PORTFOLIO

DATA SCIENCE

NASSER CHAOUCHI

SUMMARY

1. **WHO AM I?**
2. **MY WORK EXPERIENCE**
3. **MY PROJECTS**
    a. THE MOVIE RECOMMENDER SYSTEM
    b. MULTICLASS CLASSIFICATION FOR DIABETES
    c. THE CKD AND DYALISIS PREDICTION

SUMMARY

📌 My academic journey

I'm Nasser, a **French computer science engineer** passionate about **artificial intelligence**, **data**, and **innovation**. I **graduated from UTC** (Université de Technologie de Compiègne) in 2025 with **a major in AI and Data Science**.

I completed:

- A **dual-focused internship** at **Numberly** as a **Data Engineer and Project Manager**, combining technical and management responsibilities.
- An **exchange semester** at the **Escuela de Ingeniería y Arquitectura in Zaragoza** (Spain), as part of a **Data Science Master's program**.
- A **final-year internship** at **Ubisoft** as a **Data Scientist**, working on **real-world game data** and **predictive models**.

💪 Strengths

Curious	Rigorous	Positive	Patient

❤️ Interests

Artificial Intelligence	Sports	Literature	Chess

MY WORK EXPERIENCE

An **internship** at **Ubisoft** from **October 2024** to **March 2025** as a **Data Scientist**, with the following missions:

Audiences Understanding

Segmentation Based on Players' Profiles

Player Behavior Prediction

I worked on the game **Avatar: Frontiers of Pandora**. My role was **to understand the game's underperformance** and to **identify and target potential players** within the **Ubisoft ecosystem** who would most likely acquire the game.

The project was divided into **three main phases**:

Ad-hoc Analyses → **Clustering Development** → **Classifier with Prediction**

You can contact the team manager for a reference:

- Nicolas Tatin, Associate Director, Data & Analytics

Data Analysis **Data Science**

MY PROJECTS – THE MOVIE RECOMMENDER SYSTEM

CONTEXT

- **Dataset**: MovieLens 32M
- **Goal**: Recommend movies users might like, based on behavior and content
- **Type**: Hybrid Recommendation System
    - Collaborative Filtering (ratings)
    - Content-Based Filtering (genres, titles)
- **Size**: 32M+ ratings, ~270k users, 62k movies

BUILT WITH

- Scikit-learn
- Pandas, NumPy
- Seaborn
- Matplotlib
- HuggingFace datasets
- Streamlit

Open the repository

Open the interface
(with MovieLens 1M)

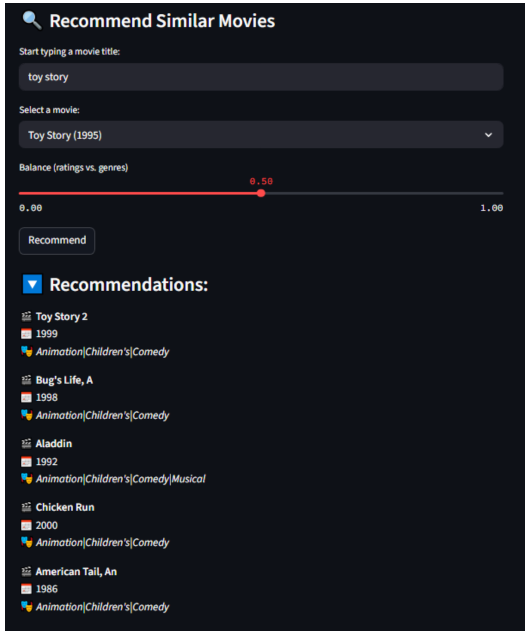
APPROACH

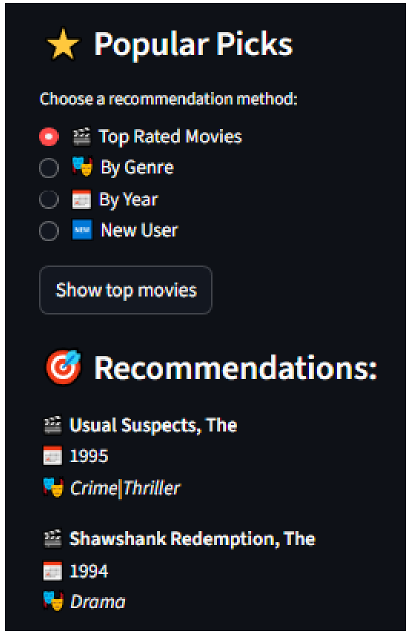
- **Data Cleaning**: Merged movies.csv and ratings.csv, extracted year, processed genres
- **Collaborative Filtering**: Built user-item matrix, applied cosine similarity
- **Content-Based Filtering**: Used TF-IDF/CountVectorizer on genres and titles
- **Hybrid Strategy**: Combined top recommendations from both approaches
- **Implemented multiple strategies**: Most rated movies, Top-rated by genre, Top-rated by year, User-user collaborative hybrid, Item-item collaborative hybrid
- **Profile-Based Recommendation**: Built a user profile from favorite movies to generate personalized suggestions

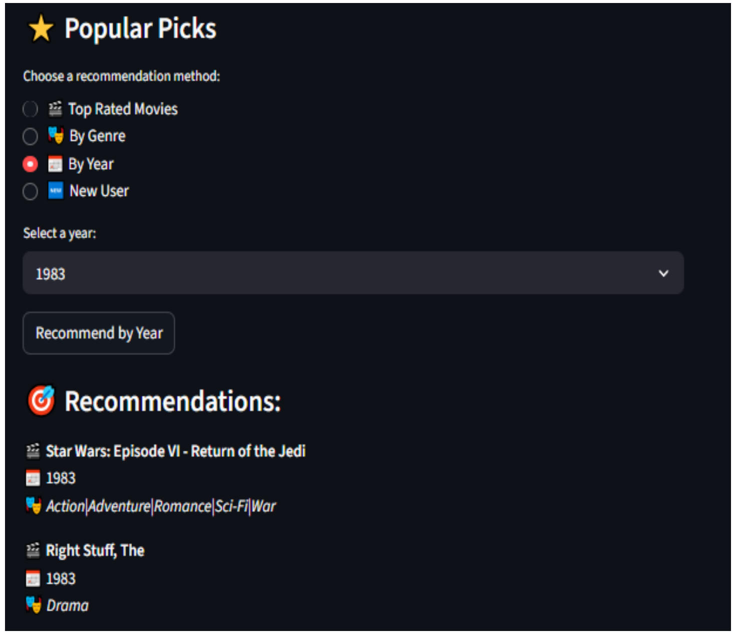
WHAT I LEARNED

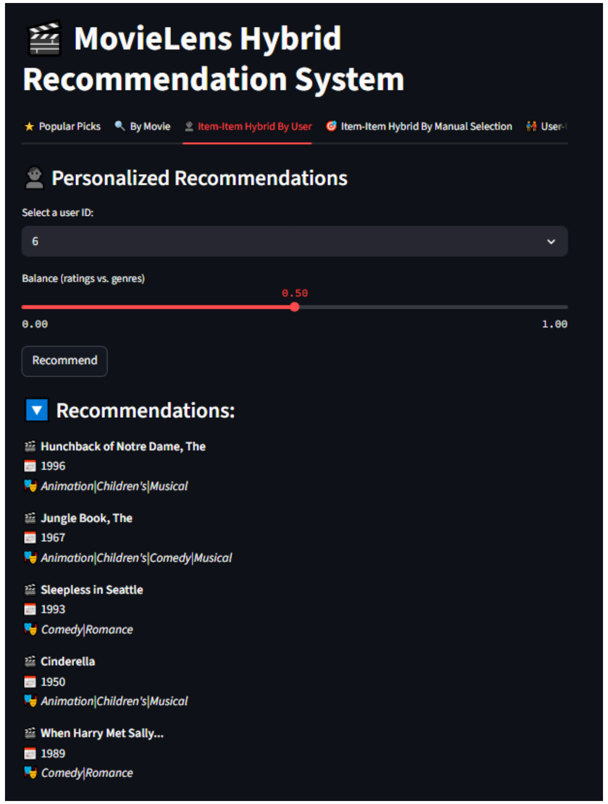
- **Designing** and **comparing recommender strategies**
- Using **similarity metrics** (cosine) on **sparse data**
- **Evaluating trade-offs** between **relevance** and **diversity**

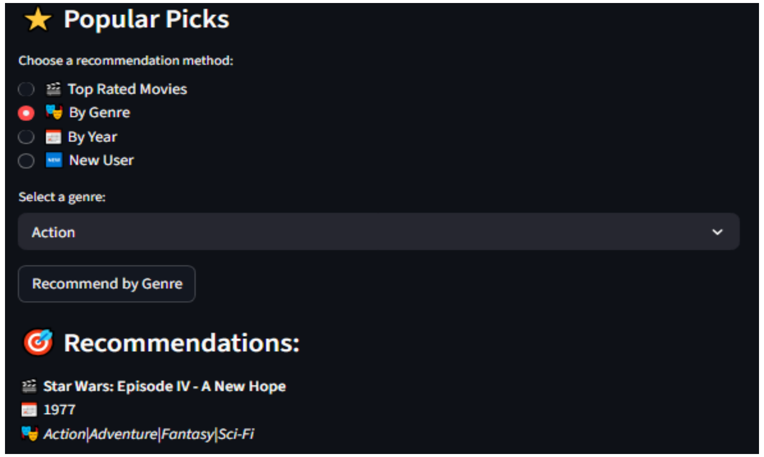
MY PROJECTS – THE MOVIE RECOMMENDER SYSTEM

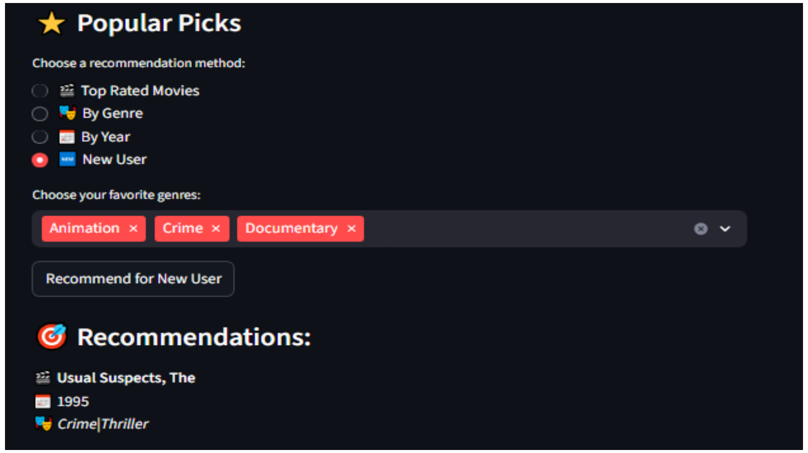




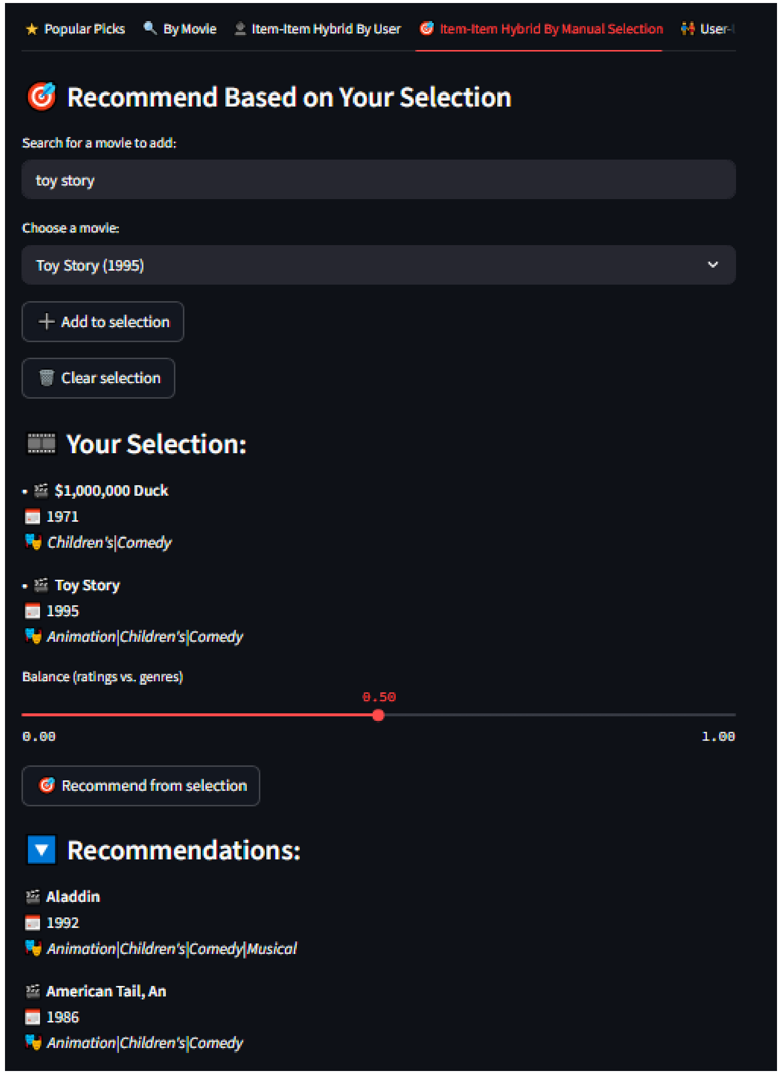


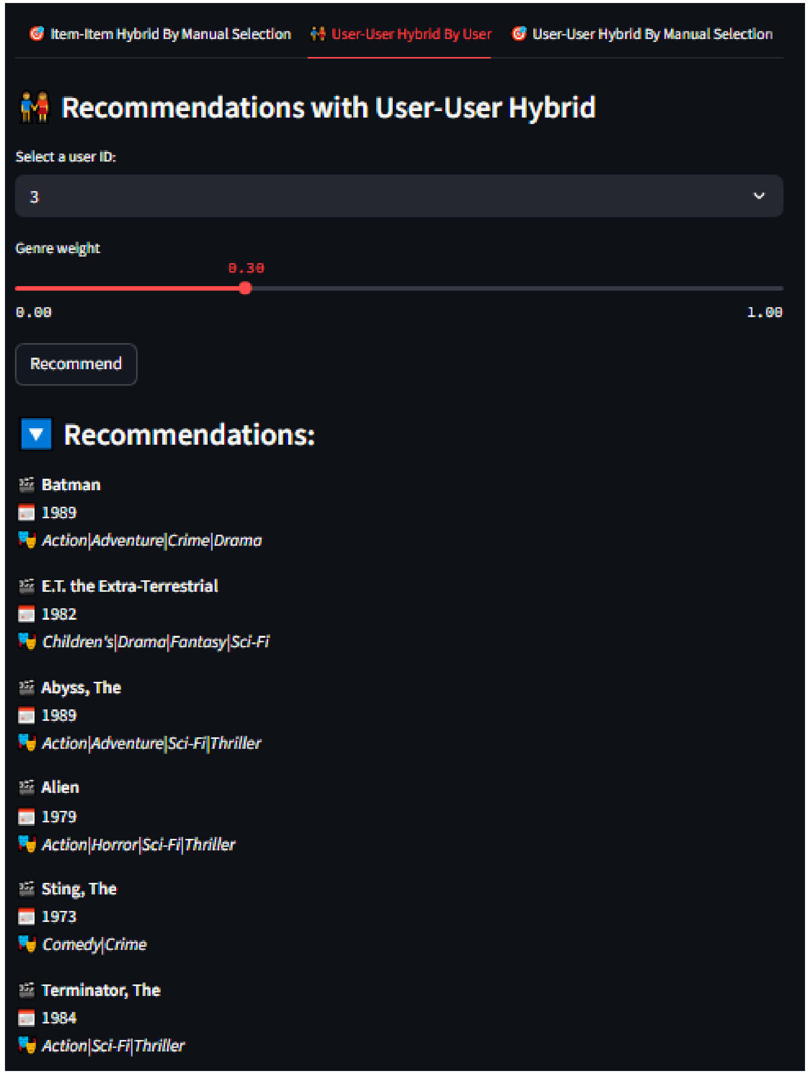


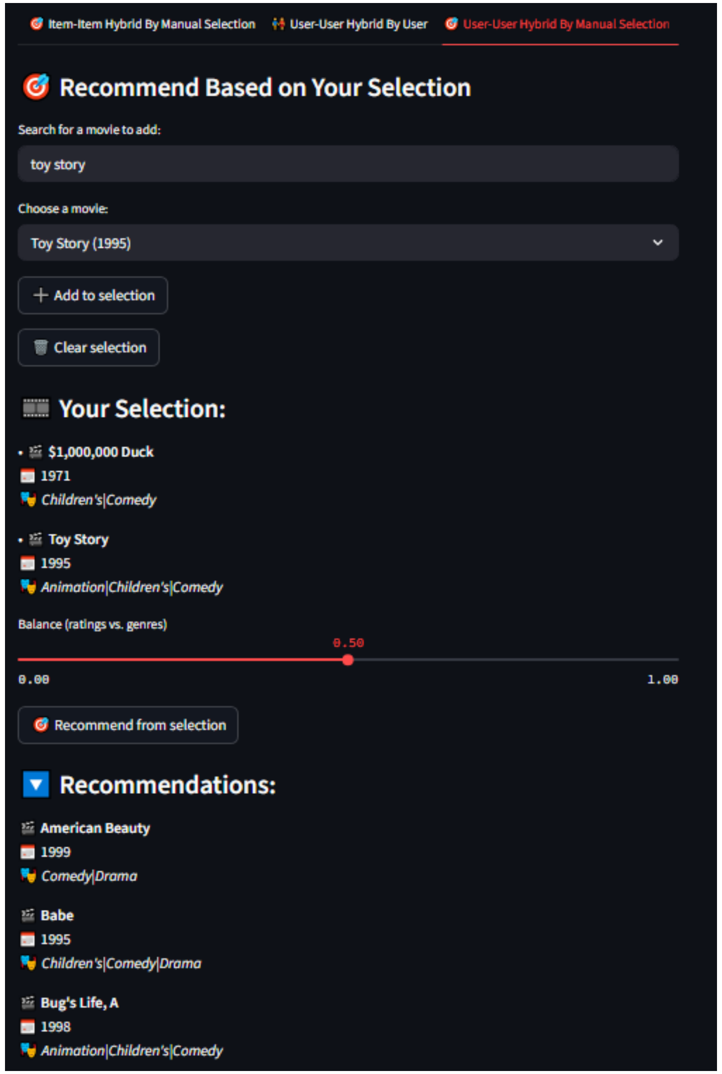




MY PROJECTS – THE MOVIE RECOMMENDER SYSTEM







MY PROJECTS – MULTICLASS CLASSIFICATION FOR

CONTEXT

- **Dataset**: Multiclass Diabetes Dataset
- **Goal**: Classify patients into several diabetes stages
- **Type**: Supervised, Multiclass classification
- **Size**: 264 patients, 12 features

BUILT WITH

- Scikit-learn
- Pandas, NumPy
- Seaborn
- Matplotlib
- Streamlit

Open the repository

Open the interface

APPROACH

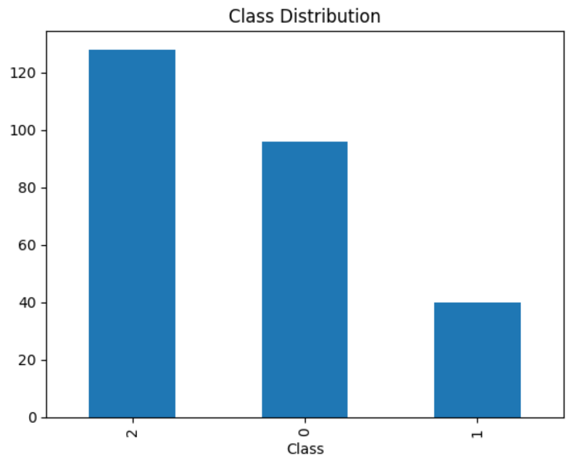
- **EDA & Preprocessing**: Analyzed feature distributions, handled missing values, balanced classes, and scaled data.
- **Model tested**: Logistic Regression, Random Forest and K-Nearest Neighbour
- **Cross Validation**: Ensured robust performance and avoided overfitting
- **Evaluation**: Confusion Matrix, Classification report (F1-Score, Accuracy, Recall)
- **Final model (Random Forest)**
  - **Accuracy**: 97%
  - **Macro F1-score** (better suited to class imbalance): 0.98

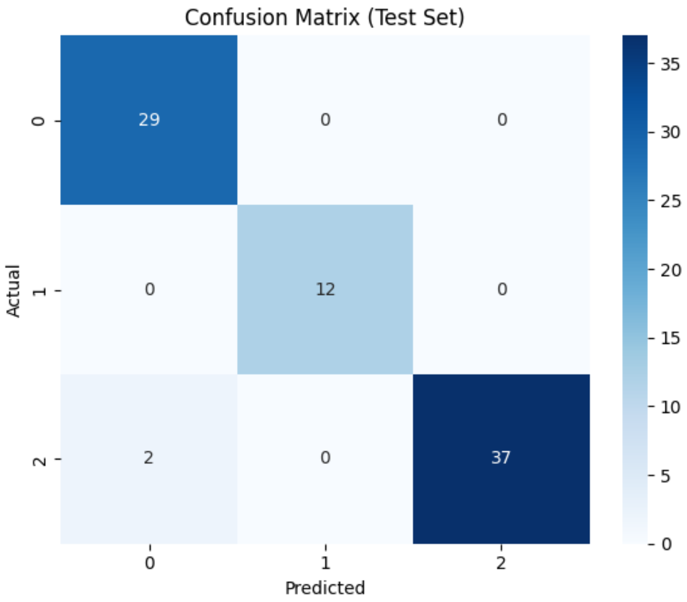
WHAT I LEARNED

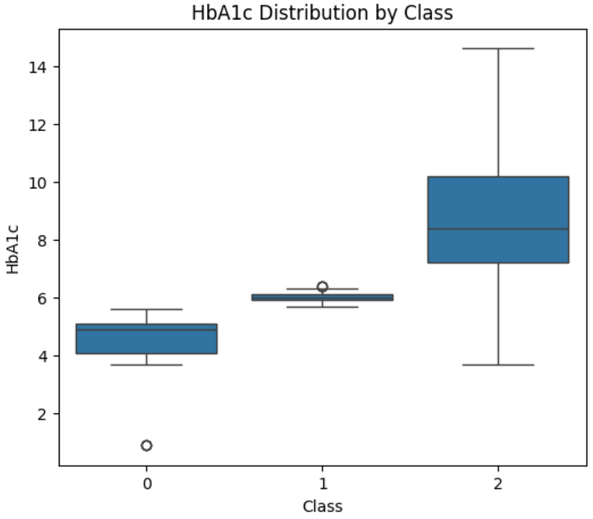
- **How to handle imbalanced multiclass data**
- The **importance** of **feature engineering** and **model tuning**
- Model explainability with **SHAP** or **feature importance**

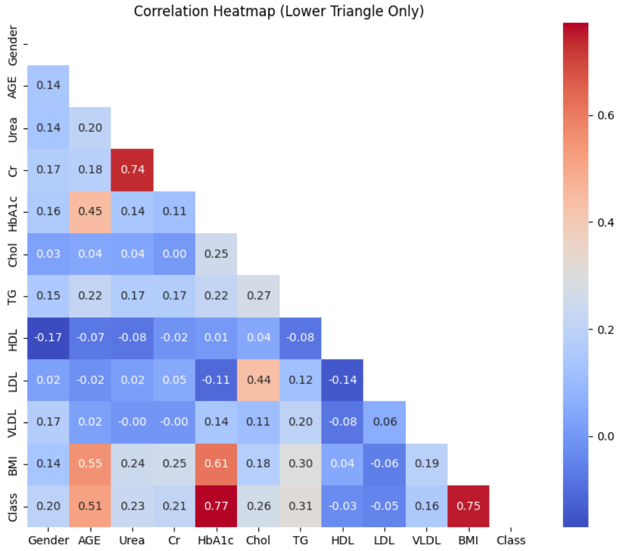
MY PROJECTS – MULTICLASS CLASSIFICATION FOR

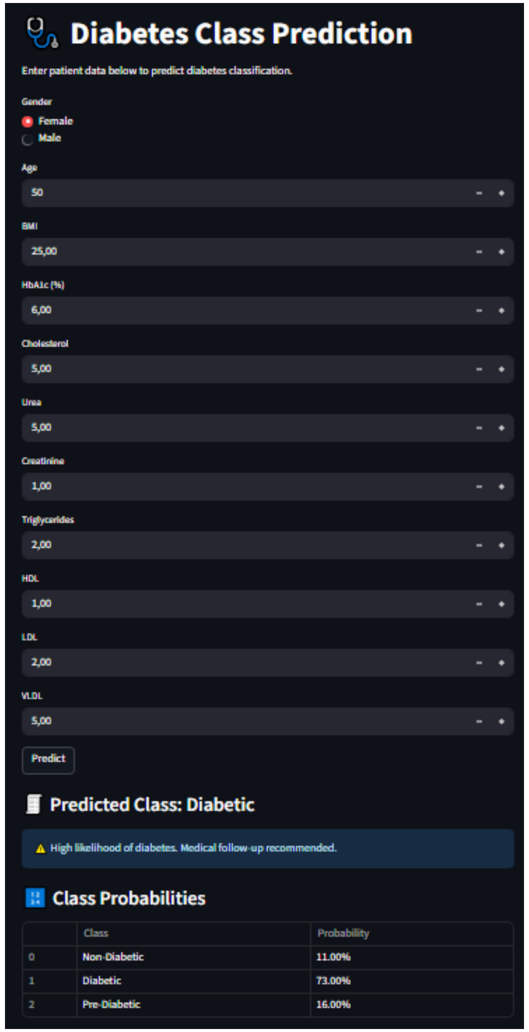
Variable	F-statistic	p-value
AGE	60.368	0.00000
BMI	190.565	0.00000
TG	14.218	0.00000
HbA1c	200.415	0.00000
Chol	9.881	0.00007
Urea	9.115	0.00015
Cr	6.466	0.00182
VLDL	3.712	0.02573
LDL	0.957	0.38526
HDL	0.488	0.61457











Portfolio

Nasser CHAOUCHI

MY PROJECTS – THE CKD AND DYALISIS PREDICTION

CONTEXT

- **Dataset**: Kidney Disease Risk Dataset
- **Goal**: Predict CKD status and dialysis need based on clinical and biological data
- **Type**: Supervised, Binary classification (2 targets: CKD_Status, Dialysis_Needed)
- **Size**: 2304 patients, 9 features

BUILT WITH

- Scikit-learn
- Pandas, NumPy
- Seaborn
- Matplotlib
- XGBoost
- Streamlit

Open the repository

Open the interface

APPROACH

- **EDA & Preprocessing**: Explored feature relationships, handled missing values, encoded categorical data, scaled numerical features.
- **Model tested**: Logistic Regression, Random Forest, Gradient Boosting, XGBoost and K-Nearest Neighbour
- **Cross Validation**: Ensured robustness and reduced overfitting risk.
- **Evaluation Classification Report**, **ROC-AUC**, **F1-Score**, **Accuracy**
- Best model was Gradient Boosting, but due to class imbalance, Random Forest gave more reliable results for generalization.
  - → **Accuracy**: 100% for CKD_Status — Accuracy 100% but a F1-Score 0.97 (class imbalance) for the Dialysis_Needed
  - → **Separate models trained for each target**

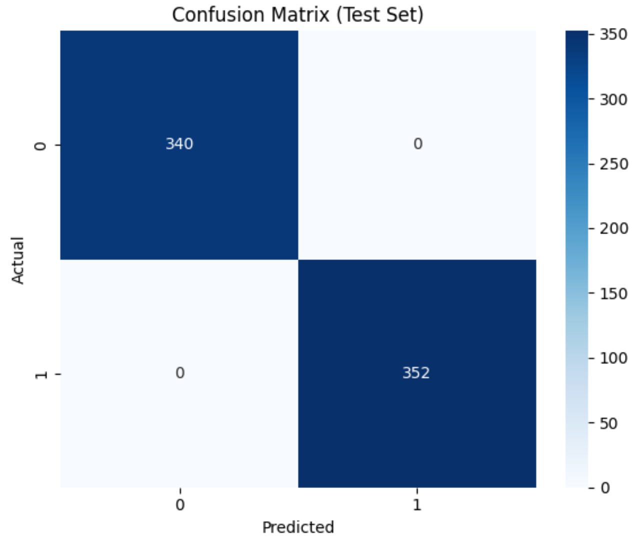
WHAT I LEARNED

- **Managing dual target classification**
- **Handling noisy** and **medical data**
- Improving interpretability with **SHAP values**

MY PROJECTS – THE CKD AND DYALISIS PREDICTION

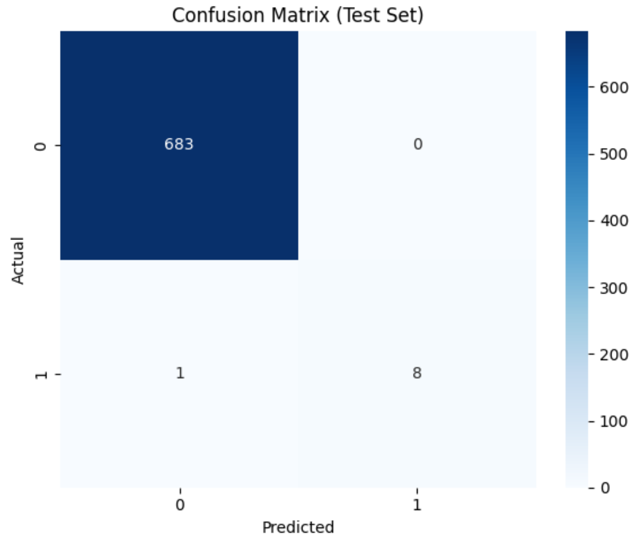
Evaluation on Test Set – CKD_Status

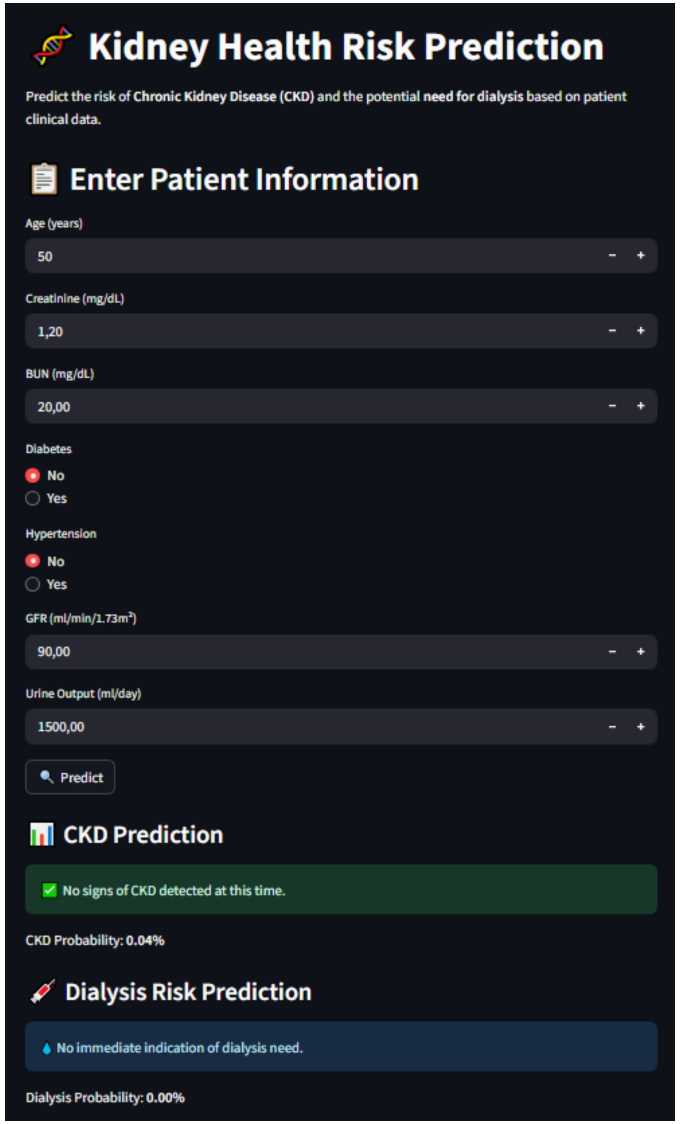
Class	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	340
1	1.00	1.00	1.00	352
Accuracy			**1.00**	692
Macro avg	1.00	1.00	1.00	692
Weighted avg	1.00	1.00	1.00	692



Evaluation on Test Set – Dialysis_Needed

Class	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	683
1	1.00	0.89	0.94	9
Accuracy			**1.00**	692
Macro avg	1.00	0.94	0.97	692
Weighted avg	1.00	1.00	1.00	692





DON’T HESITATE TO REACH ME OUT