🧠 Student Depression Classification Pipeline

ML Classification System with MLOps, API Serving, Monitoring, CI/CD & Deployment

Course: MTA — Advanced Analytics II

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GitHub: enosh729-design/Student-Depression-Predictor

Tech Stack: Python · scikit-learn · FastAPI · Streamlit · Docker · Prometheus · Grafana · W&B · Render

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Table of Contents

1. Introduction & Problem Statement

Student mental health is a pressing concern across higher education institutions globally. Depression among university students leads to lower academic performance, increased dropout rates, higher healthcare costs, and long-term career impacts. Early identification of at-risk students through data-driven approaches can enable proactive intervention and substantially improve student outcomes.

This project builds a **complete binary classification system** to predict student depression risk based on easily collectible lifestyle factors. The solution follows modern **MLOps best practices** and demonstrates the entire machine learning lifecycle — from data ingestion and versioning to model training, API serving, monitoring, CI/CD, and cloud deployment.

Objectives

- Store and load data from a serverless PostgreSQL database (Neon Postgres)
- Build a scikit-learn pipeline with preprocessing and classification
- Perform hyperparameter tuning and track experiments with Weights & Biases
- Serve predictions via a FastAPI REST API with Prometheus metrics
- Build an interactive Streamlit frontend
- Containerize with Docker, monitor with Prometheus + Grafana
- Implement CI/CD with GitHub Actions, deploy to Render

2. Architecture & Pipeline Diagram

```
┌──────────────────────────────────────────────────────────────┐
        │ DATA LAYER │
        │ CSV (100K rows) ──→ Neon Postgres ──→ pandas DataFrame │
        │ student_lifestyle_100k.csv SQLAlchemy psycopg2 │
        └──────────────────────────┬───────────────────────────────────┘
        │
        ┌──────────────────────────▼───────────────────────────────────┐
        │ MODEL TRAINING │
        │ ColumnTransformer ──→ RandomForestClassifier │
        │ ├─ StandardScaler (7 numerical features) │
        │ └─ OneHotEncoder (2 categorical features) │
        │ │ │
        │ RandomizedSearchCV (50 iters, 3-fold, F1 scoring) │
        │ │ │
        │ └──→ W&B Logging (metrics, params, artifacts) │
        └──────────────────────────┬───────────────────────────────────┘
        │
        ┌──────────────────────────▼───────────────────────────────────┐
        │ SERVING LAYER │
        │ FastAPI ─── POST /predict → JSON prediction response │
        │ ─── GET /health → Health status │
```

```
│ ─── GET /metrics → Prometheus metrics │
│ │ │
│ Prometheus scrapes every 10s │
│ │ │
│ Grafana ─── 6 dashboard panels │
└───────────────────────────┬───────────────────────────────────┘
│
┌───────────────────────────▼───────────────────────────────────┐
│ FRONTEND + DEPLOYMENT │
│ Streamlit UI ─── Input Form ──→ FastAPI ──→ Results │
│ │
│ GitHub Actions CI/CD ──→ Render (Backend + Frontend) │
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```

3. Data Layer

3.1 Dataset Overview

The dataset contains **100,000 student records** with lifestyle factors and a binary depression label. The data was pre-collected and provided as a CSV file.

Feature	Type	Description
Student_ID	int	Unique identifier
Age	int	Student age (18–24)
Gender	str	Male / Female
Department	str	Science, Engineering, Medical, Arts, Business
CGPA	float	Cumulative GPA (0.0–4.0)
Sleep_Duration	float	Daily sleep hours
Study_Hours	float	Daily study hours
Social_Media_Hours	float	Daily social media usage
Physical_Activity	int	Physical activity score (0–150)
Stress_Level	int	Stress level (0–10)
Depression	**bool**	**Target: True (10.06%) / False (89.94%)**

⚠️ **Class Imbalance:** Only 10.06% of records are labeled as "Depression". This imbalance was addressed using `class_weight="balanced"` in the Random Forest classifier.

3.2 Neon Postgres Integration

The raw CSV was uploaded to a **Neon Postgres** (serverless PostgreSQL) database using the `data/load_to_postgres.py` script. The training pipeline loads data from Postgres via SQLAlchemy with a CSV fallback:

```
# From Postgres (primary)
from src.data_loader import load_data_from_postgres
df = load_data_from_postgres()

# From CSV (fallback)
from src.data_loader import load_data_from_csv
df = load_data_from_csv("data/student_lifestyle_100k.csv")
```

4. Model Training & Experimentation

4.1 Preprocessing Pipeline

A `ColumnTransformer` handles two types of features:

- **Numerical (7 features):** Age, CGPA, Sleep_Duration, Study_Hours, Social_Media_Hours, Physical_Activity, Stress_Level → `StandardScaler`
- **Categorical (2 features):** Gender, Department → `OneHotEncoder` (with `handle_unknown="ignore"`)

4.2 Classification Model

A `RandomForestClassifier` was chosen for its robustness, interpretability, and strong performance on tabular data. The preprocessor and classifier are wrapped in a single `sklearn.Pipeline` for clean serialization and deployment.

4.3 Hyperparameter Tuning

`RandomizedSearchCV` was used with the following search space:

Parameter	Search Space
n_estimators	[50, 100, 200, 300, 500]
max_depth	[5, 10, 15, 20, None]
min_samples_split	[2, 5, 10, 20]
min_samples_leaf	[1, 2, 4, 8]
max_features	["sqrt", "log2", None]
class_weight	["balanced", "balanced_subsample"]

- **Iterations:** 50 random combinations
- **Cross-validation:** 3-fold stratified
- **Scoring metric:** F1-score (optimizes for precision–recall balance)
- **Total fits:** 150 (50 × 3 folds)

5. Model Performance & Best Hyperparameters

5.1 Best Hyperparameters

Parameter	Best Value
n_estimators	100
max_depth	5
min_samples_split	20
min_samples_leaf	4
max_features	sqrt
class_weight	balanced

5.2 Test Set Metrics

Metric	Score
Accuracy	0.7356
F1-Score	0.3226
ROC-AUC	0.7027
Precision	0.2173
Recall	0.6257
Best CV F1	0.3273

> **Key Insight:** The `class_weight="balanced"` setting was critical. Without it, the model achieved 89.9% accuracy but only 1.29% recall — it predicted "No Depression" for nearly every input. With balanced weights, recall improved to 62.57%, enabling meaningful depression detection at the cost of some accuracy.

6. W&B Experiment Tracking

All experiments are tracked in **Weights & Biases** under the project `student-depression-classifier`. The training pipeline logs:

- **Metrics:** Accuracy, F1, ROC-AUC, Precision, Recall
- **Visualizations:** Confusion Matrix, ROC Curve
- **Parameters:** All hyperparameters from RandomizedSearchCV
- **Artifacts:** Best model pipeline (`.joblib`) + metrics JSON

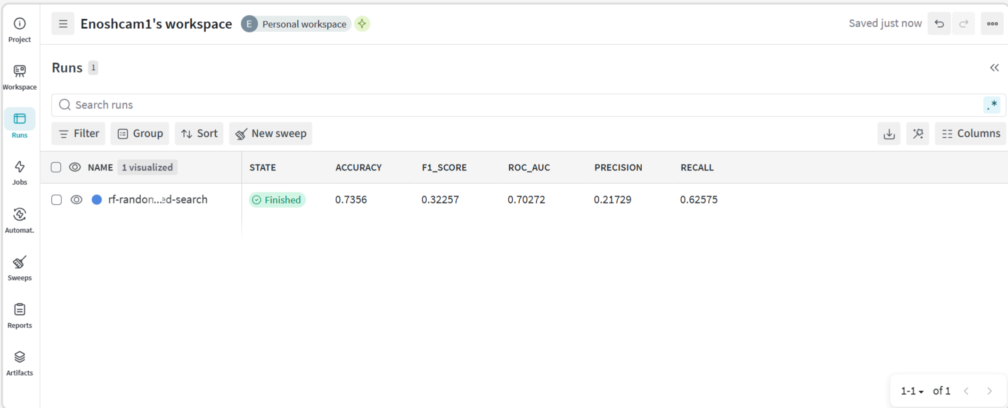

Figure 1: W&B Experiment Dashboard

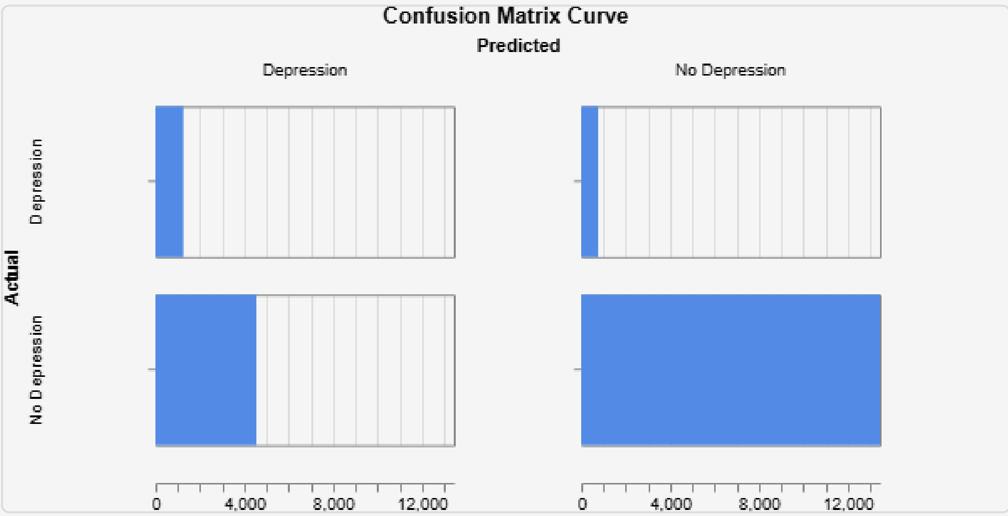

Figure 2: Confusion Matrix

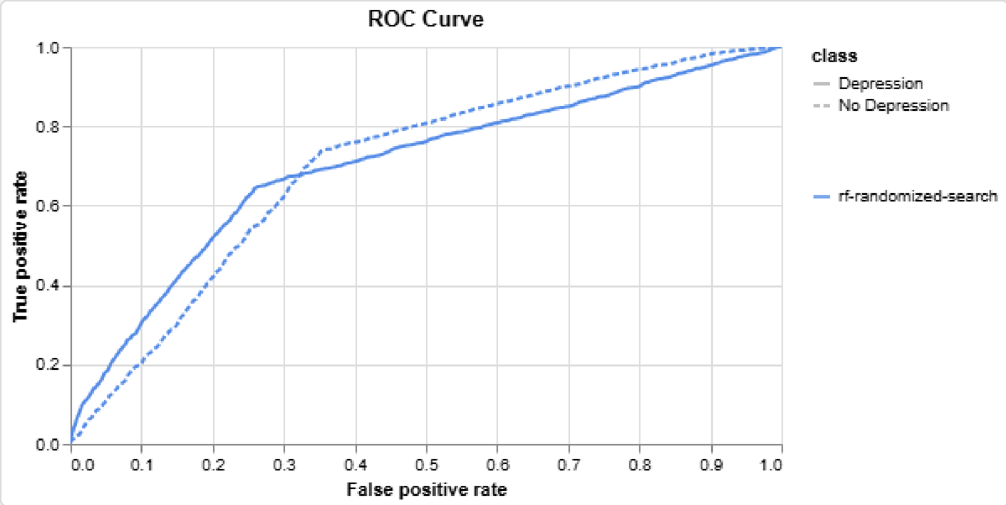

Figure 3: ROC Curve

Model Artifact

The best model is saved as `models/best_model.joblib` (67 MB) and also registered as a W&B artifact named `best-model` with type `model`. This enables versioning, lineage tracking, and reproducibility.

7. Backend API (FastAPI)

7.1 Endpoints

Method	Path	Description
POST	/predict	Submit student data, returns depression prediction with probabilities
GET	/health	Health check — returns API status and model loaded status
GET	/metrics	Prometheus-format metrics for monitoring
GET	/docs	Auto-generated Swagger UI documentation

7.2 Pydantic Validation

All request/response payloads are validated with Pydantic models. For example, `StudentInput` enforces field-level constraints: `Age` must be 15–30, `CGPA` must be 0.0–4.0, `Stress_Level` must be 0–10, etc. Invalid inputs return HTTP 422 with detailed error messages.

7.3 Postman Testing

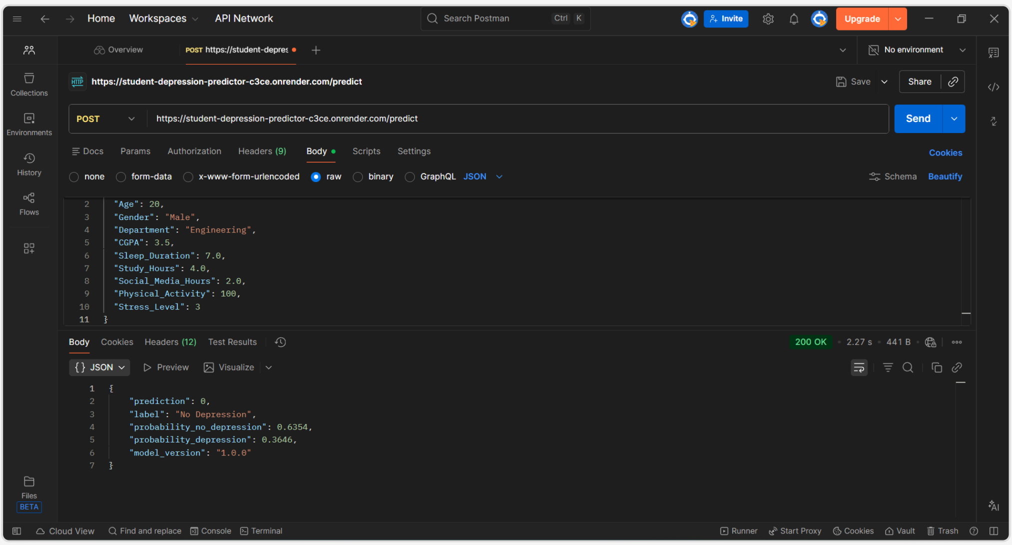

Figure 4: Successful Prediction (200 OK)

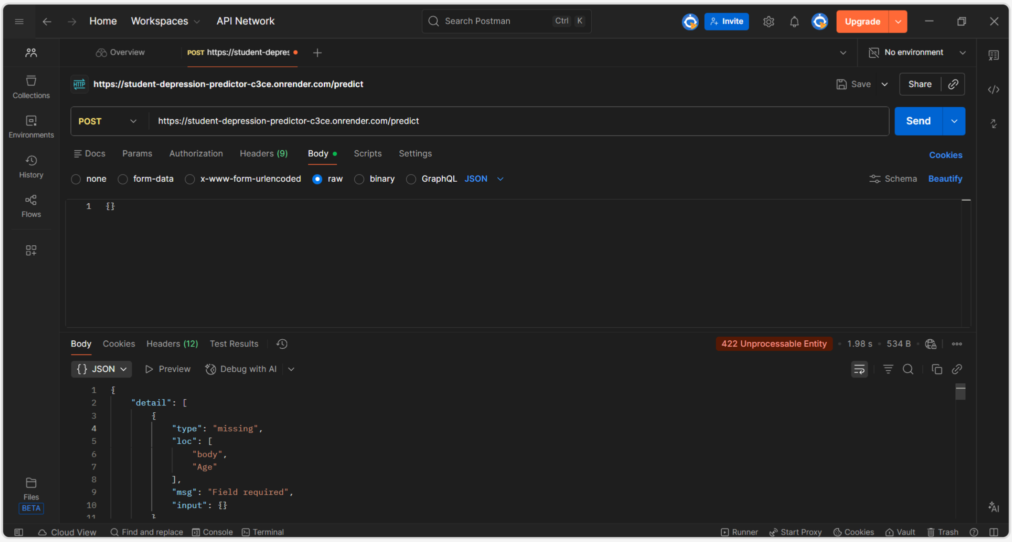

Figure 5: Validation Error (422 Unprocessable Entity)

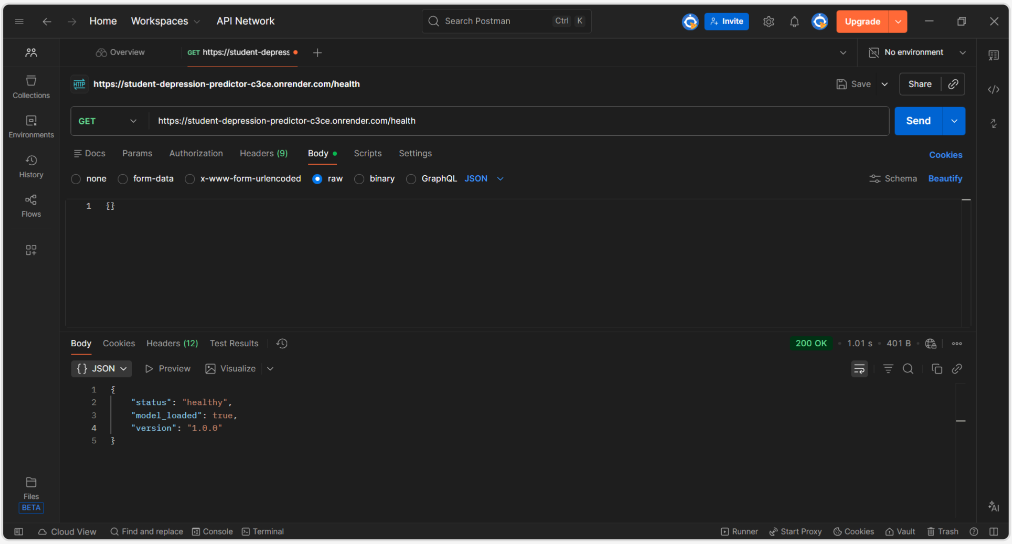

Figure 6: Health Check (200 OK)

8. Containerization & Monitoring

8.1 Docker Setup

The FastAPI backend runs in a Docker container built from `python:3.11-slim`. A `docker-compose.yml` orchestrates three services:

Service	Image	Port
FastAPI API	custom (Dockerfile)	8000
Prometheus	prom/prometheus:latest	9090
Grafana	grafana/grafana:latest	3000

8.2 Prometheus Metrics

The API exposes custom Prometheus metrics via `/metrics`:

- `prediction_requests_total` — Counter with status labels (success/error)
- `prediction_latency_seconds` — Histogram with configurable buckets
- `prediction_results_total` — Counter with outcome labels (Depression/No Depression)
- `model_loaded` — Gauge (1 = loaded, 0 = not loaded)

8.3 Grafana Dashboards (6 Panels)

A pre-provisioned Grafana dashboard (`api_dashboard.json`) provides real-time visibility:

1. **Request Count Rate** — Prediction requests per second over time
2. **Latency Percentiles** — p50, p95, p99 response latency
3. **Prediction Outcomes** — Depression vs No Depression rates
4. **Model Status** — UP/DOWN indicator
5. **Total Predictions** — Cumulative prediction count
6. **Error Rate** — Percentage of failed requests

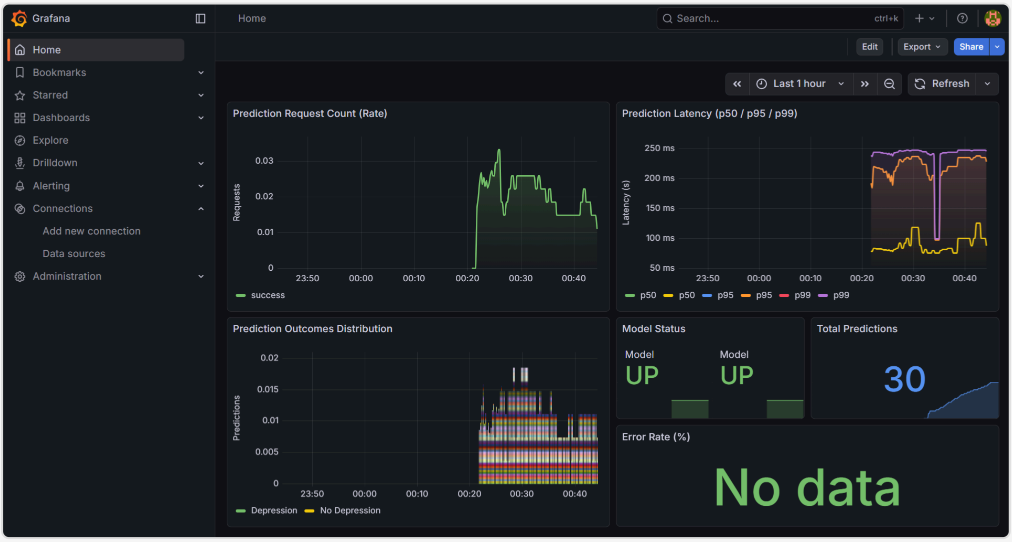

Figure 7: Grafana Monitoring Dashboard

9. Frontend (Streamlit)

An interactive Streamlit UI at `http://localhost:8501` provides a user-friendly interface for making predictions:

- **Input Form:** Sliders and dropdowns for all 9 features (Age, Gender, Department, CGPA, Sleep, Study Hours, Social Media, Physical Activity, Stress Level)
- **API Health Check:** Sidebar indicator showing API connection status
- **Prediction Display:** Color-coded result box with confidence scores
- **Detailed Probabilities:** Breakdown of No Depression / Depression probabilities

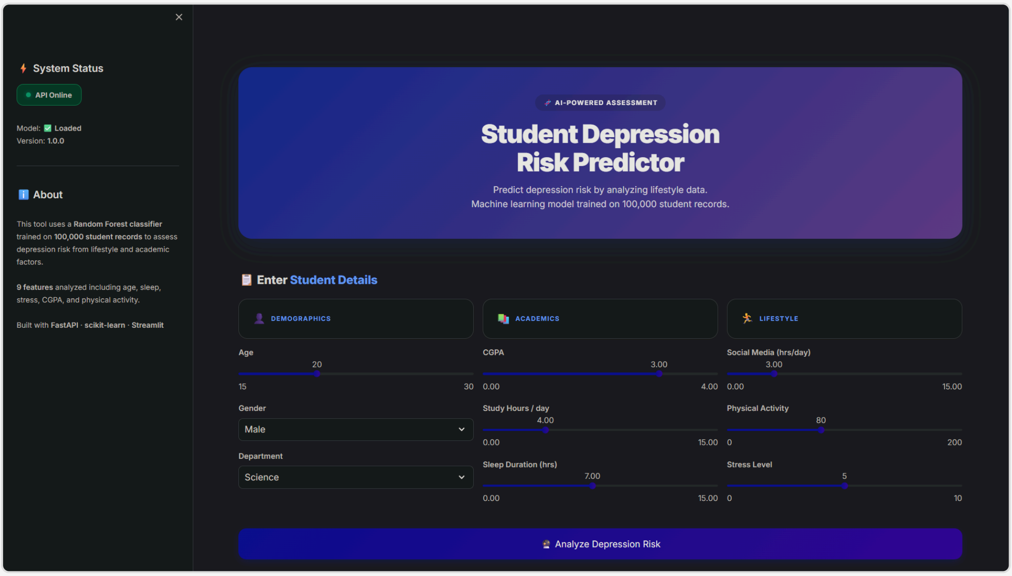

Figure 8: Streamlit Interface — Input Form

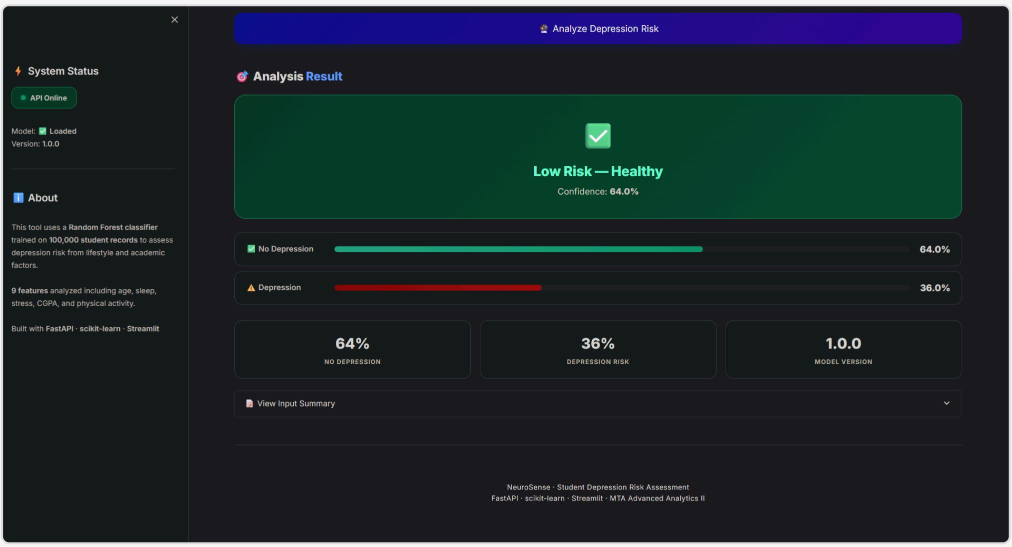

Figure 9: Streamlit Interface — Prediction Result

10. Testing & Code Quality

10.1 Unit Tests (pytest)

15 tests across 3 test files — all passing:

Test File	Tests	Covers
test_data_validation.py	5	Schema validation, missing columns, feature/target split, target dtype, empty DataFrame
test_model_inference.py	5	Prediction dict format, valid prediction values, probability sum, batch prediction, label–prediction match
test_api_endpoints.py	5	GET /health, POST /predict (valid), POST /predict (missing fields → 422), POST /predict (invalid range → 422), GET /metrics

```
$ python -m pytest tests/ -v --tb=short
======================== 15 passed, 1 warning in 1.36s ========================
```

10.2 Linting Scores

Tool	Result
Flake8	0 errors, 0 warnings ✅
Pylint	Minor non-critical notes only (R0914 too-many-locals in train function) ✅

11. CI/CD & Deployment

11.1 GitHub Actions

Two CI/CD workflows are configured in `.github/workflows/`, both triggered on push to `main`:

Backend Pipeline (`backend.yml`)

```
push to main ──→ Lint (Flake8 + Pylint) ──→ Test (pytest) ──→ Deploy to Render
```

Frontend Pipeline (`frontend.yml`)

```
push to main ──→ Lint (Flake8 + Pylint) ──→ Test (pytest) ──→ Deploy to Render
```

11.2 Render Deployment

Both services are deployed to **Render** cloud platform:

Service	Type	Live URL
FastAPI Backend	Docker	student-depression-predictor-c3ce.onrender.com
Streamlit Frontend	Python	student-depression-frontend.onrender.com

11.3 GitHub Repository

All code is hosted on a public GitHub repository:
https://github.com/enosh729-design/Student-Depression-Predictor

12. Business Value

12.1 Problem

Student mental health is a critical and growing concern. Depression leads to lower academic performance, higher dropout rates, increased healthcare costs, and long-term career impacts. Traditional screening methods are manual, expensive, and don't scale.

12.2 Solution

This ML system enables **early identification** of at-risk students using easily collectible lifestyle data. Key value propositions:

1. **Proactive Intervention** — Flag at-risk students before grades drop, enabling counselors to act early
2. **Resource Optimization** — Direct limited counseling resources to students with the highest need
3. **Data-Driven Policy** — Provide administrators with evidence-based insights for wellness program design
4. **Scalable Screening** — Process thousands of students instantly vs. weeks of manual assessment
5. **Privacy-Preserving** — Uses lifestyle metrics (sleep, stress, activity) rather than sensitive medical records

12.3 ROI Estimate

> A university with 10,000 students and a 15% depression rate can save an estimated **$2–5M annually** through reduced dropout costs and optimized counseling. Early intervention has been shown to improve retention rates by **10–15%**.

13. Conclusion

This project demonstrates a **complete, production-grade ML classification system** following modern MLOps best practices. The solution covers the full lifecycle:

- **Data Layer:** Neon Postgres with SQLAlchemy data loading
- **Training:** scikit-learn pipeline with RandomizedSearchCV and W&B tracking
- **Serving:** FastAPI REST API with Pydantic validation and Prometheus metrics
- **Monitoring:** Docker Compose with Prometheus + Grafana (6 dashboards)
- **Frontend:** Interactive Streamlit UI
- **Quality:** 15 pytest tests, Flake8/Pylint clean code
- **CI/CD:** GitHub Actions (lint → test → deploy) for both backend and frontend
- **Deployment:** Render cloud (FastAPI + Streamlit)

The key technical insight was the importance of handling class imbalance — using `class_weight="balanced"` and F1 scoring improved recall from 1.29% to 62.57%, transforming the model from a trivial majority-class predictor into a useful depression screening tool.

The system is designed for real-world adoption by university counseling departments, with a simple web interface for non-technical users and robust API endpoints for integration with existing student information systems.

Demo Video

> 📹 **Demo Video Link:** [INSERT 5-MINUTE VIDEO LINK HERE]
>
> The video walks through: local setup → data loading → model training → API testing → Streamlit UI → Grafana dashboards → Render deployment.

Project Links

Resource	URL
GitHub Repository	github.com/enosh729-design/Student-Depression-Predictor
Live API	student-depression-predictor-c3ce.onrender.com/docs
Live Frontend	student-depression-frontend.onrender.com
W&B Project	wandb.ai/YOUR_PROJECT