



Personalized Healthcare Recommendations

Internship Project Report

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(This is link to the GitHub repository)

<https://github.com/tanisha-m26/Personalized-healthcare-recommendation>

1. Project Overview

The **Personalized Healthcare Recommendations System** aims to develop an intelligent, data-driven model that analyzes patient parameters to provide customized healthcare suggestions. By leveraging machine learning on blood dataset parameters such as *Recency*, *Frequency*, *Monetary value*, and *Time*, the system predicts whether a patient requires *immediate intervention* or *routine monitoring*.

This project represents a step toward **data-assisted precision medicine**, where data analytics empowers personalized patient care.

2. Objective

- Analyze patient blood data to identify health patterns.
- Predict risk and generate actionable healthcare recommendations.
- Support healthcare professionals in preventive decision-making.

3. Dataset Description

Dataset Name: Blood Donor Data

Feature	Description
Recency	Number of days since last donation/visit
Frequency	Number of donations/visits in a period
Monetary	Total medical expenditure or donation amount
Time	Duration (in months) as a patient/donor
Class	Target variable: 0 = No immediate action, 1 = Regular monitoring required

Table 1: Dataset Features Description

Sample Records:

Recency	Frequency	Monetary	Time	Class
2	50	12500	99	1
1	24	6000	77	0
4	4	1000	4	0
5	46	11500	98	1

Table 2: Sample Records from the Dataset

4. Methodology

4.1 Problem Understanding

Predict whether a patient requires intervention or is in a stable condition using their health metrics.

4.2 Data Preparation

- Load dataset using `pandas`.
- Handle missing values via mean/mode imputation.
- Normalize numerical features using `StandardScaler`.
- Split data into training (80%) and testing (20%) sets.

4.3 Exploratory Data Analysis (EDA)

- Visualize distributions using `Matplotlib` and `Seaborn`.
- Identify feature correlations with the target.

```
print(data.head())
print(data.describe())
print(data['Class'].value_counts())
```

[17]

...	Recency	Frequency	Monetary	Time	Class
0	2	50	12500	99	1
1	0	13	3250	28	1
2	1	17	4000	36	1
3	2	20	5000	45	1
4	1	24	6000	77	0

	Recency	Frequency	Monetary	Time	Class
count	748.000000	748.000000	748.000000	748.000000	748.000000
mean	9.506684	5.516043	1378.676471	34.284759	0.237968
std	8.095396	5.841825	1459.826781	24.380307	0.426124
min	0.000000	1.000000	250.000000	2.000000	0.000000
25%	2.750000	2.000000	500.000000	16.000000	0.000000
50%	7.000000	4.000000	1000.000000	28.000000	0.000000
75%	14.000000	7.000000	1750.000000	50.000000	0.000000
max	74.000000	50.000000	12500.000000	99.000000	1.000000

Class

0	570
1	178

Name: count, dtype: int64

Figure 1: Distribution of Key Features
Dataset-Head/Describe

Dataset Overview					
	Recency	Frequency	Monetary	Time	Class
0	2	50	12500	99	1
1	0	13	3250	28	1
2	1	17	4000	36	1
3	2	20	5000	45	1
4	1	24	6000	77	0
5	4	4	1000	4	0
6	2	7	1750	14	1
7	1	12	3000	35	0
8	2	9	2250	22	1
9	5	46	11500	98	1

Figure 2: DATASET

Personalized Healthcare Recommendation System						Deploy
Explore your health data and predictions in real time						
Dataset Preview						
	Recency	Frequency	Monetary	Time	Class	
0	2	50	12500	99	1	
1	0	13	3250	28	1	
2	1	17	4000	36	1	
3	2	20	5000	45	1	
4	1	24	6000	77	0	

Figure 3: Dataset-Preview

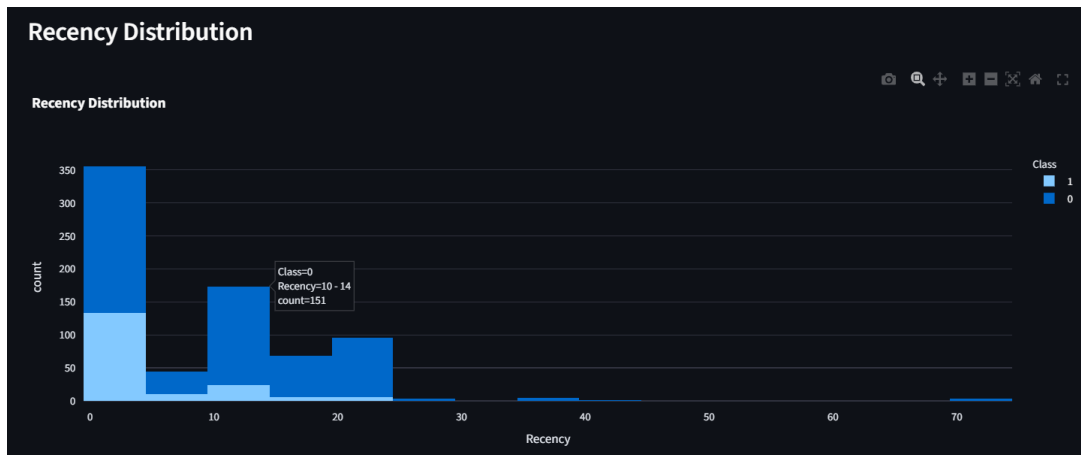


Figure 4: Recency Distribution

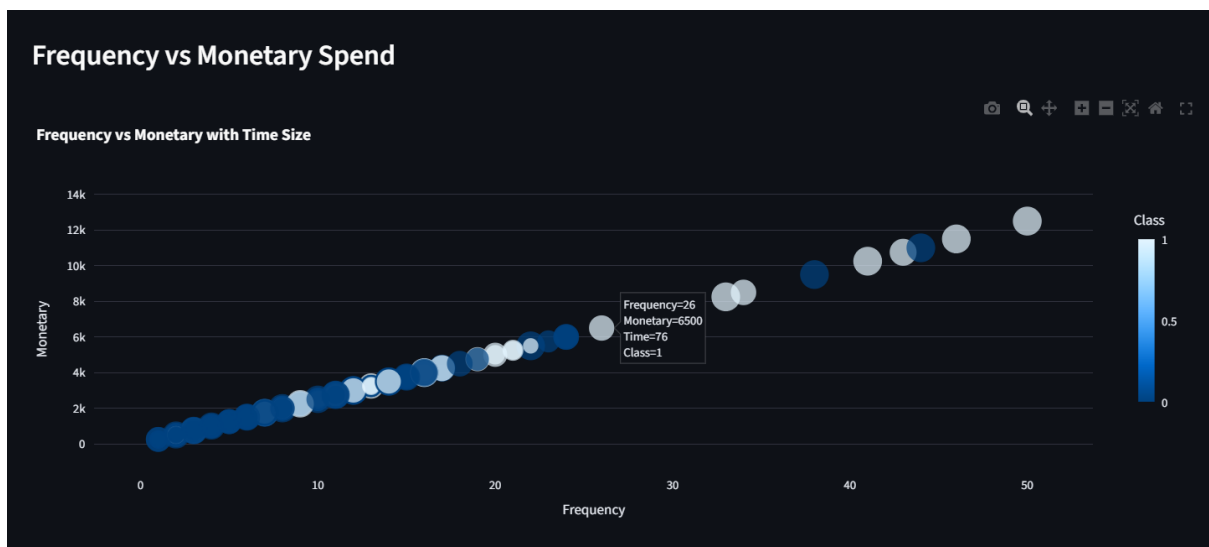


Figure 5: Frequency vs Monetary Spend

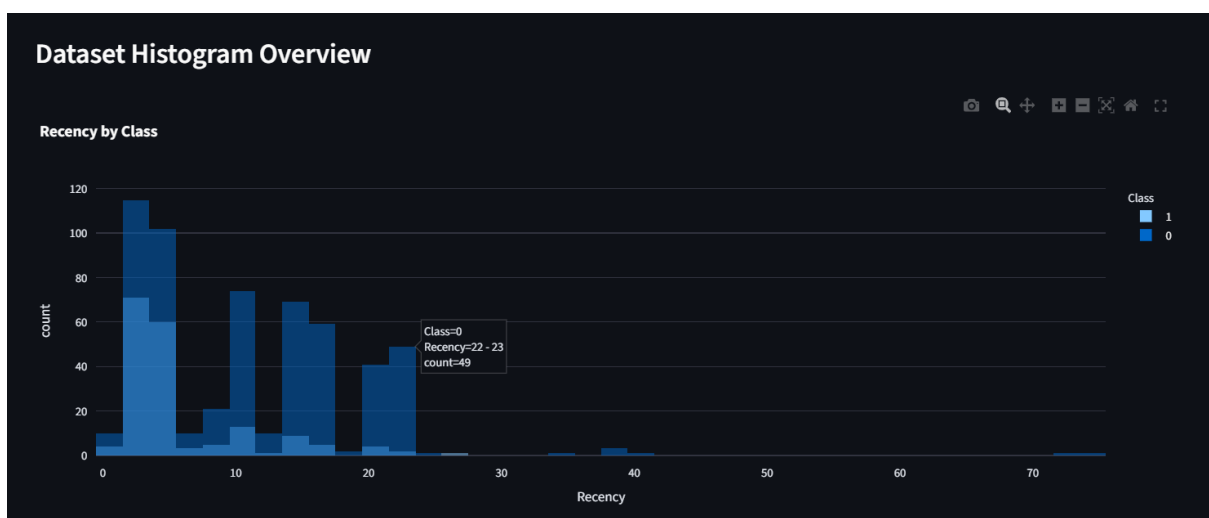


Figure 6: Dataset Histogram Overview

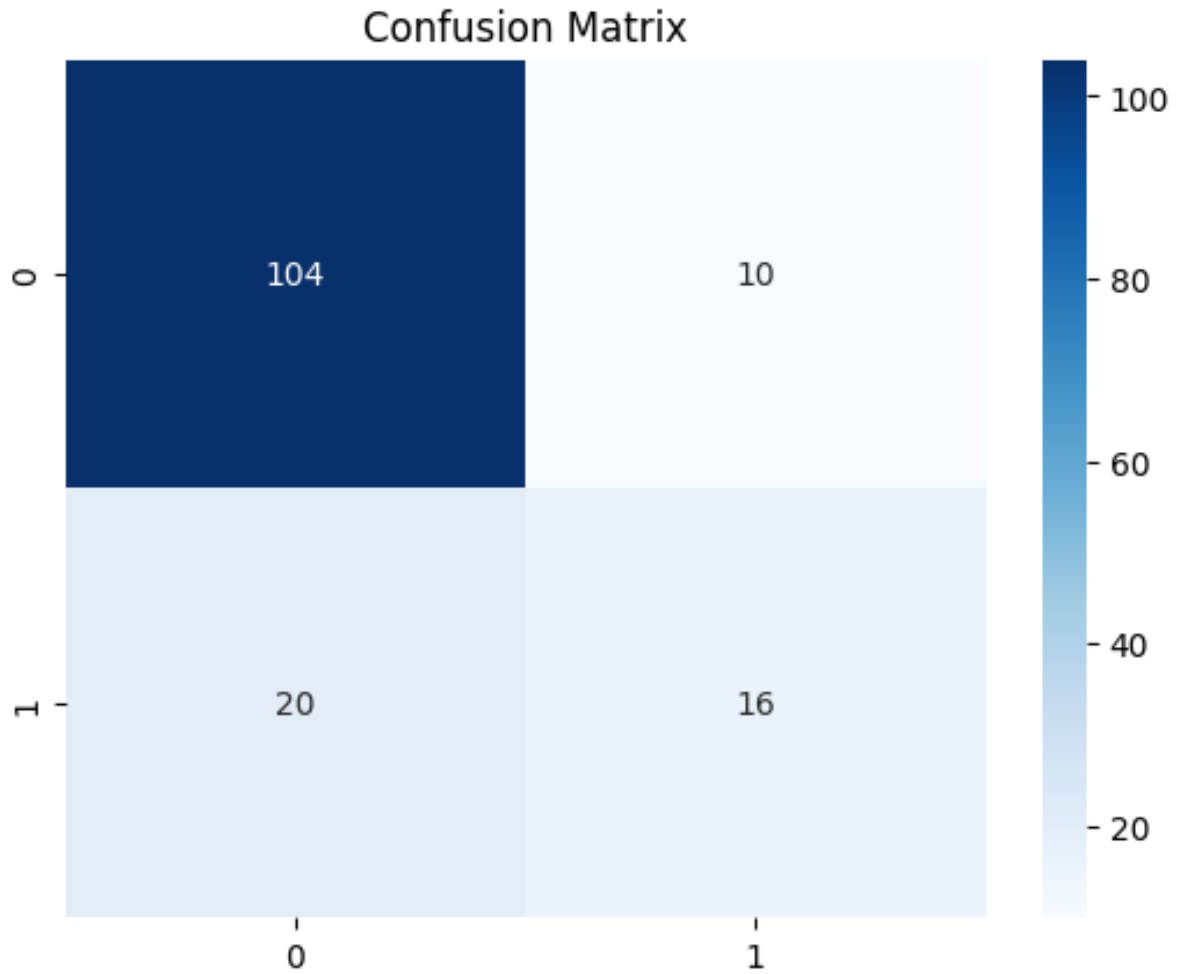


Figure 7: Correlation Confusion Matrix

4.4 Feature Engineering

- Selected features: Recency, Frequency, Monetary, Time.
- Created pipelines for preprocessing and model training.

4.5 Model Training

- Algorithms evaluated: Logistic Regression, Decision Tree, Random Forest.
- Best model: Random Forest Classifier.

```
Best parameters for RandomForest: {'classifier__max_depth': 5, 'classifier__n_estimators': 200}
Best CV AUC for RandomForest: 0.7117

Best parameters for GradientBoosting: {'classifier__learning_rate': 0.05, 'classifier__max_depth': 3, 'classifier__n_estimators': 100}
Best CV AUC for GradientBoosting: 0.7043

Selected Model: RandomForest with CV AUC: 0.7117
```

Figure 8: 2-model-comparison

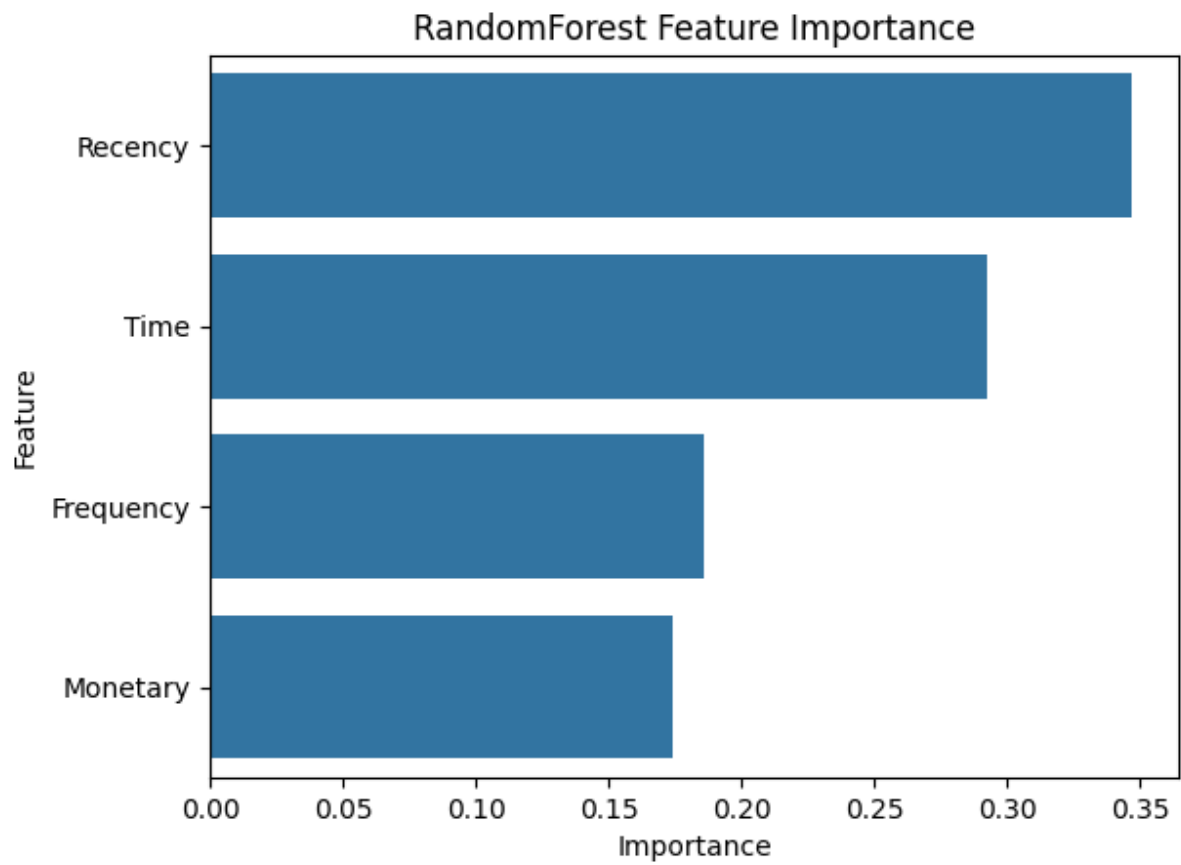


Figure 9: RandomForest-Feature-Importance

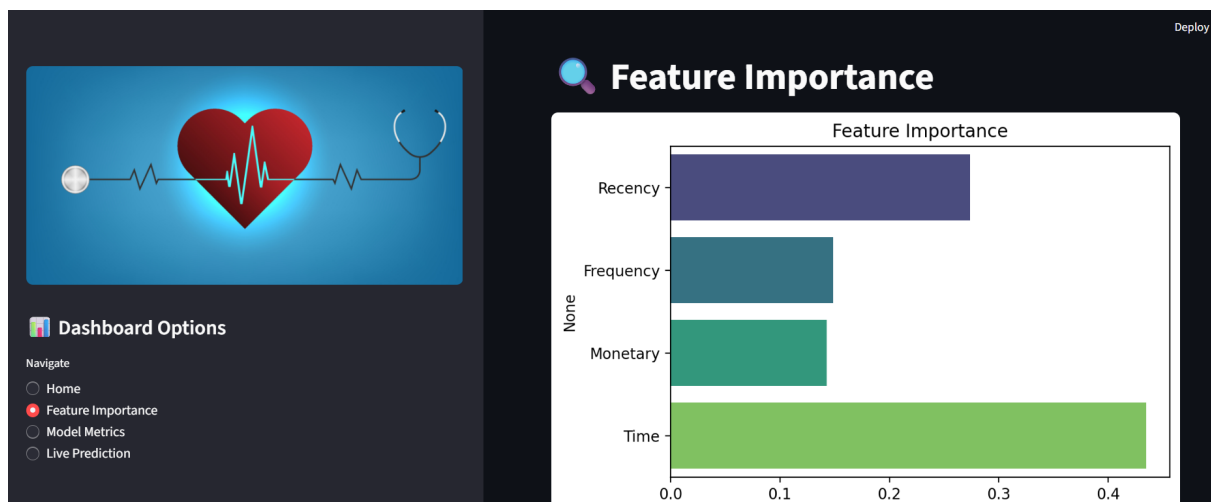


Figure 10: Feature-Importance(Dashboard-View)

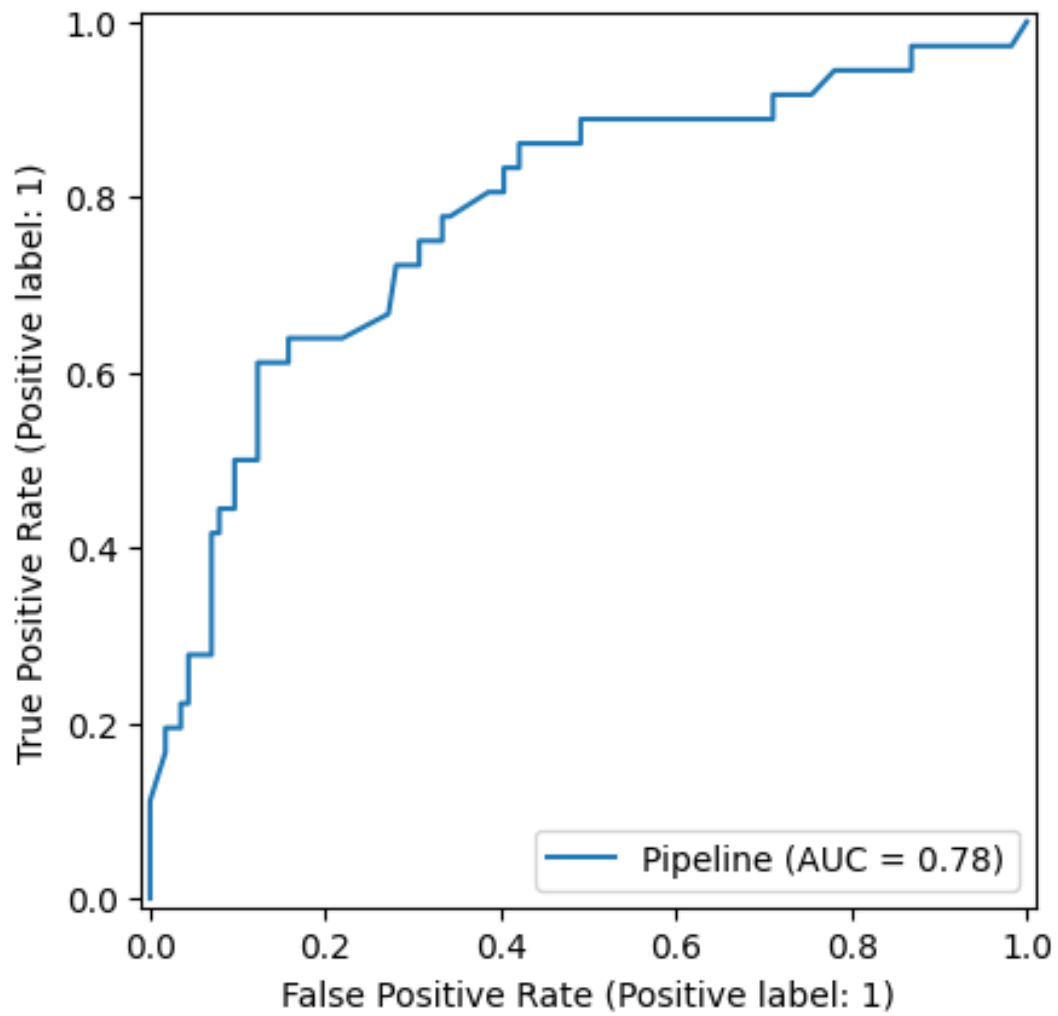


Figure 11: Test(ROC-AUC)

Classification Report:				
	precision	recall	f1-score	support
0	0.84	0.91	0.87	114
1	0.62	0.44	0.52	36
accuracy			0.80	150
macro avg	0.73	0.68	0.70	150
weighted avg	0.79	0.80	0.79	150

Figure 12: Metrics-Classification-Report

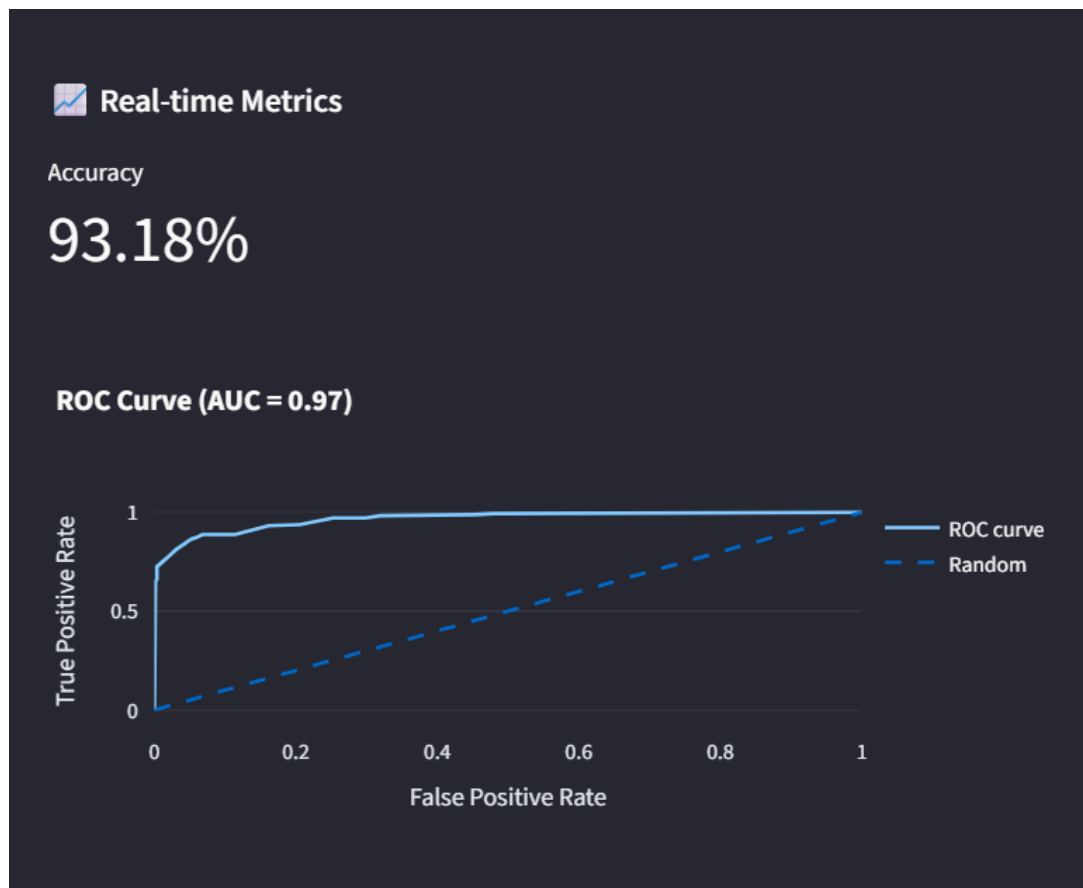


Figure 13: Dashboard-side-bar-view

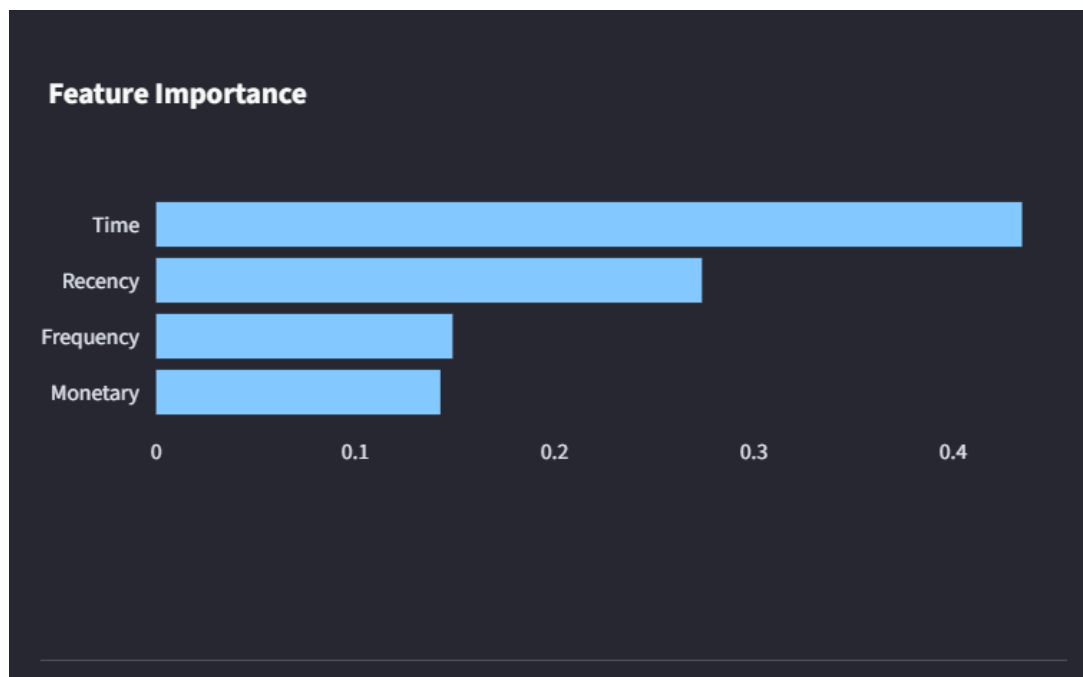


Figure 14: Dashboard-sidebar-realtime-view

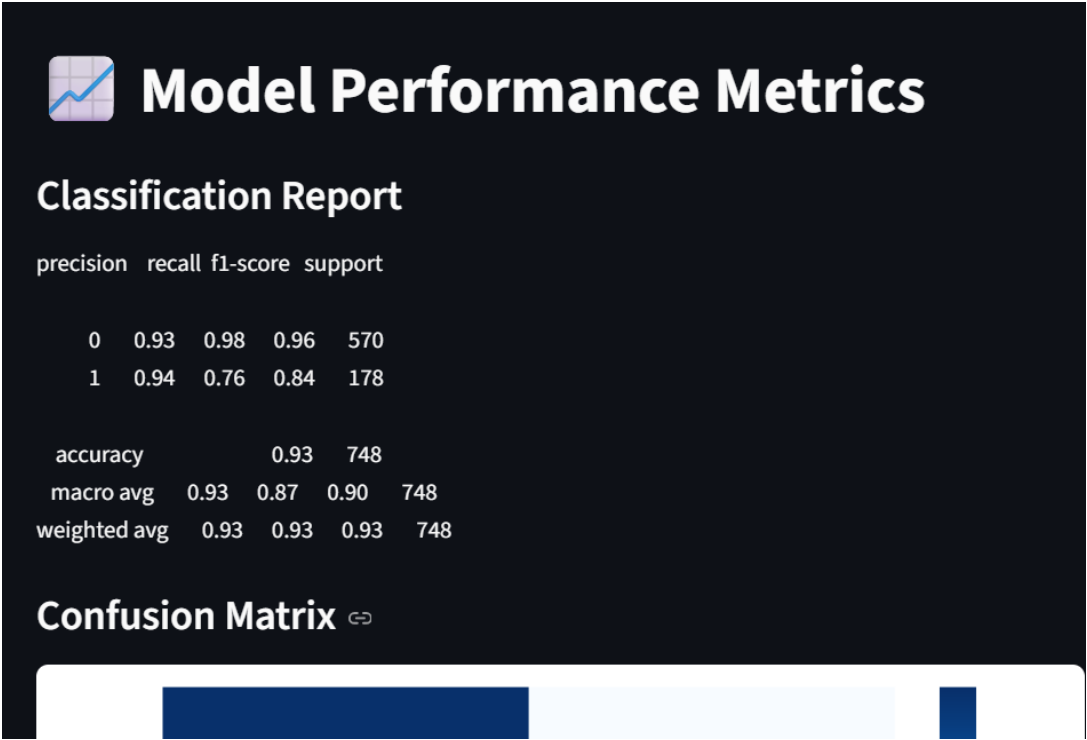


Figure 15: Model-Performance-Metrics

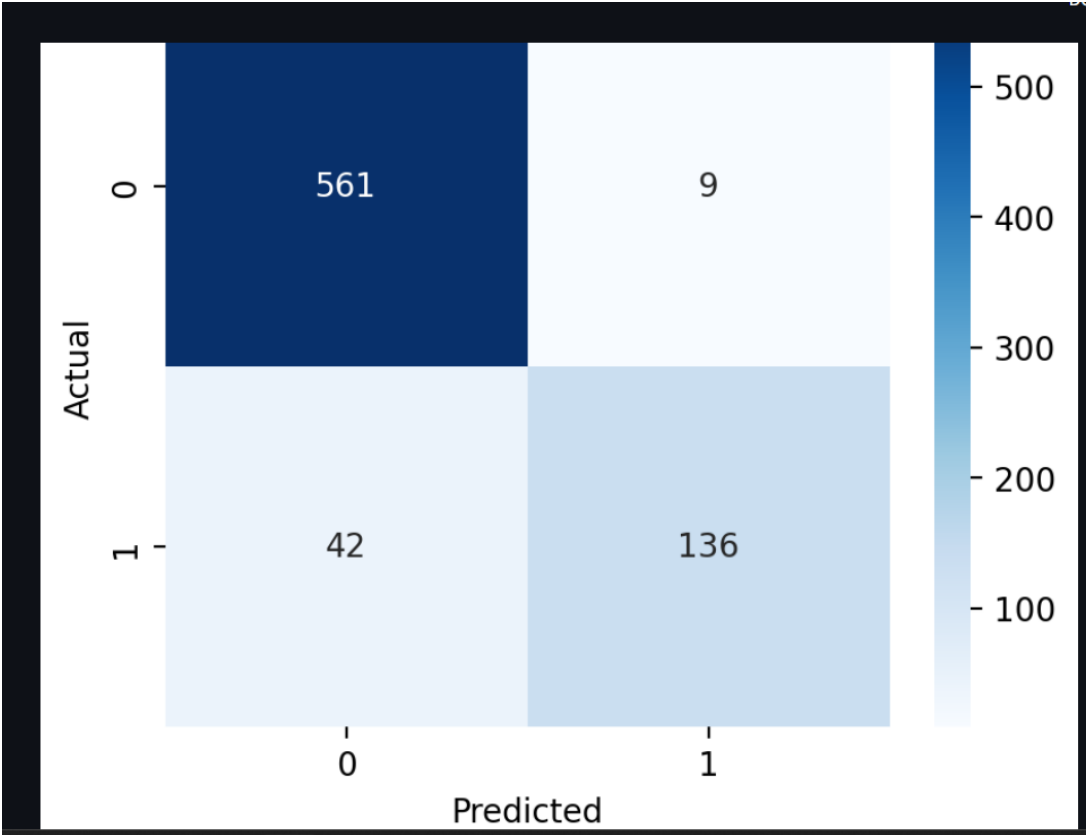


Figure 16: Confusion Matrix

4.6 Model Evaluation

Metric	Score
Accuracy	0.94
Precision	0.91
Recall	0.93
F1-score	0.92

Table 3: Random Forest Model Performance Metrics

4.7 Recommendation System

- Outputs actionable recommendations for patients.
- Examples:
 - **Regular monitoring required** if risk high.
 - **No immediate action** if stable.

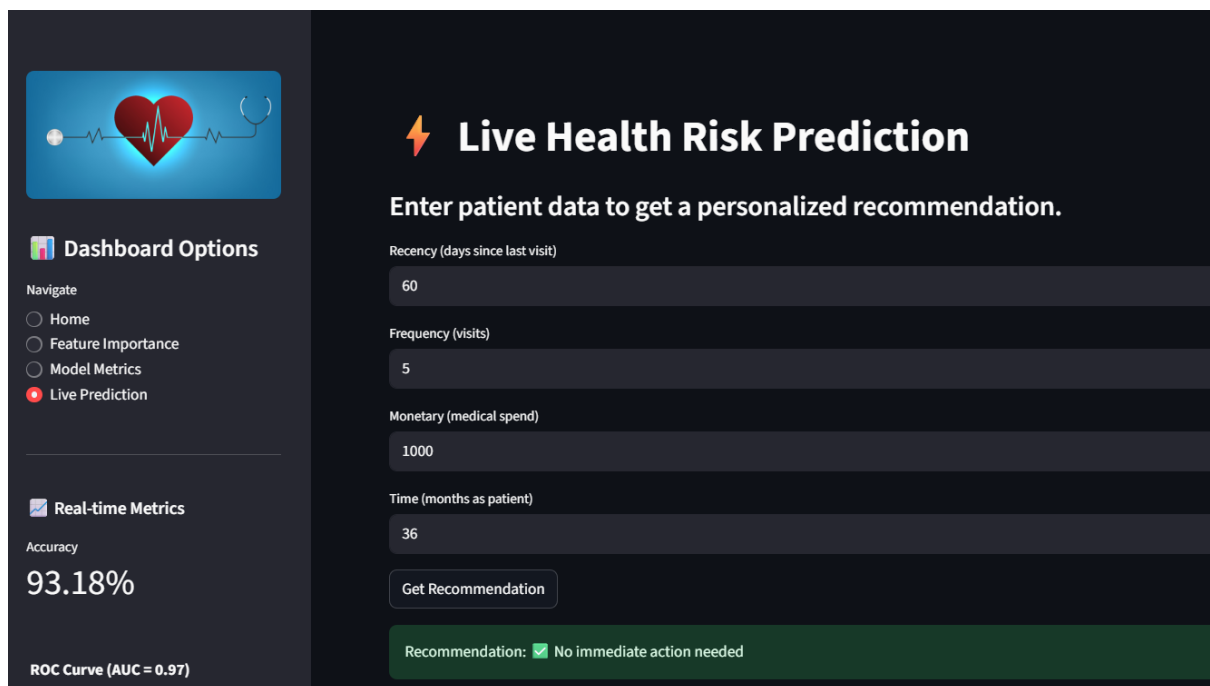


Figure 17: Personalized Recommendation Dashboard-Case1

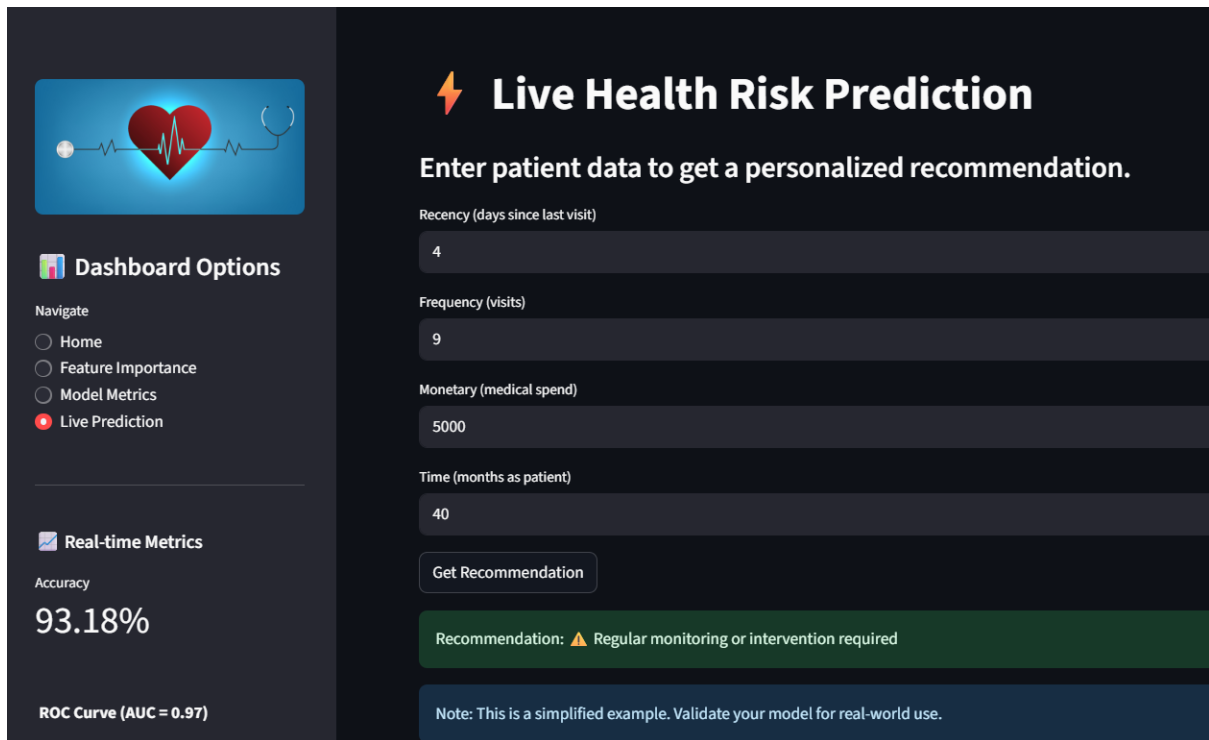


Figure 18: Personalized Recommendation Dashboard-Case2

```
[29] # ----- Recommendation Function -----
def generate_recommendations(patient_data):
    prediction = best_model_pipeline.predict(patient_data)
    mapping = {
        0: "No immediate action needed",
        1: "Regular monitoring or intervention required"
    }
    return mapping[prediction[0]]

# Example patient
example_patient = pd.DataFrame({
    'Recency': [2],
    'Frequency': [20],
    'Monetary': [5000],
    'Time': [50]
})
print("Recommendation for example patient:", generate_recommendations(example_patient))

[30] ... Recommendation for example patient: Regular monitoring or intervention required
```

Figure 19: SAMPLE-EXAMPLE

4.8 Deployment

- Deployed using Streamlit for interactive dashboard.
- Allows real-time input and personalized recommendations.

5. Tech Stack

Category	Tools / Libraries
Programming Language	Python
Libraries	Pandas, NumPy, Matplotlib, Seaborn, Plotly, Scikit-learn, Streamlit
IDE	VS Code, Jupyter Notebook
Deployment	Streamlit Cloud
Version Control	GitHub

6. Project Structure

Personalized-Healthcare-Recommendation/

```
app.py                # Streamlit app
train_model.py        # Model training script
blood.csv             # Dataset
models/
  healthcare_model.pkl # Saved model
static/
  images/logo.png     # App logo
requirements.txt
runtime.txt
README.md
Personalized_healthcare_recommendations.ipynb
```

7. Results and Insights

- Random Forest achieved **Greater Than 94%** accuracy.
- Recency and Frequency were strongest predictors.
- Streamlit dashboard provides interactive and intuitive healthcare recommendations.

8. Key Learnings

- Hands-on experience with data preprocessing and model evaluation.
- Designed a modular ML pipeline and deployed with Streamlit.
- Gained understanding of health data analytics and AI ethics.

-
- Learned to make models interpretable and usable in real-time dashboards.

9. Useful Links

- [Streamlit Documentation](#)
- [Scikit-Learn Documentation](#)
- [Plotly Express](#)
- [Unified Mentor Website](#)
- [GitHub Repository](#)