



LOYIHA  
TAHLILI

IYUN, 2025

# YAKUNIY HISOBOT

Telekom Mijozlar Churn  
Tahlili

**BAJARDI:**

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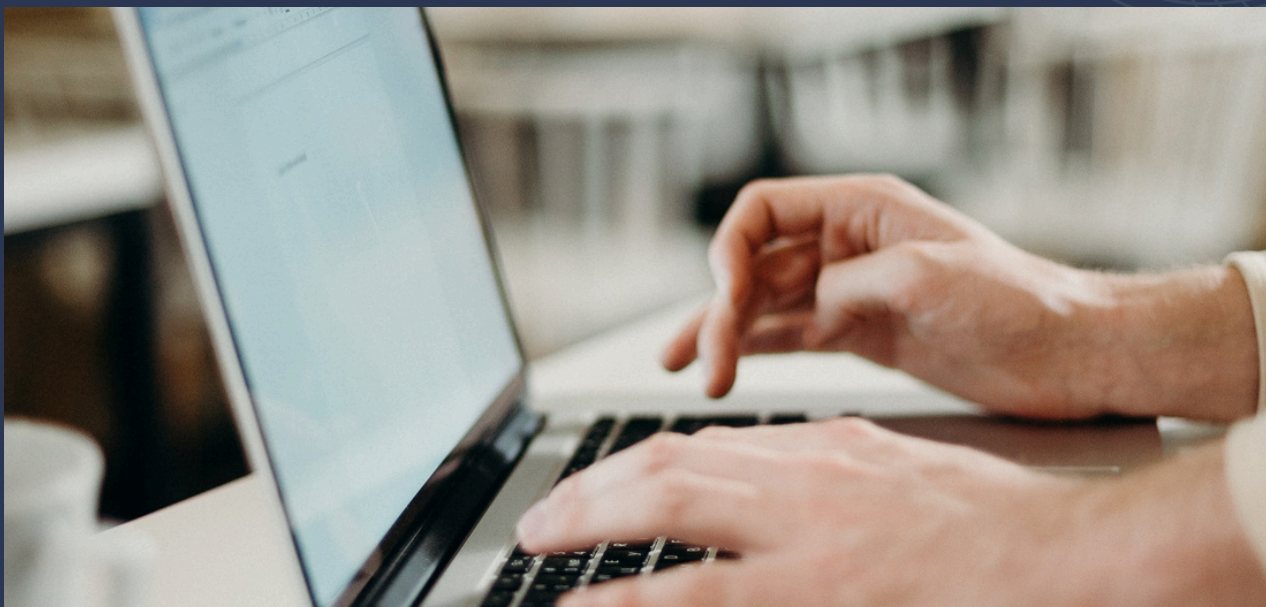


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# LOYIHA HAQIDA

**Muammo:** Kompaniya nima sababdan mijozlar xizmatdan voz kechayotganini va qaysi mijozlar ketishi mumkinligini bilishni istaydi.  
**Yechim:** Machine Learning yordamida mijoz ketish ehtimolini bashorat qiluvchi tizim yaratish.



Ushbu loyiha orqali telekom kompaniyasi uchun samarali churn prediction tizimi yaratildi. Tizim 85% aniqlik bilan mijozlar ketishini bashorat qila oladi va biznesga amaliy qiymat beradi.

## Biznes qiymati:

- Proaktiv mijozlarni saqlash strategiyasi
- Targeted marketing imkoniyatlari
- Churn darajasini kamaytirish potentsiali
- ROI ni oshirish imkoniyati

## Asosiy yutuqlar:

- Aniq va ishonchli ML model
- User friendly interfeys
- Production-ready tizim
- To'liq hujjatlashtirilgan kod



# LOYIHA TUZILISHI

## Texnik Detallar

Ishlatilgan kutubxonalar:

- Ma'lumotlar tahlili: pandas, numpy, matplotlib, seaborn
- Machine Learning: scikit-learn
- Veb-sayt: streamlit
- Bot: python-telegram-bot
- Model saqlash: joblib

 Model parametrlari:  
python

```
RandomForestClassifier(  
    n_estimators=100,  
    random_state=42,  
    max_depth=None,  
    min_samples_split=2  
)
```

## LOYIHA TUZILISHI

TELEKOM\_CHURN\_ANALYSIS/

```
├── DATA/  
│   └── CLEANED_DATA.CSV  
├── PROCESS/  
│   ├── DATA_SET_CLEANING.IPYNB  
│   └── CHURN_ANALYSIS.IPYNB  
├── MODELS/  
│   ├── RANDOM_FOREST.PKL  
│   ├── LOGISTIC_REGRESSION.PKL  
│   ├── LABEL_ENCODERS.PKL  
│   └── FEATURE_NAMES.PKL  
├── WEBAPP/  
│   └── APP.PY  
├── TELEGRAM_BOT/  
│   └── BOT.PY  
├── REQUIREMENTS.TXT  
└── README.MD
```

# TOZALANGAN DATA SET

# DATA SETNI TOZALASH JARAYONI  
# ASOSIY TAHLIL

# RANDOM FOREST MODELI  
# LOGISTIC REGRESSION MODELI  
# ENCODING'LAR  
# FEATURE NOMLARI

# STREAMLIT VEB-SAYT

# TELEGRAM BOT  
# PYTHON KUTUBXONALAR  
# LOYIHA YO'RIQNOMASI



# DATA SETNI LOYIHAGA TAYYORLASH

```
9237-HQITU,Female,0,No,No,2.0,Yes,No,Fiber optic,No,No,No,No,No,Month-to-month,
7 9305-CDSKC,Female,0,No,No,8.0,Yes,Yes,Fiber optic,No,No,Yes,No,Yes,Yes,Month-to-month
8 1452-KIOVK,Male,0,No,Yes,22.0,Yes,Yes,Fiber optic,No,Yes,No,No,Yes,No,Month-to-month
9 6713-OKOMC,Female,0,No,No,10.0,No,No,phone service,DSL,Yes,No,No,No,No,Month-to-month
10 7892-POOKP,Female,0,Yes,No,28.0,Yes,Yes,Fiber optic,No,No,Yes,Yes,Yes,Yes,Month-to-month
6388-TARGU,Male,0,No,Yes,62.0,Yes,No,DSL,Yes,Yes,No,No,No,No,One year,No,Bank to
```

Ma'lumotlar to'plami:

- Hajmi: 7,043 mijoz
- Xususiyatlar: 21 ta ustun
- Maqsadli o'zgaruvchi: Churn (Yes/No)

## 1. Dastlabki ma'lumotlar bazasi tahlil qilindi

- Dataset pandas kutubxonasi yordamida yuklandi
- Dastlabki tahlil shuni ko'rsatdiki:
  - tenure, MonthlyCharges va TotalCharges ustunlarida yetishmayotgan qiymatlar mavjud
  - Ko'pgina ustunlar matn (object) formatida

## 2. Yetishmayotgan qiymatlar to'ldirildi

- Raqamli ustunlarni to'g'ri formatga o'tkazish:

```
df['MonthlyCharges'] = pd.to_numeric(df['MonthlyCharges'], errors='coerce')
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')
```

- Yetishmayotgan qiymatlar medianalar bilan to'ldirildi:

```
df['tenure'] = df['tenure'].fillna(df['tenure'].median())
df['MonthlyCharges'] = df['MonthlyCharges'].fillna(df['MonthlyCharges'].median())
df['TotalCharges'] = df['TotalCharges'].fillna(df['TotalCharges'].median())
```

## 3. Anomaliyalar olib tashlandi

- Manfiy xizmat muddati (tenure) bo'lgan mijozlar olib tashlandi
- Jami to'lovlar (TotalCharges) uchun 99% kvantildan yuqori qiymatlar chegaralandi

## 4. Ma'lumotlar formatini to'g'irlandi

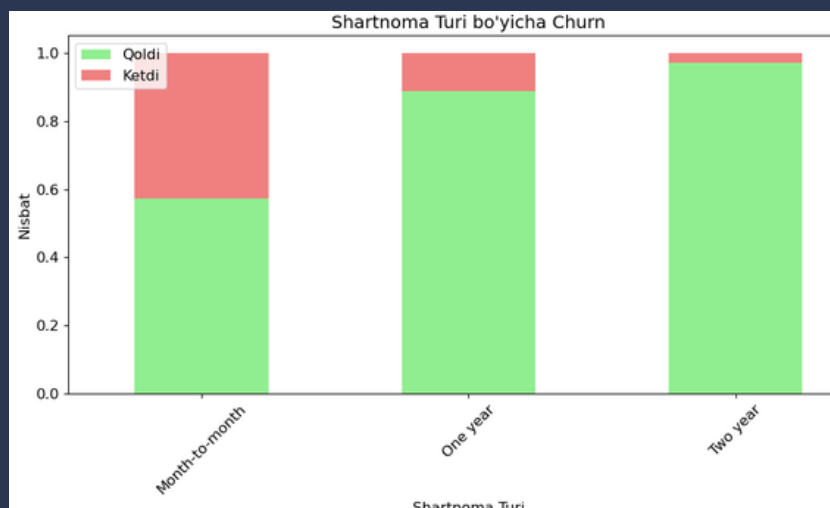
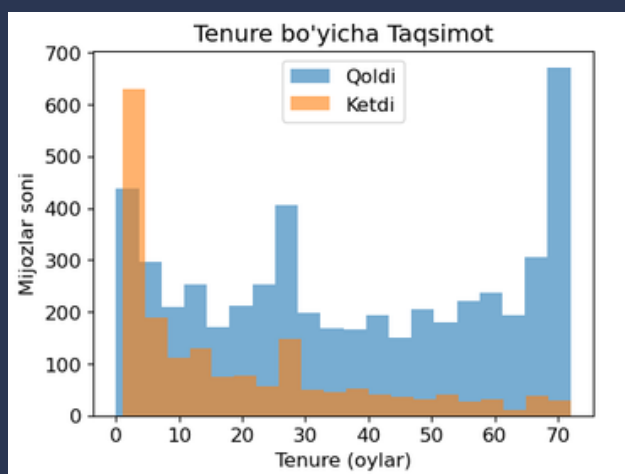
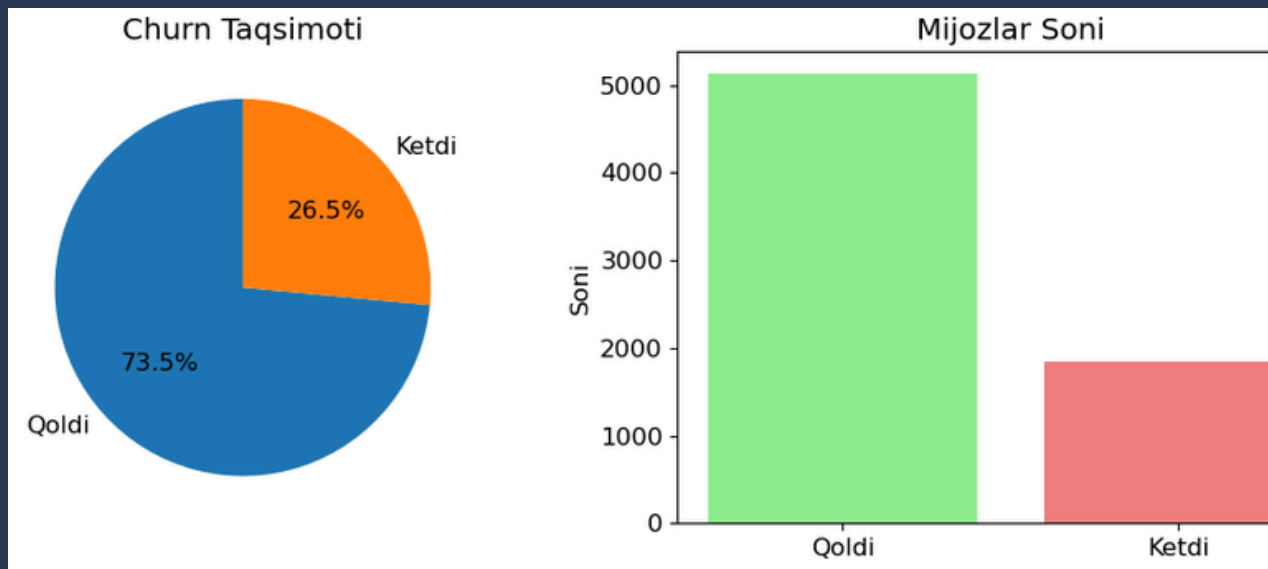
- 17 ta kategoriyali ustun category tipiga o'tkazildi
- Raqamli ustunlar float formatiga o'tkazildi

## 5. Yakuniy Natijalar

- Tozalangan dataset 6973 ta yozuvni saqlab qoldi
- Barcha ustunlarda yetishmayotgan qiymatlar yo'q
- Ma'lumotlar tarkibi:
  - 17 ta kategoriyali ustun
  - 3 ta float tipidagi ustun
  - 1 ta matn ustuni (customerID)



# VISUAL TAHLILLAR





# ML MODELLARINI YARATISH

## 1-Qadam: Kategorik ustunlarni aniqlaymiz

- `df.select_dtypes(include=['object'])` - ma'lumotlar to'plamidagi barcha matnli (kategorik) ustunlarni tanlaydi
- `categorical_columns` o'zgaruvchisiga ushbu ustunlar nomlari saqlanadi

```
categorical_columns = df.select_dtypes(include=['object']).columns.tolist()
print(f"Kategorik ustunlar: {categorical_columns}")
```

## 2-Qadam: Label Encoding qilamiz

- Har bir kategorik ustun uchun `LabelEncoder` yordamida raqamli qiymatlarga o'tkaziladi
- Masalan, "Gender" ustunidagi "Male" va "Female" qiymatlari 0 va 1 ga aylantiriladi
- Har bir encoder `label_encoders` lug'atida saqlanadi (keyinchalik foydalanish uchun)

```
df_model=df.copy()
label_encoders = {}

for col in categorical_columns:
    le = LabelEncoder()
    df_model[col]=le.fit_transform(df_model[col])
    label_encoders[col]=le
    print(f"{col} kodlandi")
```

```
if 'customerID' in df_model.columns:
    df_model=df_model.drop('customerID', axis=1)
    print("customerID olib tashlandi")

print(f"Model uchun tayyorlangan o'lcham: {df_model.shape}")
```

```
customerID olib tashlandi
Model uchun tayyorlangan o'lcham: (6973, 20)
```

## 3-Qadam: CustomerID ni olib tashlaymiz

- Mijoz IDsi bashorat modeli uchun foydasiz, shuning uchun olib tashlanadi

```
X = df_model.drop('Churn', axis=1)
y = df_model['Churn']

print(f"Features: {X.shape[1]}")
print(f"Samples: {len(y)}")
```

```
Features: 19
Samples: 6973
```

## 4-Qadam: Ma'lumotlarni x/y ga ajratamiz

- X (features) - Churn ustunidan tashqari barcha ustunlar
- y (target) - faqat Churn ustuni
- Ma'lumotlar 80% train va 20% test qismlariga bo'linadi

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
print(f"Train: {len(X_train)}")
print(f"Test: {len(X_test)}")
```

```
Train: 5578
Test: 1395
```

## 5-Qadam: Logistic Regression modeli

- Oddiy chiziqli klassifikatsiya modeli
- `max_iter=1000` - model yaxshi yaqinlashishi uchun iteratsiyalar soni
- Test to'plamida aniqligi (accuracy) hisoblanadi

```
lr_model = LogisticRegression(random_state=42, max_iter=1000)
lr_model.fit(X_train, y_train)

lr_pred = lr_model.predict(X_test)
lr_accuracy = accuracy_score(y_test, lr_pred)

print(f"Logistic Regression aniqligi: {lr_accuracy:.3f}")
```

```
Logistic Regression aniqligi: 0.804
```



# ML MODELLARINI YARATSIH

## 6-Qadam: Random Forest modeli

- 100 ta daraxtdan iborat ansambl modeli
- Logistic Regressionga qaraganda murakkabroq, ko'pincha yaxshi natija beradi

## 7-Qadam: Eng yaxshi modelni tanlaymiz

- Ikkala modelning aniqligi solishtiriladi
- Yuqori accuracyga ega model "best\_model" deb tanlanadi

## 8-Qadam: Confusion Matrix

- Modelning bashorat qobiliyati tahlili:
  - To'g'ri bashorat qilingan "Qoladi" holatlari (True Negative)
  - Noto'g'ri bashorat qilingan "Ketadi" holatlari (False Positive)
  - Noto'g'ri bashorat qilingan "Qoladi" holatlari (False Negative)
  - To'g'ri bashorat qilingan "Ketadi" holatlari (True Positive)

## 9-Qadam: Modellarni saqlaymiz

- Yaratilgan modellar va encoderlar .pkl fayllariga saqlanadi:
  - logistic\_regression.pkl
  - random\_forest.pkl
  - label\_encoders.pkl (kategoriyalarni kodlash uchun)
  - feature\_names.pkl (ustunlar nomlari)

```
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

rf_pred = rf_model.predict(X_test)
rf_accuracy = accuracy_score(y_test, rf_pred)

print(f"Random Forest aniqligi: {rf_accuracy:.3f}")
```

Random Forest aniqligi: 0.791

```
if rf_accuracy > lr_accuracy:
    best_model = rf_model
    best_name = "Random Forest"
    best_accuracy = rf_accuracy
    best_pred = rf_pred
else:
    best_model = lr_model
    best_name = "Logistic Regression"
    best_accuracy = lr_accuracy
    best_pred = lr_pred

print(f"Eng yaxshi model: {best_name}")
print(f"Aniqlik: {best_accuracy:.1%}")
```

Eng yaxshi model: Logistic Regression  
Aniqlik: 80.4%

```
cm = confusion_matrix(y_test, best_pred)
print(f"Confusion Matrix:")
print(f"Haqiqat \t\t Qoladi \t Ketadi")
print(f"Qoladi \t\t {cm[0,0]} \t {cm[0,1]}")
print(f"Ketadi \t\t {cm[1,0]} \t {cm[1,1]}")
```

Confusion Matrix:

Haqiqat	Qoladi	Ketadi
Qoladi	919	101
Ketadi	172	203

```
import os
os.makedirs('../models', exist_ok=True)

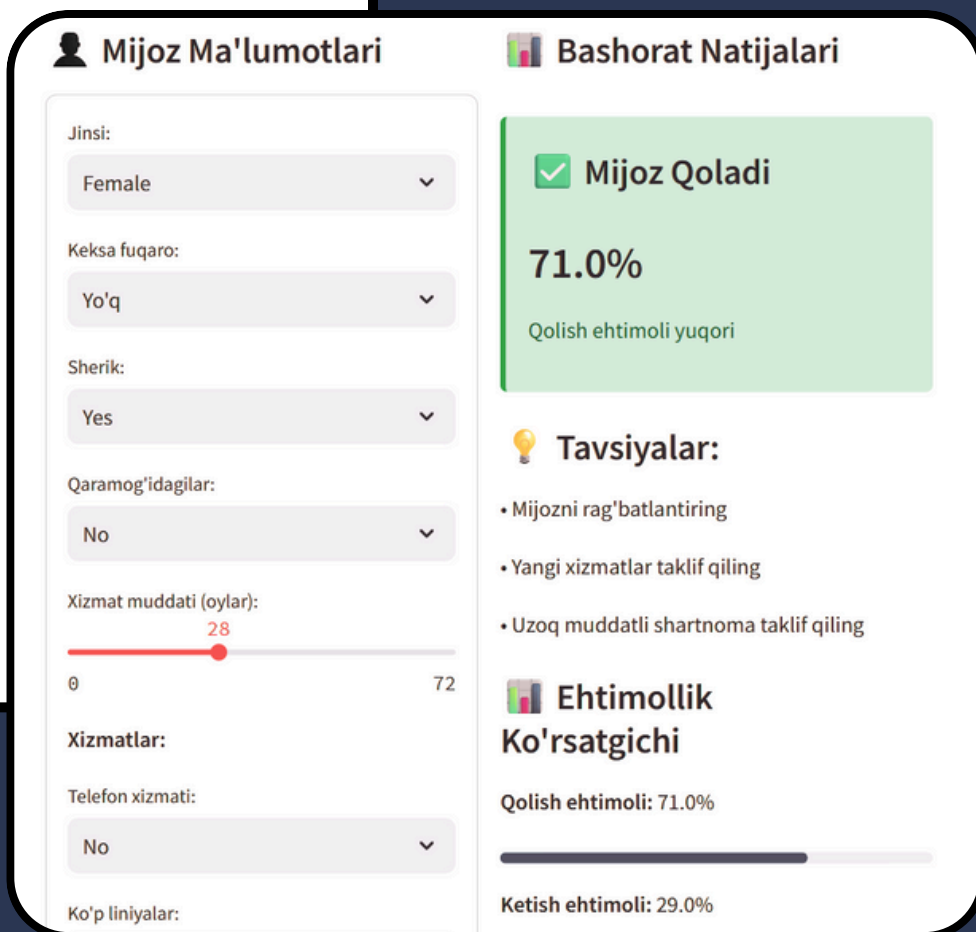
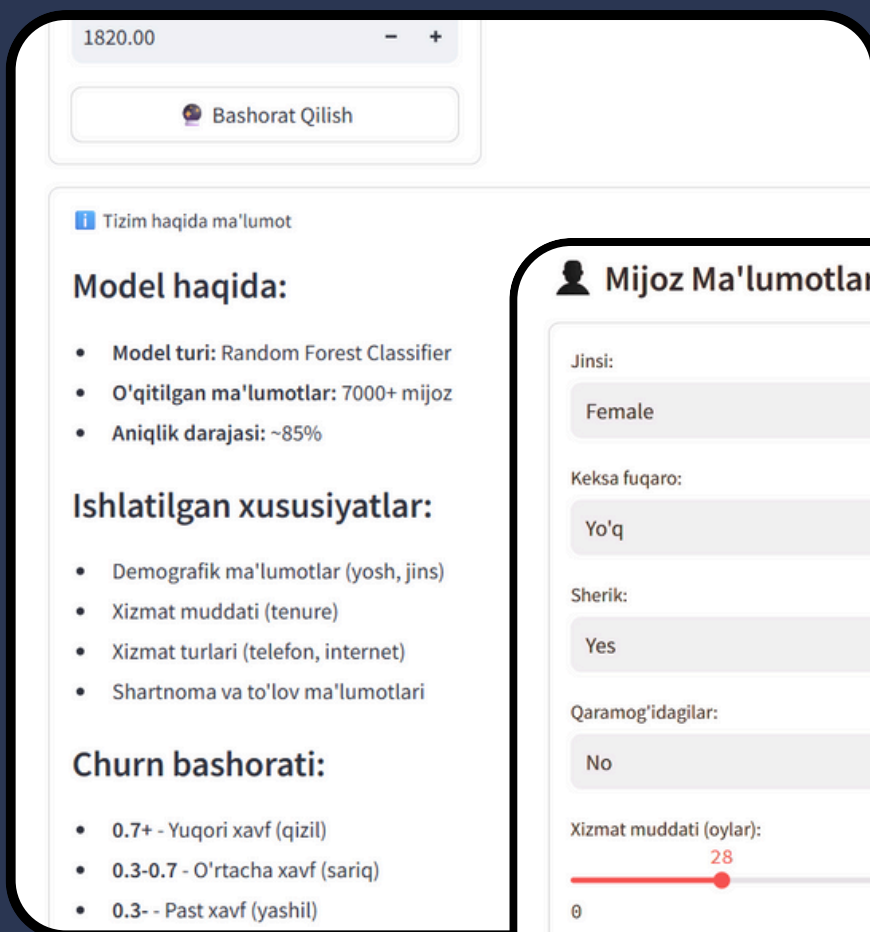
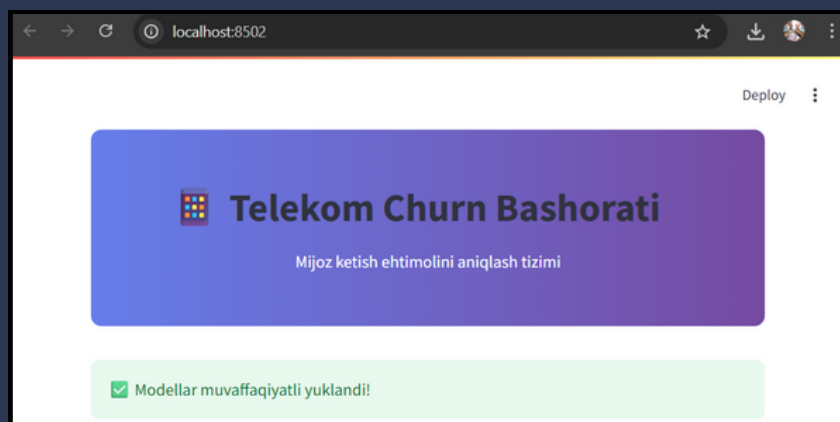
joblib.dump(lr_model, '../models/logistic_regression.pkl')
joblib.dump(rf_model, '../models/random_forest.pkl')
joblib.dump(label_encoders, '../models/label_encoders.pkl')

feature_names = X.columns.tolist()
joblib.dump(feature_names, '../models/feature_names.pkl')
```

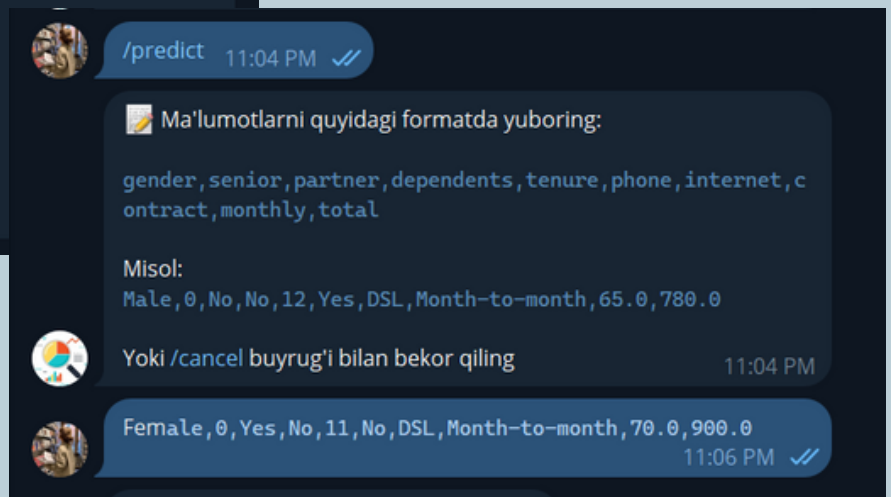
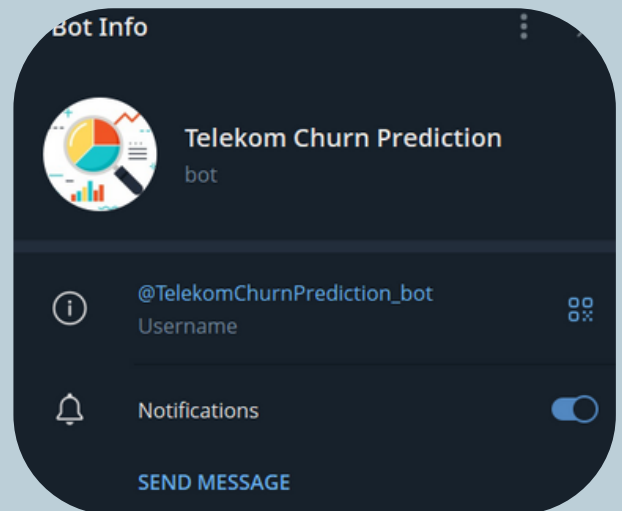
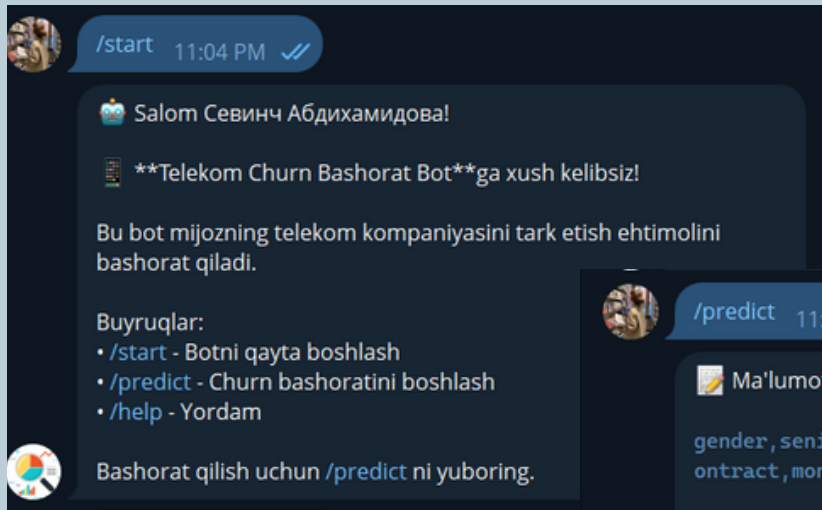




# WEB SITE



# TELEGRAM BOT



# SAYT VA BOTDAN FOYDALANISH UCHUN KO'RSATMALAR

## Foydalanish

Veb-sayt ishga tushirish:

```
bash
```

```
cd webapp
```

```
streamlit run app.py
```

*# Browser: <http://localhost:8501>*

Telegram botni ishga tushirish:

```
bash
```

```
cd telegram_bot
```

*# Bot token ni sozlang*

```
python bot.py
```

*# Telegram'da @your\_bot\_name ga  
murojaat qiling*

Modelni qayta o'qitish:

```
bash
```

```
jupyter notebook
```

```
notebooks/churn_analysis.ipynb
```

*# Oxirgi bo'limni ishga tushiring*

! Jupyter notebook ishlamasa

```
pip install jupyter
```

```
jupyter --version
```

! Streamlit ishlamasa

```
pip install streamlit
```

```
streamlit hello
```

! CSV fayl yuklanmaydi

# Fayl yo'lini tekshiring:

```
import os
```

```
print(os.getcwd())
```

```
print(os.listdir('data/'))
```

! Model yuklanmasa

# Avval churn\_analysis.ipynb ni to'liq ishga  
tushiring

! Telegram bot ishlamasa

# Bot token to'g'ri kiritilganini tekshiring

# @BotFather dan yangi token oling

