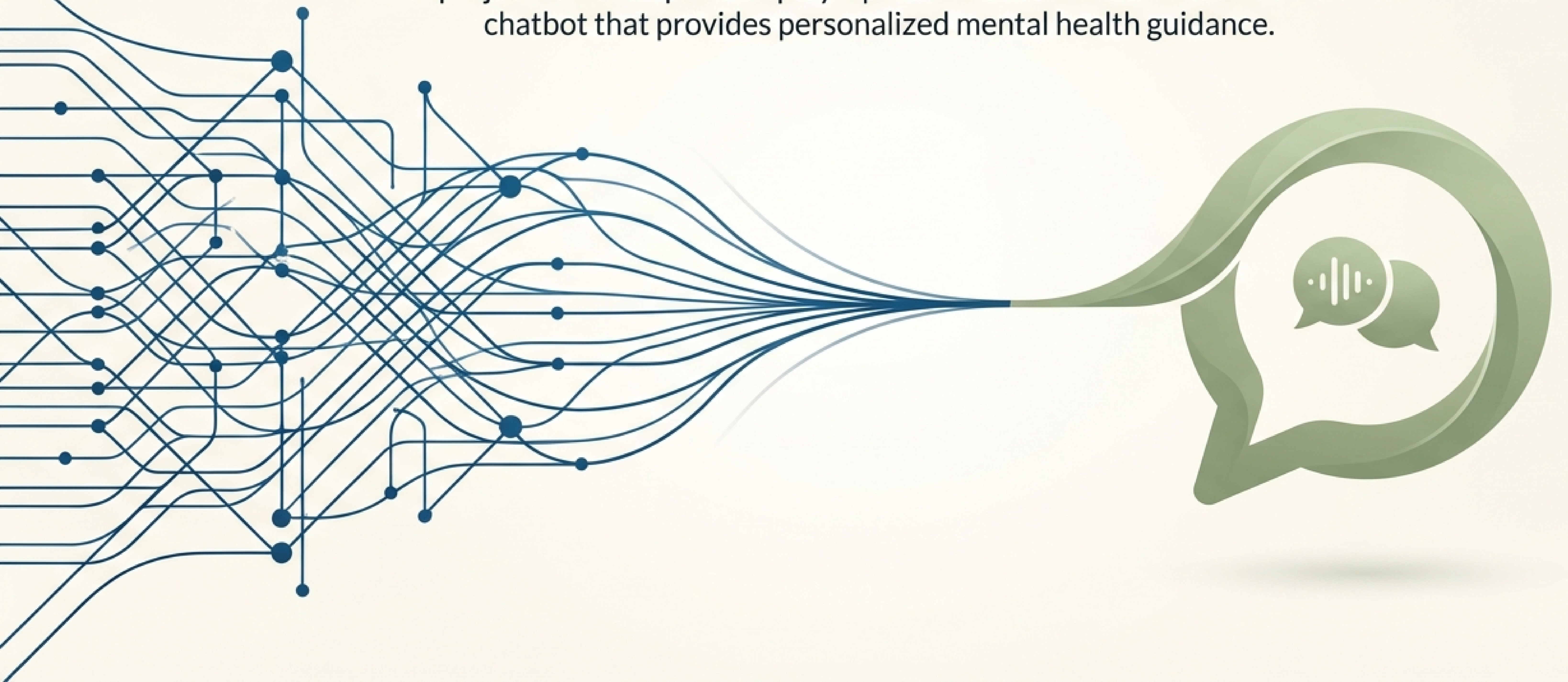
# From Data to Dialogue: Building a Trusted AI for Mental Health

A project to develop and deploy a predictive model and conversational chatbot that provides personalized mental health guidance.



# The Project's Core Objective and Success Criteria

The primary goal was to develop a highly accurate and reliable machine learning model to predict the likelihood of an individual seeking professional mental health treatment. This model would serve as the core intelligence for a conversational chatbot.

### 1. High Predictive Performance

Achieve a classification model with strong discriminatory power, measured by high ROC-AUC and F1-Score.

### 2. Model Interpretability

Ensure the final model provides clear insight into the most influential factors, enabling the chatbot to offer explainable and trustworthy recommendations.

# The Project Team and Individual Roles

### Yahya Mustafa
**Data Science Lead**

Data Collection, Analysis, Visualization, Feature Engineering, Model Development & Optimization, Final Presentation

### Ahmed Fahmy
**Data Engineering**

Data Collection, Exploration & Preprocessing

### Marwan Gaber
**Data Science**

Data Analysis, Visualization & Feature Engineering

### Abdelkader
**MLOps & Deployment**

MLOps, Deployment & Monitoring

### Adham Fouad
**Application Development**

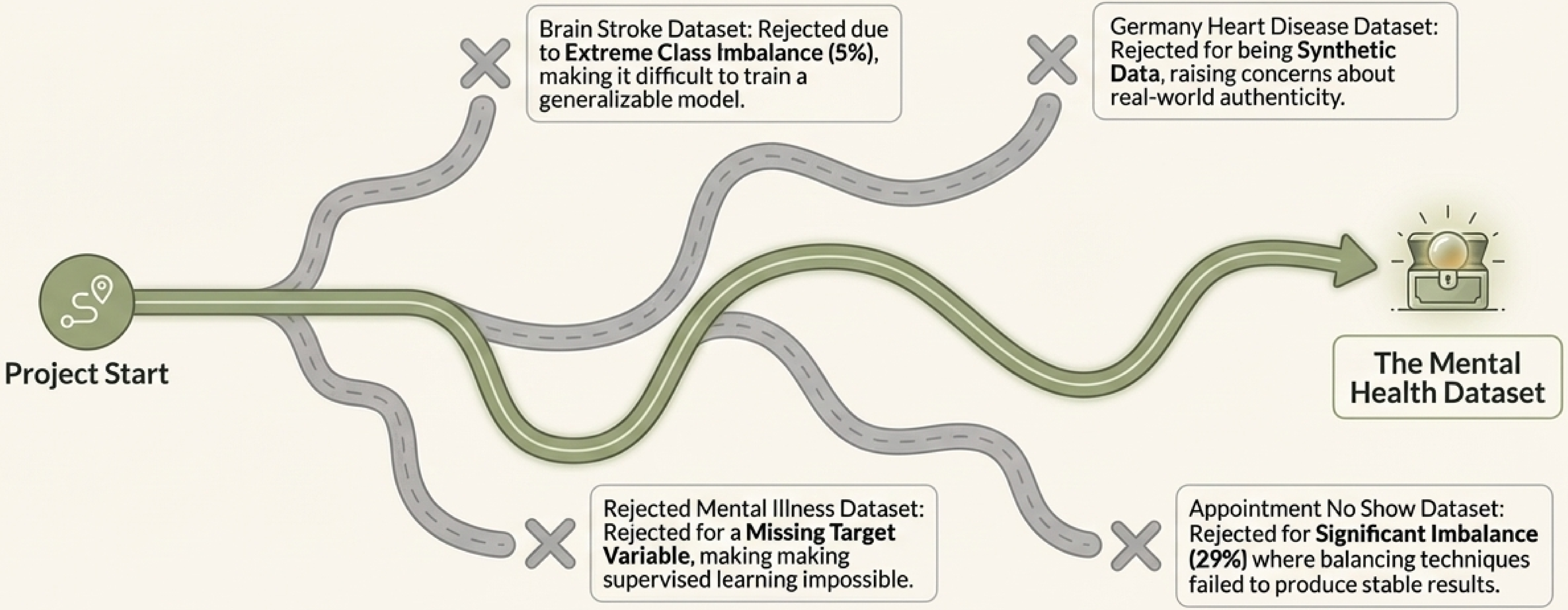
Chatbot Deployment

### Muhanad Mustafa
**Project Management**

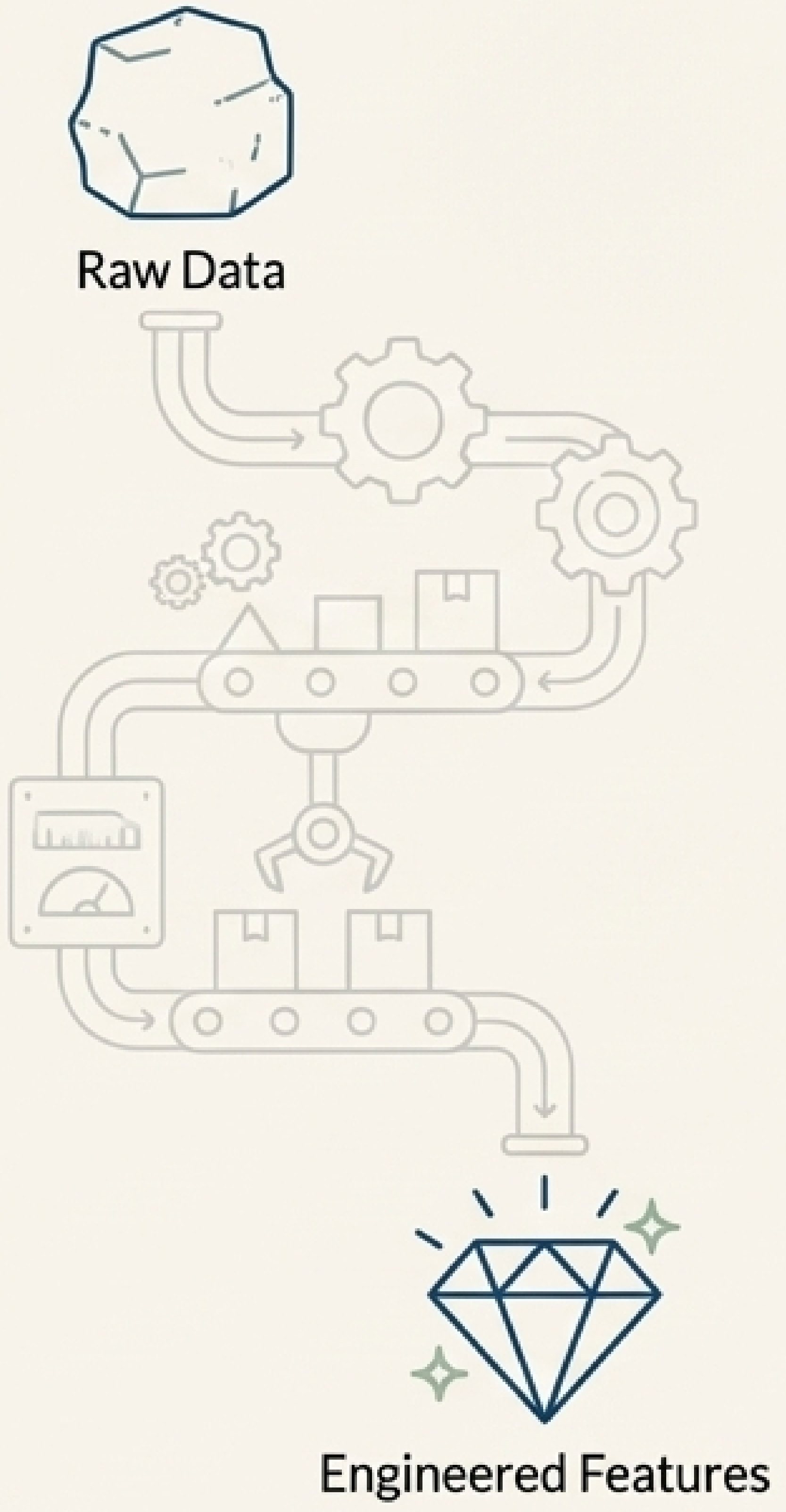
Final Documentation

# The Quest for Quality: Overcoming Data Sourcing Hurdles

**Securing a suitable, high-quality dataset** required **extensive validation.** Our initial search revealed four unsuitable candidates, demonstrating the importance of rigorous data selection.



# Engineering a Powerful Dataset: From Raw Data to Rich Features




## Data Cleaning

Identified and removed **2,313 duplicate records** to prevent data leakage.

Analyzed and imputed **5,193 missing values** in the `self_employed` column.

## Intelligent Feature Creation

- **Temporal Features:** Decomposed the `Timestamp` into `Year`, `Month`, `Day`, and `Hour`, creating boolean flags like **`Is_Winter`** and **`Is_Night`** to capture behavioral patterns.
- **High-Cardinality Solution:** Addressed the challenge of the `Country` feature by using **Target Encoding with 5-fold Cross-Validation**, preventing data leakage while creating a highly informative numeric feature.
- **Composite Features:** Engineered new variables to capture complex relationships, such as:
  - `Stress_Score`: An aggregate of five stress-related indicators.
  - `Family_Support_Impact`: An interaction term combining `family_history` with `Coping_Struggles`.

# The Model Gauntlet: A Comparative Analysis of Leading Algorithms

To identify the optimal model, we trained and evaluated several strong **baseline classifiers** on the engineered dataset. Each was assessed for its predictive power on unseen test data.

| Model | Type | F1 Score | ROC-AUC | Accuracy |
|---|---|---|---|---|
| **CatBoost (Raw)** | **Gradient Boosting** | **0.9229** | **0.9868** | **0.9223** |
| Stacking Classifier | Ensemble | 0.9166 | 0.9823 | 0.9146 |
| MLP Classifier | Neural Network | 0.9118 | 0.9814 | 0.9114 |
| CatBoost (Encoded) | Gradient Boosting | 0.9193 | 0.9844 | 0.9191 |
| XGBoost (Baseline) | Gradient Boosting | 0.8822 | 0.9636 | 0.8817 |

A solid, interpretable foundation with significant potential for optimization.

# The Strategic Choice: Prioritizing Interpretability for a Trustworthy Chatbot

While other models showed slightly higher initial metrics, the final selection was driven by a crucial deployment constraint: the model must be transparent, auditable, and relevant to a user-facing chatbot.

## Rejected Top Performers

**High Reliance on Spurious Features:** CatBoost models relied on non-causal temporal features like `Hour`, making chatbot logic fragile.

**Black Box Nature:** Stacking & MLP models lack clear feature importance, making it impossible to explain predictions—a critical failure for a health application.

## Selected: XGBoost

**Focus on Relevant Features:** Demonstrated strong focus on domain-relevant features like `Mental_Health_History` and stress scores.

**Auditable and Explainable:** Offered a clear, reliable measure of feature importance.

**Prime Optimization Opportunity:** Its solid baseline performance was identified as the ideal starting point for tuning.

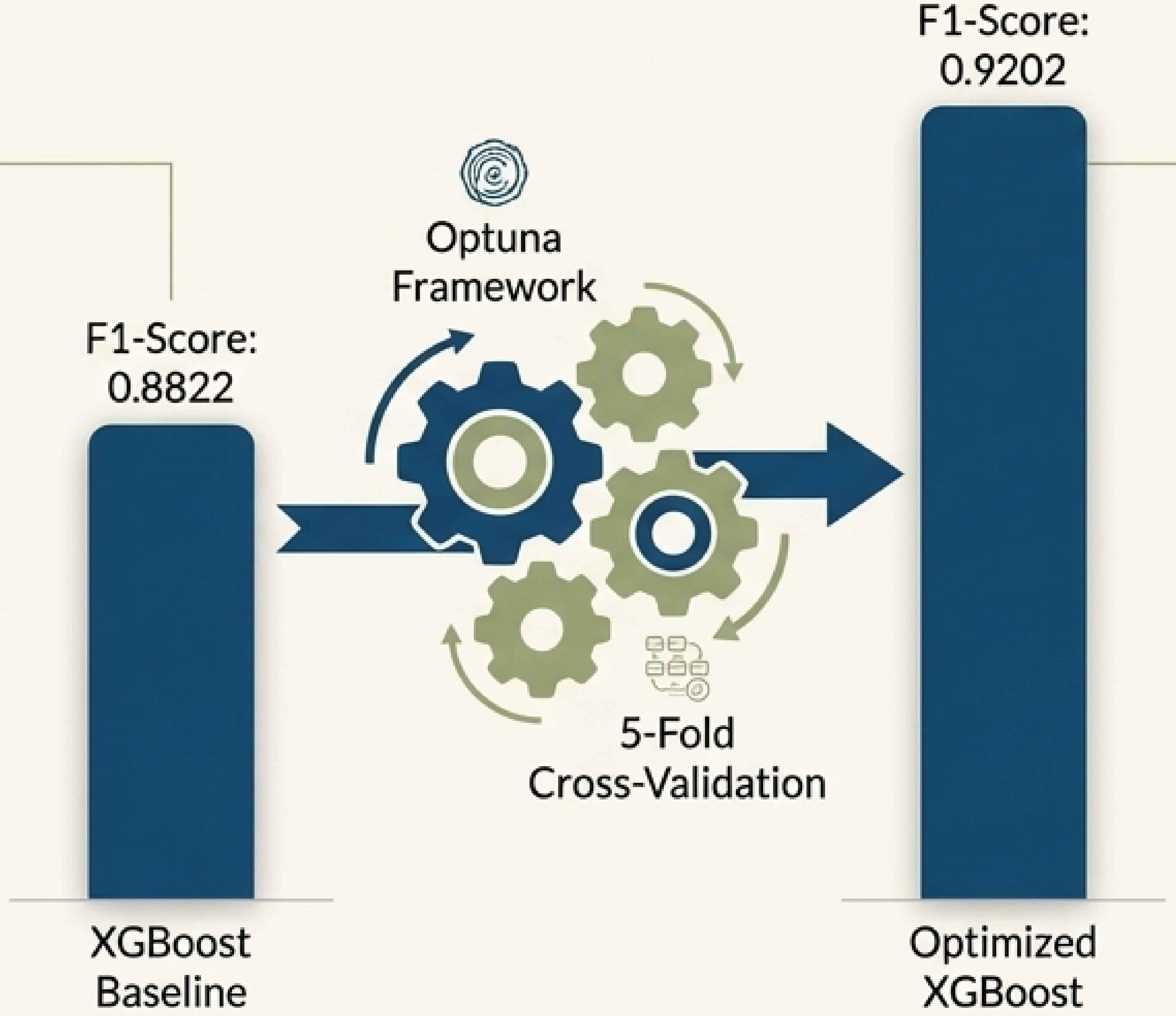
# From Solid Baseline to State-of-the-Art: Optimizing XGBoost

We chose XGBoost for its interpretability and solid foundation. The next step was to elevate its performance to a production-ready level through rigorous hyperparameter tuning.

## Optimization Process

We integrated the **Optuna** framework to systematically search and discover the globally optimal hyperparameters for the XGBoost model.

The tuning was performed using a 5-fold cross-validation strategy on the target-encoded dataset to ensure the resulting model was both highly accurate and robust against overfitting.




## Result

This process significantly improved the model's predictive power, making it competitive with the initially rejected models while preserving its crucial interpretability.

F1 Score
**0.8822**

F1 Score
**0.9202**

**+0.038**
Improvement

# Final Model Performance: Accurate, Robust, and Ready for Deployment

Model: XGBoost Classifier (Optimized with Optuna)

## Accuracy: 92.00%

Correctly classifies individuals 92% of the time.

## F1 Score: 0.9202

An excellent balance between false positives and false negatives.

## ROC-AUC: 0.9858

Outstanding ability to distinguish between classes (treatment vs. no treatment).

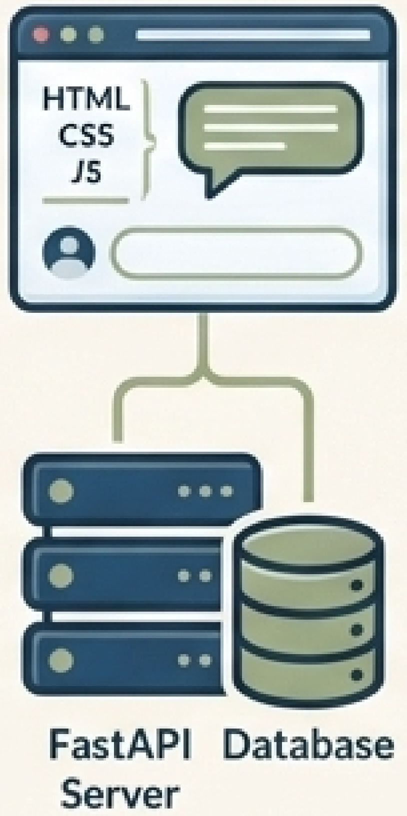

These high-performance metrics confirm the model's robustness and its readiness for deployment within the chatbot application.

# From Code to Conversation: The MoodMate Chatbot

The optimized model serves as the brain for MoodMate, an AI assistant for psychological analysis. Its development followed a structured, three-phase journey.

### Phase One: Fundamentals & Console Prototype

Established core Python logic, a state machine for conversation flow, and local data storage with SQLite. Ensured model persistence with `joblib`.




### Phase Two: Front-End & Back-End Split

Architected the system for the web, separating the user interface (JavaScript/HTML) from the complex prediction logic (Python/FastAPI).

### Phase Three: Full Web Deployment

Transformed the project into a live, scalable web service using specialized hosting platforms.

# A Modern, Scalable System Architecture

### User interacts with Front-End (Hosted on Vercel)

- A static web interface built with HTML & JavaScript.
- Manages the UI, conversation flow, and collects 15 required user answers.

### API Call is sent to Back-End (Hosted on Hugging Face Spaces)

- A FastAPI application running in a Docker container.
- Applies 8 preprocessing steps to generate 30 features from user input.

.joblib

### Prediction is made by the ML Model (`health_chatbot_model.joblib`)

The final, tuned XGBoost model receives the features and returns a prediction.

### Result is returned to the Front-End

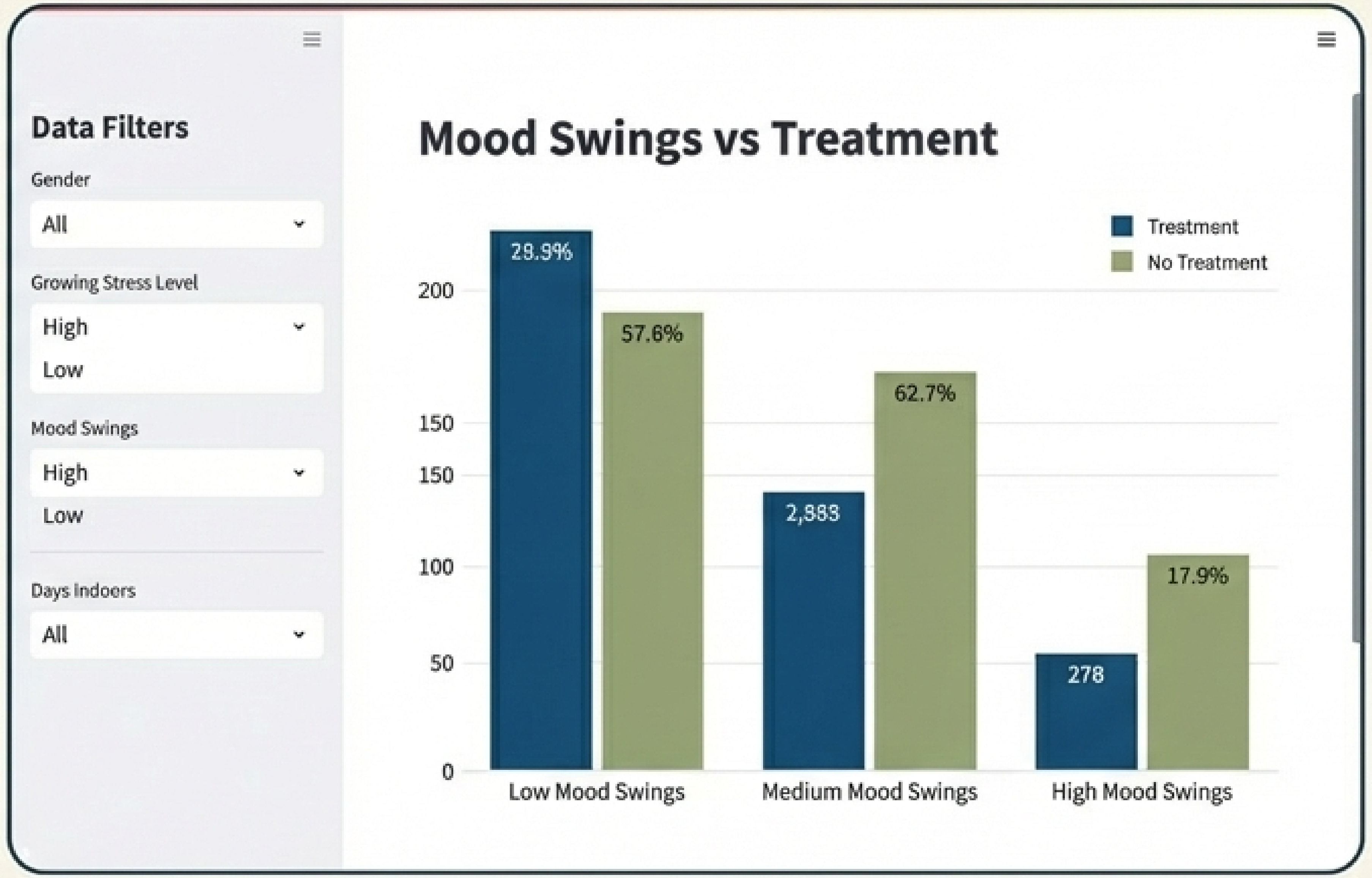
The API sends back the prediction score and a full solutions report, including ready-to-use HTML buttons for resources.

# An Interactive Dashboard for Deeper Insight

To complement the chatbot, we developed an interactive dashboard using Streamlit for visualizing and analyzing the underlying mental health data.

## Key Features

- **Interactive Filters:** Users can dynamically filter the dataset by Gender, Growing Stress Level, Mood Swings, and Days Indoors.
- **Rich Visualizations:** The dashboard offers 8 different graph types to explore relationships, including:
    - Country vs Treatment
    - Stress vs Treatment
    - Mood Swings vs Treatment
    - Mental Health History vs Treatment



# Ensuring Quality and Reproducibility with MLOps

We utilized **MLflow** to track and manage all machine learning experiments, ensuring a transparent and reproducible development process.

## Key Practices

- **Comprehensive Tracking:** The 'Milestone 5' deployment logged 6 distinct experimental runs, comparing algorithms from XGBoost to complex ensembles.
- **Performance Insights:** Tracking revealed key insights, such as Target Encoding reducing CatBoost training time from 4.5 minutes to 48.7 seconds.
- **Version Control:** Each model was versioned and logged, allowing for systematic comparison and selection of the best candidate for deployment.

### Experiment Runs

| Run Name | Duration | Version | F1 Score | AUC |
|---|---|---|---|---|
| Final_XGBoost_Optuna | 2.1 min | v3 | 0.912 | 0.945 |
| Stacked_Model_Run | 5.3 min | v2 | 0.905 | 0.938 |
| CatBoost_Target_Encoding | 48.7s | v2 | 0.898 | 0.921 |
| CatBoost_Raw_Data | 4.5 min | v1 | 0.854 | 0.890 |

8x Speed Improvement

# The Road Ahead: Future Plans for Marketing and Development

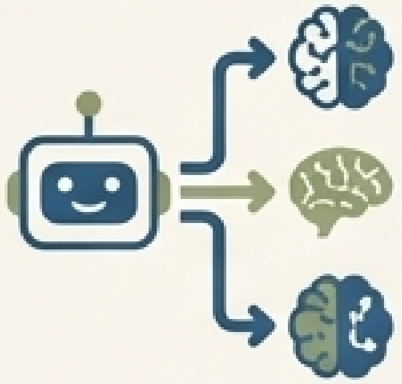
To ensure the project's future growth and expand its reach, we have identified three key areas for development.

### 1. Persistent Database Integration

Implement PostgreSQL for continuous and permanent storage of conversation logs and prediction data, enabling long-term analysis and model improvement.


### 2. Multilingual Support

Add support for other languages, beginning with Arabic, to make the tool accessible to a wider, more diverse user base.



### 3. Multi-Model Architecture

Evolve the chatbot to operate with more than one ML model, allowing it to handle different states, such as switching between a psychological consultation and a general information-providing mode.

# A Complete Solution for Accessible Mental Health Guidance

This project successfully delivered a complete, end-to-end AI system: from a rigorously validated dataset and a strategically selected, high-performance model (**92% F1-Score**) to a fully deployed and scalable web application. Our process emphasized not just accuracy, but the interpretability required to build a truly trustworthy tool.

## MoodMate represents a robust, auditable, and accessible first step for individuals seeking personalized mental health guidance.

**The prediction score obtained is a value derived from an ML Model trained on specific data and features. It may not be completely realistic or serve as a substitute for professional consultation.**