15.9s
10:     test: 0.8817105 best: 0.8817105 (10)    total: 335ms    remaining:
14.9s
20:     test: 0.8915978 best: 0.8915978 (20)    total: 667ms    remaining:
15.2s
30:     test: 0.8953196 best: 0.8953196 (30)    total: 973ms    remaining:
14.7s
40:     test: 0.8976419 best: 0.8976419 (40)    total: 1.27s    remaining:
14.2s
50:     test: 0.8991662 best: 0.8991662 (50)    total: 1.63s    remaining:
14.4s
60:     test: 0.9000271 best: 0.9000271 (60)    total: 2.02s    remaining:
14.6s
70:     test: 0.9001630 best: 0.9003464 (63)    total: 2.32s    remaining:
14s
80:     test: 0.9006937 best: 0.9007923 (79)    total: 2.61s    remaining:
13.5s
90:     test: 0.9013607 best: 0.9014487 (89)    total: 2.92s    remaining:
13.1s
100:    test: 0.9014217 best: 0.9014487 (89)    total: 3.21s    remaining:
12.7s
110:    test: 0.9012560 best: 0.9018015 (105)   total: 3.5s     remaining:
12.3s
120:    test: 0.9013372 best: 0.9018015 (105)   total: 3.8s     remaining:
11.9s
Stopped by overfitting detector  (20 iterations wait)

bestTest = 0.9018015027
bestIteration = 105

Shrink model to first 106 iterations.
```

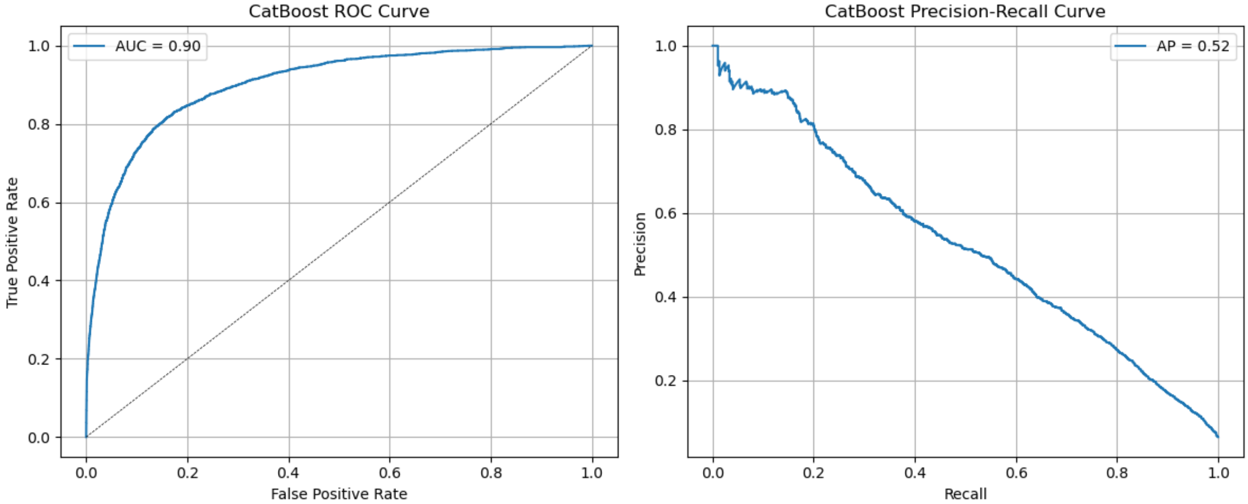
In [26]:
```
# plot loss on train and validation
plot_learning_curve(model, X_train, y_train, X_test, y_test)
```



4. Model Evaluation

In [27]:
```
# Plot ROC curves for comparison
print("Generating ROC curve comparison...")

plot_roc_pr_curves(y_test, prob_pred, title_prefix='CatBoost')

print("ROC curve analysis completed!")
```

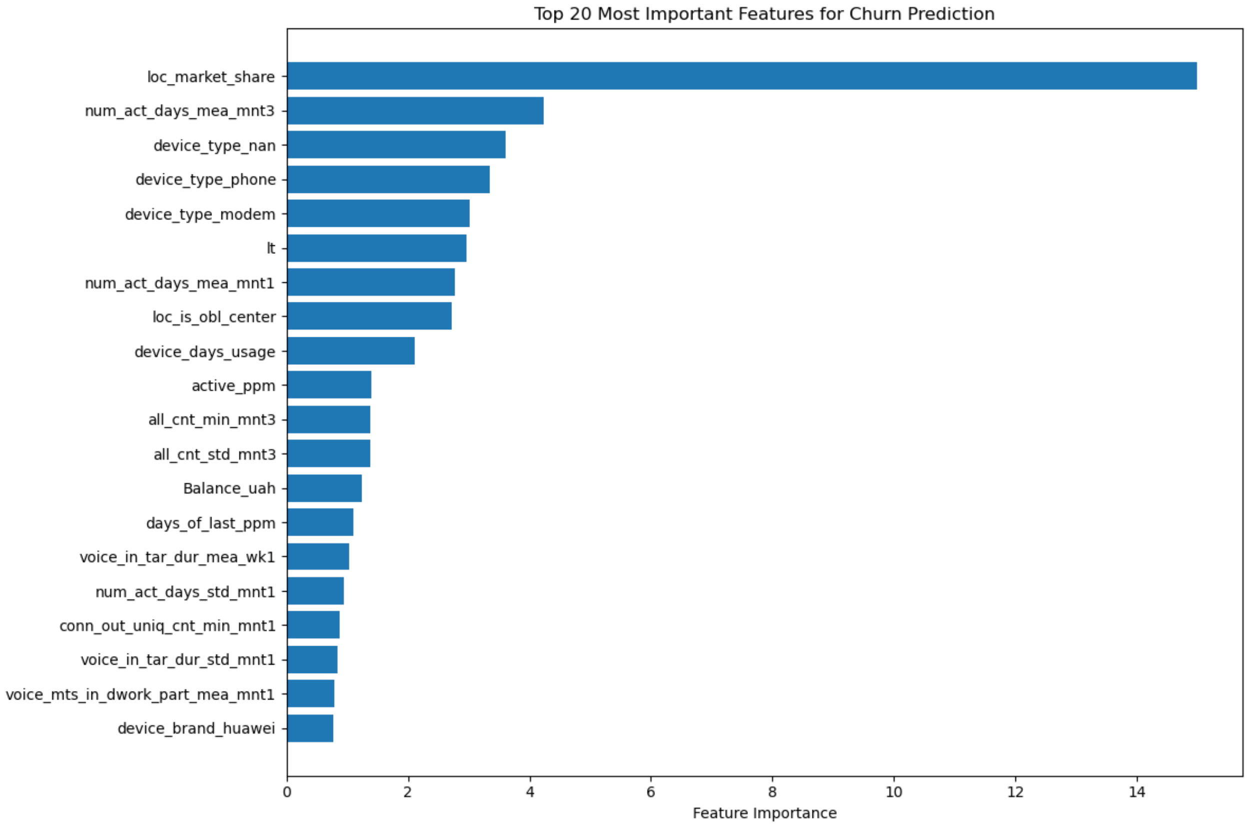
```
Generating ROC curve comparison...
```




```
ROC curve analysis completed!
```

In [28]:
```
# Analyze feature importance
print("Analyzing feature importance...")

# Get top features and all important features
top_features, important_features = get_features(model, X_train, y_train,

print(f"\nTop 20 most important features identified")
print(f"Total features with importance > 0: {len(important_features)}")

# Visualize top features
feature_importance = pd.DataFrame({
     'Feature': X_train.columns,
     'Importance': model.feature_importances_
 }).sort_values('Importance', ascending=False).head(20)

plt.figure(figsize=(12, 8))
plt.barh(range(len(feature_importance)), feature_importance['Importance']
plt.yticks(range(len(feature_importance)), feature_importance['Feature'])
plt.xlabel('Feature Importance')
plt.title('Top 20 Most Important Features for Churn Prediction')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()

print("Feature importance analysis completed!")
```

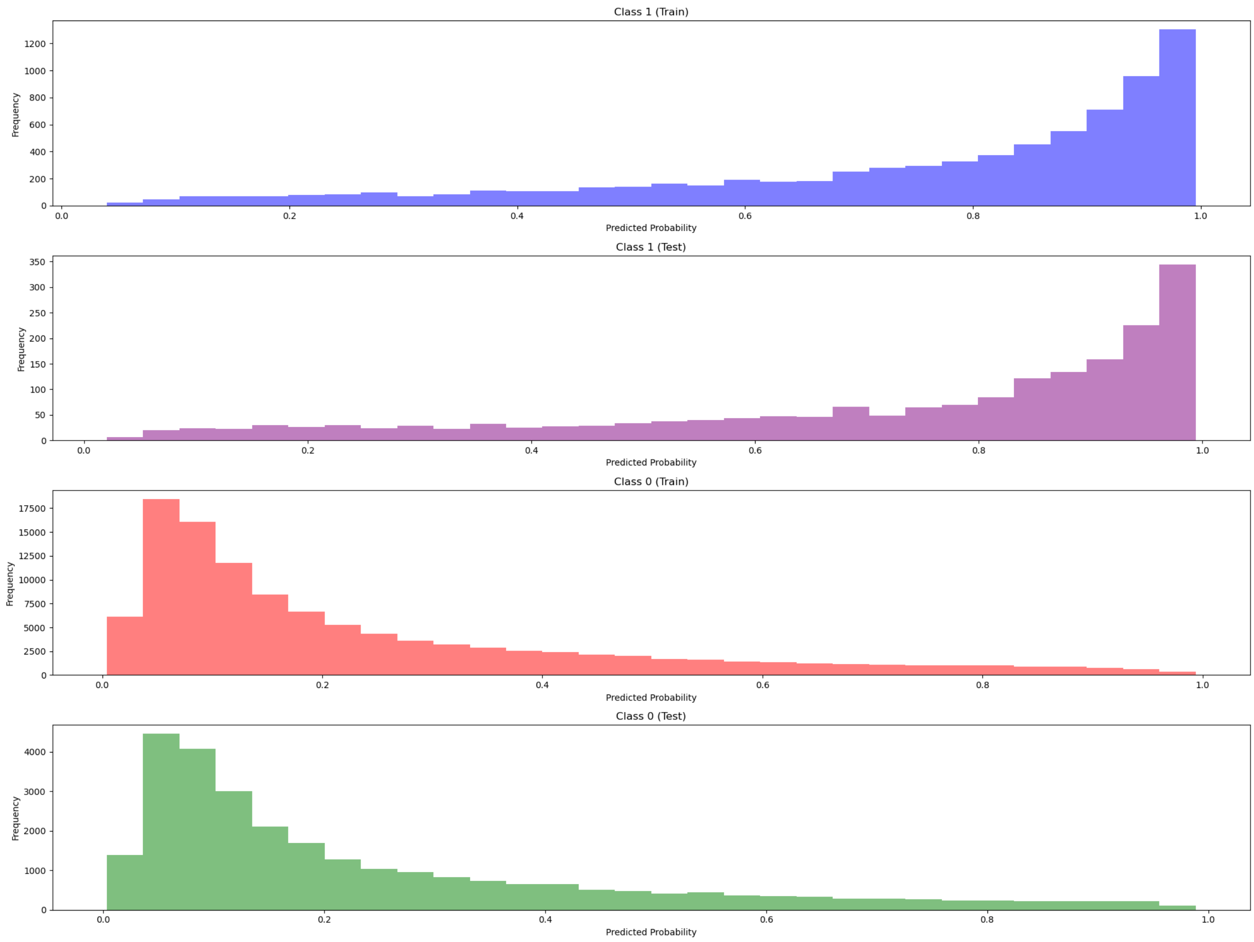
```
Analyzing feature importance...
Feature Importance:
                       Feature  Importance
257            loc_market_share   14.991926
200       num_act_days_mea_mnt3    4.234254
265             device_type_nan    3.598976
278           device_type_phone    3.347024
274           device_type_modem    3.016326
..                          ...         ...
112             all_cnt_td_mnt3    0.000000
238        data_3g_dou_std_mnt1    0.000000
237  voice_out_tar_dur_std_mnt3    0.000000
47     data_3g_tar_vol_mea_mnt1    0.000000
102            all_cnt_mea_mnt3    0.000000

[315 rows x 2 columns]

Top 20 Features:
                             Feature  Importance
257                 loc_market_share   14.991926
200            num_act_days_mea_mnt3    4.234254
265                  device_type_nan    3.598976
278                device_type_phone    3.347024
274                device_type_modem    3.016326
251                               lt    2.959417
203            num_act_days_mea_mnt1    2.770951
255                loc_is_obl_center    2.718872
259                device_days_usage    2.116950
248                       active_ppm    1.397445
148                 all_cnt_min_mnt3    1.385086
229                 all_cnt_std_mnt3    1.375491
249                      Balance_uah    1.243001
247                 days_of_last_ppm    1.104200
217          voice_in_tar_dur_mea_wk1    1.029268
147            num_act_days_std_mnt1    0.951006
115         conn_out_uniq_cnt_min_mnt1    0.870035
19           voice_in_tar_dur_std_mnt1    0.839326
104  voice_mts_in_dwork_part_mea_mnt1    0.788617
269               device_brand_huawei    0.767560

Number of Features with Importance > 0.0: 245

Top 20 most important features identified
Total features with importance > 0: 245
```




```
Feature importance analysis completed!
```

In [29]:
```python
# Plot probability distributions
print("Generating probability distribution plots...")

# For training data (probability of class 1)
y_train_pred_proba = model.predict_proba(X_train)[:, 1]
y_test_pred_proba = model.predict_proba(X_test)[:, 1]


# Get probability predictions for both classes
train_proba_1 = y_train_pred_proba[y_train == 1]
test_proba_1 = y_test_pred_proba[y_test == 1]
train_proba_0 = y_train_pred_proba[y_train == 0]
test_proba_0 = y_test_pred_proba[y_test == 0]

plot_probabilities_hist(train_proba_1, test_proba_1, train_proba_0, test_

print("Probability distribution analysis completed!")
```

```
Generating probability distribution plots...
```

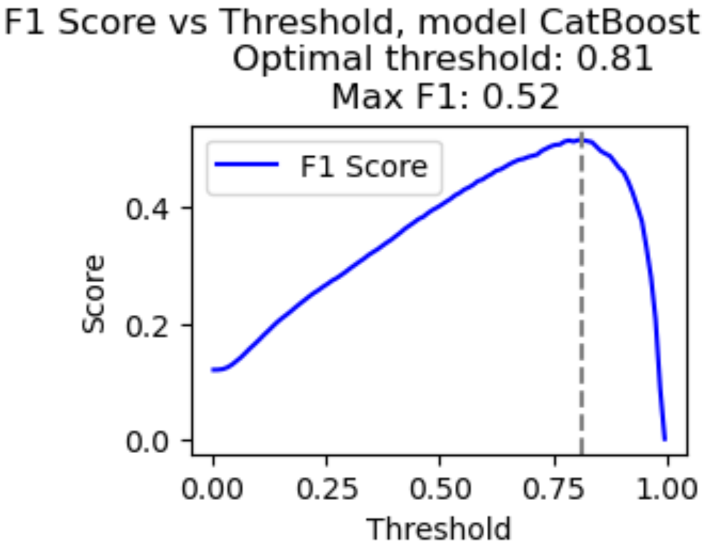



```
Probability distribution analysis completed!
```

Model Optimization Finding optimal decision threshold

In [30]:
```python
print("Finding optimal decision threshold...")

# Get test predictions for threshold optimization
catboost_test_probs = model.predict_proba(X_test)[:, 1]

# Find optimal threshold on test set (better: use validation set in real
optimal_threshold, max_f1 = calculate_optimal_threshold(y_test, catboost_

# Apply optimal threshold to test probabilities to get binary predictions
y_pred_optimal = (catboost_test_probs >= optimal_threshold).astype(int)

print("Threshold optimization completed!")
```

```
Finding optimal decision threshold...
Optimal threshold value: 0.81
Maximum F1 Score: 0.52
```

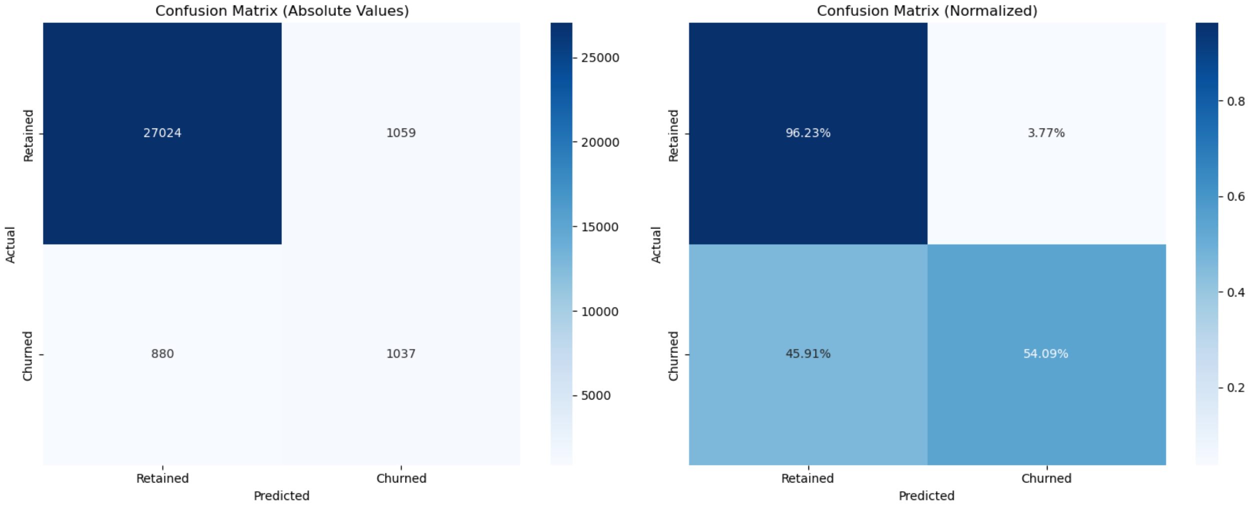



```
Date and time:  2025-06-23 11:40:56
Threshold optimization completed!
```

Confusion matrix

In [31]:
```python
plotting_confusion_matrix(y_test, y_pred_optimal)
```

```
Generating confusion matrix...
```




```
Business Impact Analysis:

True Negatives (Correctly identified retained): 27,024
False Positives (Incorrectly flagged as churn): 1,059
False Negatives (Missed churners): 880
True Positives (Correctly identified churn): 1,037
Confusion matrix analysis completed!
```

In [32]:
```python
print('Model Evaluation')
print(classification_report(y_test, y_pred_optimal))
```

```
Model Evaluation
              precision    recall  f1-score   support

         0.0       0.97      0.96      0.97     28083
         1.0       0.49      0.54      0.52      1917

    accuracy                           0.94     30000
   macro avg       0.73      0.75      0.74     30000
weighted avg       0.94      0.94      0.94     30000
```

In [33]:
```
# Evaluate
results_df = evaluate_classification_model(
    y_true=y_test,
    y_pred_binary=y_pred_optimal,
    y_pred_proba=catboost_test_probs,
    model_name='catboost'
)
```

CROSS VALIDATION

In [34]:
```
# Define the stratified splitter
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Define your model
cat = CatBoostClassifier(iterations=106, verbose=0, random_seed=42)

# Use F1 as the scoring metric
scorer = make_scorer(f1_score)

# Perform cross-validation
scores = cross_val_score(cat, X, y, cv=skf, scoring=scorer)

print("F1 scores for each fold:", scores)
print("Average F1 score:", scores.mean())
```

```
F1 scores for each fold: [0.41918665 0.44177259 0.44528562 0.44459644 0.44
657534]
Average F1 score: 0.4394833282328839
```

Final train on all train data

In [57]:
```
# Train final optimized model
print("Training tuned model...")
final_model = CatBoostClassifier(auto_class_weights='Balanced', eval_metr
final_model.fit(X, y)
print("Final model training completed!")
```

```
Training tuned model...
Learning rate set to 0.5
0:	total: 32.2ms	remaining: 1.58s
10:	total: 337ms	remaining: 1.2s
20:	total: 629ms	remaining: 868ms
30:	total: 915ms	remaining: 561ms
40:	total: 1.2s	remaining: 263ms
49:	total: 1.52s	remaining: 0us
Final model training completed!
```

Save the final model

In [58]:
```python
print("Saving the final model...")
save_model(final_model, list(X.columns), optimal_threshold)
print("Model saved successfully!")
print(f"Analysis completed at: {datetime.now().strftime('%Y-%m-%d %H:%M:%
```

```
Saving the final model...
Save CatBoostClassifier_23062025_12_05.pickle
Model saved successfully!
Analysis completed at: 2025-06-23 12:05:46
```

PREDICTIONS ON TEST DATA

In [59]:
```python
# Load saved data
model, feature_names, threshold = load_data('CatBoostClassifier_22062025_
```

In [60]:
```python
# Load test data
test = load_data('churn_test_model_fe.pickle')
print("Test data structure:")
print(f"Dataset shape: {test.shape}")
```

```
Test data structure:
Dataset shape: (150000, 817)
```

In [61]:
```python
# Do the same transformation as with train data
df_test = test[feature_names].fillna(-1)
y = test['target']
X = df_test
# Predict
predictions_proba = model.predict_proba(X)[:, 1]
predictions_binary = (predictions_proba >= threshold).astype(int)
predictions_binary
```

Out[61]:
```
array([0, 0, 0, ..., 0, 0, 1])
```

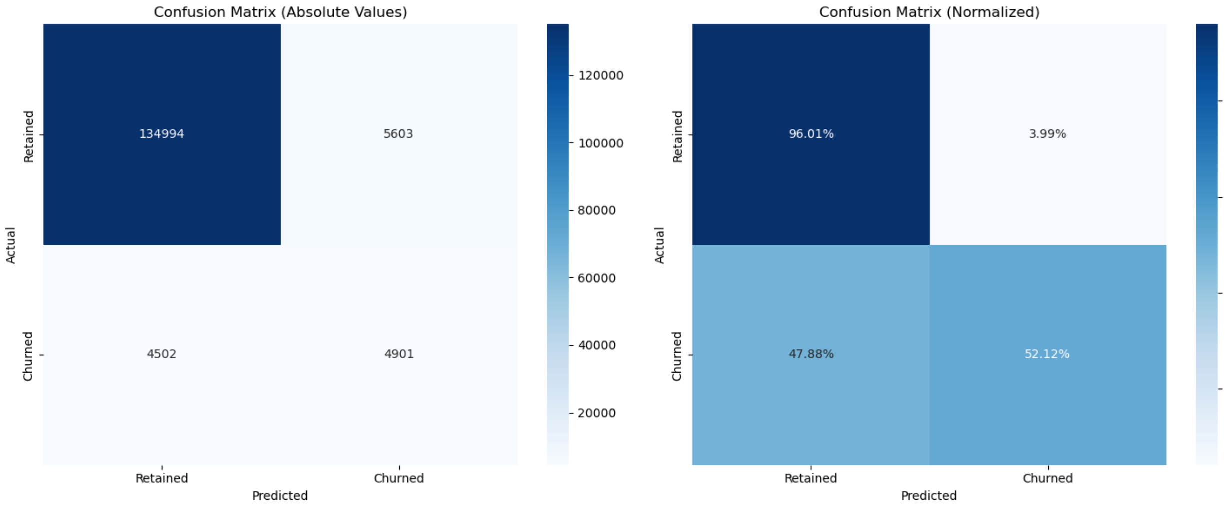
In [67]:
```python
# Evaluate
results_df = evaluate_classification_model(
    y_true=y,
    y_pred_binary=predictions_binary,
    y_pred_proba=predictions_proba,
    model_name='catboost'
)
results_df
```

Out[67]:

	Model	AUC-ROC	Recall	F1	Precision
0	catboost	0.880256	0.521217	0.49239	0.466584

In [63]:
```
plotting_confusion_matrix(y, predictions_binary)
```

```
Generating confusion matrix...
```




```
Business Impact Analysis:

True Negatives (Correctly identified retained): 134,994
False Positives (Incorrectly flagged as churn): 5,603
False Negatives (Missed churners): 4,502
True Positives (Correctly identified churn): 4,901
Confusion matrix analysis completed!
```

In [64]:
```
print('Model Evaluation')
print(classification_report(y, predictions_binary))
```

```
Model Evaluation
              precision    recall  f1-score   support

         0.0       0.97      0.96      0.96    140597
         1.0       0.47      0.52      0.49      9403

    accuracy                           0.93    150000
   macro avg       0.72      0.74      0.73    150000
weighted avg       0.94      0.93      0.93    150000
```

5. Business Recommendations and ROI Analysis

In [65]:
```
print("Calculating business impact and ROI potential for multiple retenti

# Metrics from the model/results
total_customers = len(y)
actual_churners = sum(y)
predicted_churners = sum(predictions_binary)
correctly_identified = sum((y == 1) & (predictions_binary == 1))

# Business assumptions
avg_customer_value = 50  # Monthly revenue per customer
```

```
campaign_cost_per_customer = 20  # Cost of retention campaign per custome

# Retention rates to analyze (from 3% to 30%)
retention_rates = [0.03, 0.05, 0.0715, 0.1, 0.15, 0.2, 0.25]

roi_results = []

for rate in retention_rates:
    potential_savings = correctly_identified * avg_customer_value * 12 *
    campaign_cost = predicted_churners * campaign_cost_per_customer
    net_roi = potential_savings - campaign_cost
    roi_percentage = (net_roi / campaign_cost) * 100 if campaign_cost > 0

    roi_results.append({
        "Retention Rate (%)": f"{rate*100:.0f}%",
        "Potential Savings ($)": potential_savings,
        "Campaign Cost ($)": campaign_cost,
        "Net ROI ($)": net_roi,
        "ROI (%)": roi_percentage
    })

roi_df = pd.DataFrame(roi_results)

print(f"\nBusiness Impact Analysis (Retention Scenarios):")
print(f"Total customers in test set: {total_customers:,}")
print(f"Actual churners: {actual_churners:,} ({actual_churners/total_cust
print(f"Predicted churners: {predicted_churners:,} ({predicted_churners/t
print(f"Correctly identified churners: {correctly_identified:,}\n")

print(roi_df.to_string(index=False))
```

```
Calculating business impact and ROI potential for multiple retention scena
rios...

Business Impact Analysis (Retention Scenarios):
Total customers in test set: 150,000
Actual churners: 9,403.0 (6.3%)
Predicted churners: 10,504 (7.0%)
Correctly identified churners: 4,901

Retention Rate (%)  Potential Savings ($)  Campaign Cost ($)  Net ROI ($)
ROI (%)
                3%                88218.0             210080    -121862.0
-58.007426
                5%               147030.0             210080     -63050.0
-30.012376
                7%               210252.9             210080        172.9
0.082302
               10%               294060.0             210080      83980.0
39.975248
               15%               441090.0             210080     231010.0
109.962871
               20%               588120.0             210080     378040.0
179.950495
               25%               735150.0             210080     525070.0
249.938119
```

Business Impact Reflection

This analysis shows how leveraging modern data tools can directly enhance our business outcomes. By running a test campaign, we can measure actual retention rates and assess the financial impact - even when initial costs are incurred. Importantly, as retention success rates exceed 10%, the campaign shifts into profitability, delivering a strong ROI and substantial net gains for the business.

It's also important to remember that retaining an existing client is up to six times less expensive than acquiring a new one, underscoring the value of investing in effective retention strategies.

Summary and Key Findings

Model Performance on unseen data

- **ROC AUC: 0.88** - Excellent discrimination ability due to hard unbalanced data
- **F1 Score: 0.49** - Good balance between precision and recall
- **Optimal Threshold: 0.81** - Maximizes business value

Churn Prevention: The Precision-Recall Trade-Off

When deploying a churn prediction model, there is always a fundamental trade-off between campain costs and over-targeting:

- But ! the cost of losing a customer is high relative to the cost of a retention offer, it may be better to maximize recall, even if that means higher campaign costs.

- If budget constraints are critical, you may prefer to maximize precision and accept some churn.