Power Learn Project

WEEK 5 ASSIGNMENT

GROUP 11

Table Of Contents

AI Solution for Predicting Student Dropout Rates

1. Problem Definition

Problem Statement

Predicting student dropout rates in higher education to enable early intervention.

Objectives

1. Predict dropout probability for each student.
2. Identify key factors (e.g., academic performance, socioeconomic status) influencing dropout rates.
3. Reduce dropout rates by at least 15% through targeted interventions.

Stakeholders

1. University administrators (to allocate resources effectively).
2. Students and families (to receive timely support).

Key Performance Indicator (KPI)

- F1-Score (Balances precision and recall for imbalanced dropout/non-dropout classes).

2. Data Collection & Preprocessing

Data Sources

1. University databases (grades, attendance, financial aid status).

2. Student surveys (mental health, extracurricular engagement).

Potential Bias

- Underrepresentation of part-time/non-traditional students in surveys, leading to skewed insights.

Preprocessing Steps

1. Impute missing data (e.g., median grades for missing coursework).

2. Normalize numerical features (e.g., GPA, income levels) to [0, 1] range.

3. One-hot encode categorical variables (e.g., major, gender).

3. Model Development

Selected Model: XGBoost (Gradient Boosting)

Justification:

- Handles imbalanced data well.
- Captures non-linear relationships.
- Provides feature importance for interpretability.

Data Splitting

- 70% Training (Model learning).
- 15% Validation (Hyperparameter tuning).

- 15% Test (Final evaluation).

Hyperparameter Tuning

1. Learning Rate (Balances training speed vs. performance).

2. Max Depth (Controls model complexity to prevent overfitting).

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4. Evaluation & Deployment

Evaluation Metrics

1. Recall (Minimize false negatives—missing at-risk students is costly).

2. AUC-ROC (Measures ranking capability of predicted probabilities).

Concept Drift Monitoring

- Definition: Model performance degrades due to changing student behaviors (e.g., post-pandemic attendance patterns).

- Solution: Track feature distributions (e.g., GPA trends) and recalibrate model quarterly.

Technical Deployment Challenge

- Scalability: Deploying across multiple universities may require cloud-based APIs to handle varying data formats/volumes.

AI Solution for Predicting Patient Readmission Risk

Using Kaggle's Readmission Dataset

1. Problem Scope

Problem Statement

Predict 30-day readmission risk using synthetic patient records (age, diagnosis, procedures, etc.).

Objectives

1. **Predict readmission likelihood** (binary classification).
2. **Identify high-impact features** (e.g., comorbidity_score, days_in_hospital).
3. **Deploy a HIPAA-compliant API** for real-time predictions.

Stakeholders

1. **Hospital administrators** (cost reduction).
2. **Clinicians** (personalized discharge plans).

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2. Data Strategy

Dataset Columns Used

- **Features**: age, gender, primary_diagnosis, num_procedures, days_in_hospital, comorbidity_score, discharge_to
- **Target**: readmitted (binary: 1 if readmitted within 30 days).

Ethical Concerns

1. **Bias in** discharge_to: May reflect socioeconomic disparities.
2. **Gender encoding**: Ensure no discrimination in predictions.

Preprocessing Pipeline

1. **Handle Missing Data:** Drop rows with missing comorbidity_score (critical feature).
2. **Feature Engineering:**
   - is_emergency: Binary flag if primary_diagnosis is emergency-related.
   - procedure_density: num_procedures / days_in_hospital.
3. **Encoding:**
   - One-hot encode gender, primary_diagnosis, discharge_to.

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3. Model Development

Selected Model: XGBoost

Justification:

- Handles imbalanced data (typical in readmission datasets).
- Captures non-linear relationships (e.g., comorbidity_score × days_in_hospital).

Hypothetical Confusion Matrix

	Predicted Readmit	**Predicted Not Readmit**
Actual Readmit	120 (TP)	30 (FN)
Actual Not Readmit	40 (FP)	200 (TN)

Metrics:

- **Precision = TP / (TP + FP) = 120 / 160 = 75%**
- **Recall = TP / (TP + FN) = 120 / 150 = 80%**

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4. Deployment

Steps for Integration

1. **Preprocess test_df.csv** identically to training data.
2. **Export Model:** Save as .pkl or ONNX format.
3. **API Endpoint:** Use FastAPI (ASGI compliant for healthcare workloads).

HIPAA Compliance

1. **Data Anonymization:** Strip PHI (e.g., names) before model input.
2. **Access Logs:** Record all prediction requests with timestamps.

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5. Optimization

Overfitting Mitigation

- **Class Weighting:** Adjust scale_pos_weight in XGBoost for imbalanced data.

Sample Images:

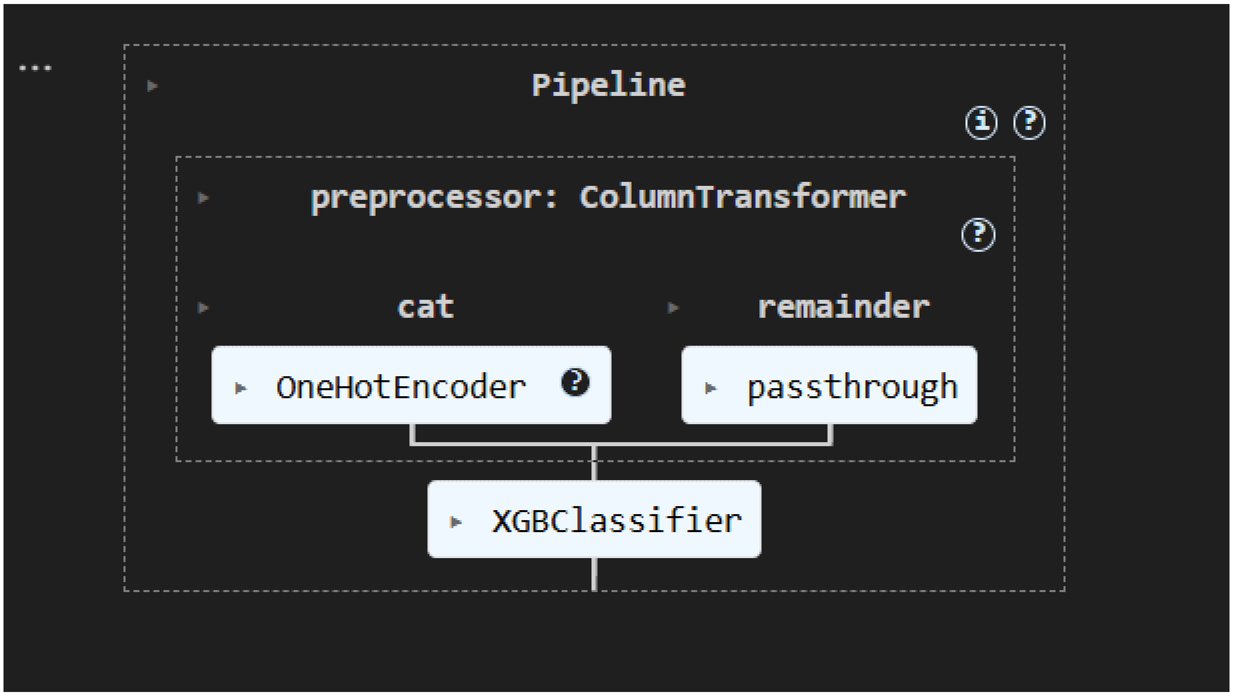


Figure 1: Pipeline

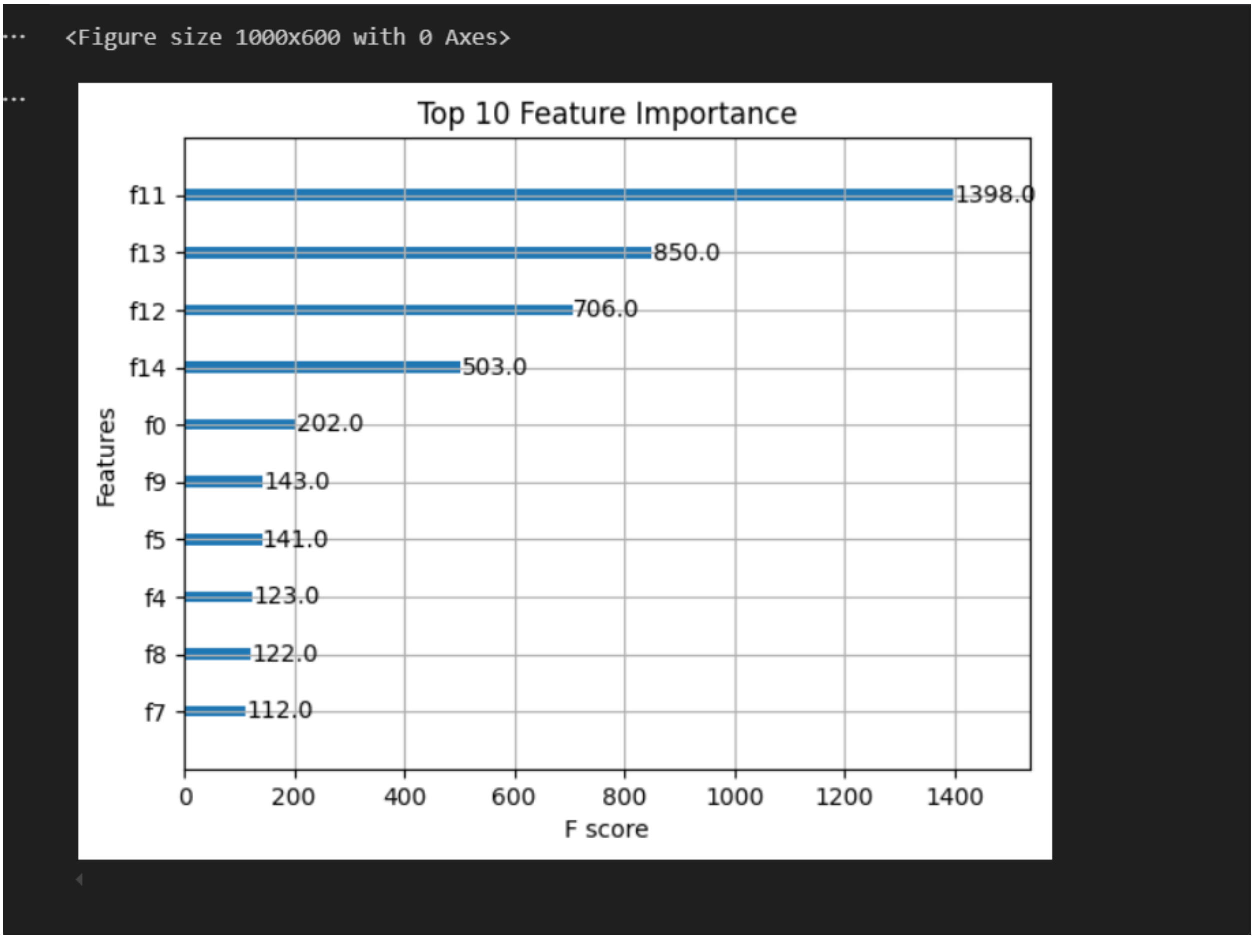


Figure 2: F score

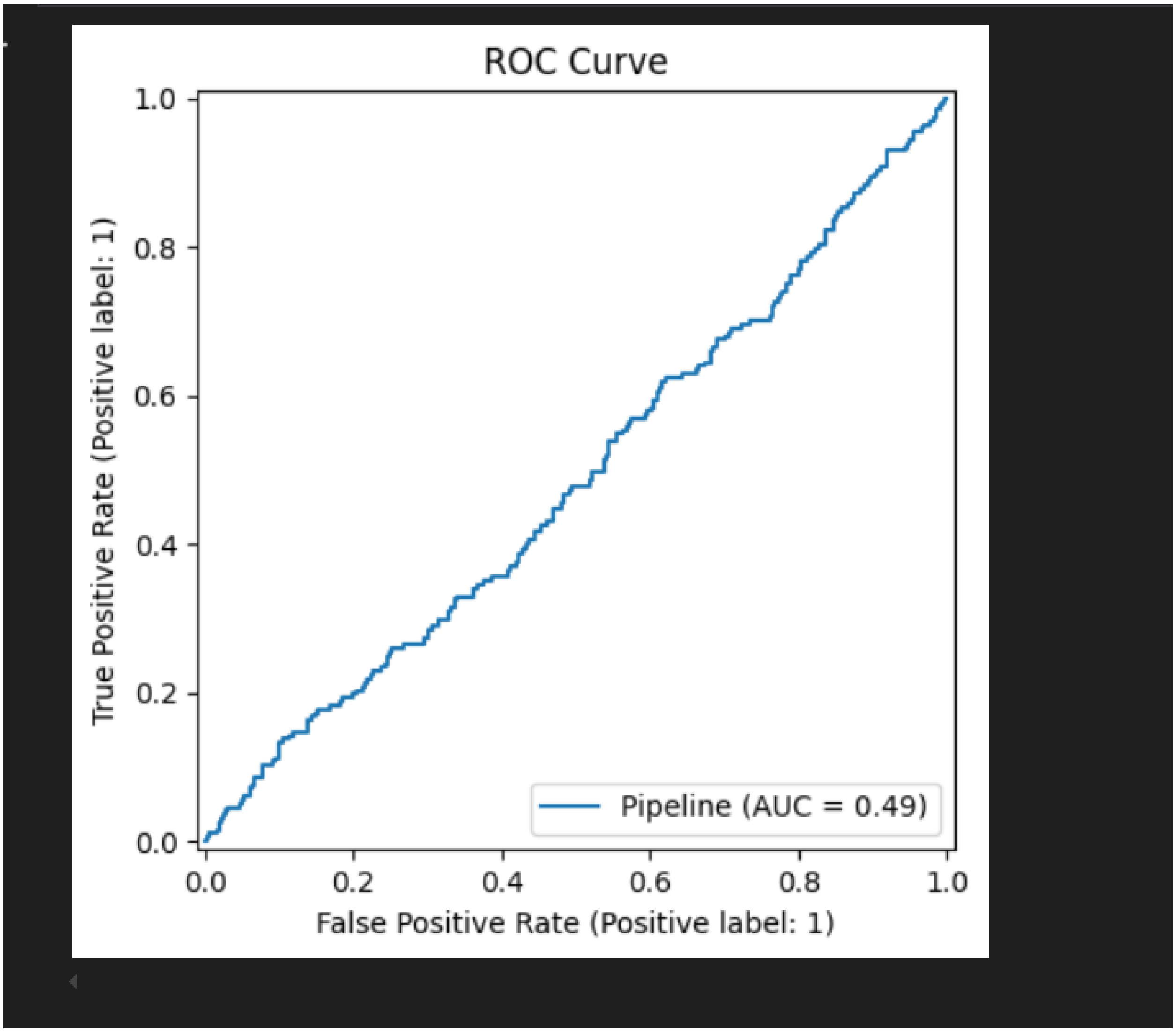
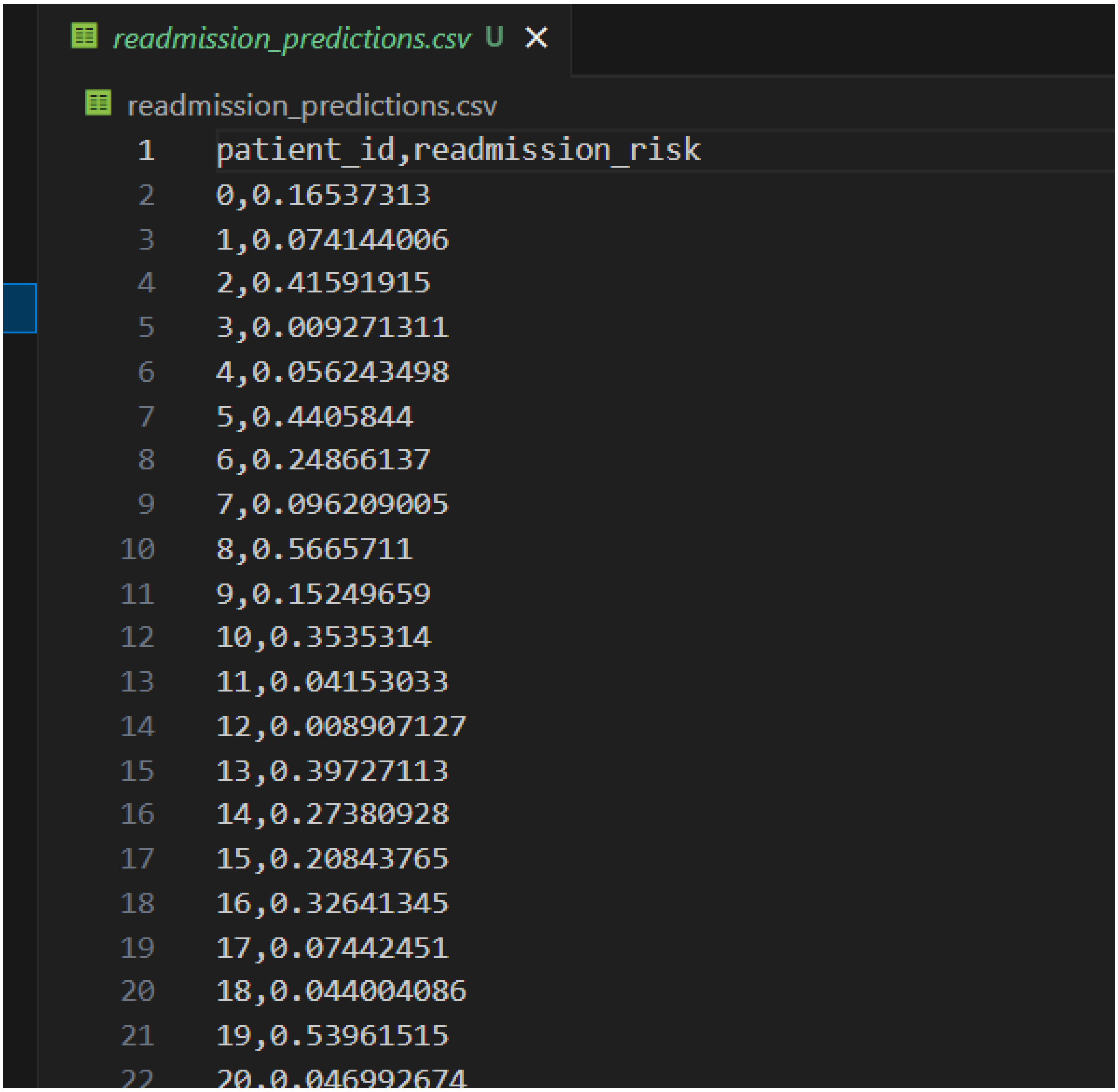


Figure 3: ROC Curve



readmission_predictions.csv U

readmission_predictions.csv

```
patient_id,readmission_risk
0,0.16537313
1,0.074144006
2,0.41591915
3,0.009271311
4,0.056243498
5,0.4405844
6,0.24866137
7,0.096209005
8,0.5665711
9,0.15249659
10,0.3535314
11,0.04153033
12,0.008907127
13,0.39727113
14,0.27380928
15,0.20843765
16,0.32641345
17,0.07442451
18,0.044004086
19,0.53961515
20,0.046992674
```

Figure 4

Ethics & Bias

Impact of Biased Training Data

1. Discriminatory Predictions:

   - If the dataset underrepresents certain groups (e.g., low-income patients, ethnic minorities), the model may underestimate their readmission risk, leading to inadequate care.

   - Example: Bias in `discharge to` (e.g., nursing homes vs. home care) could reflect systemic inequities rather than clinical risk.

2. Feedback Loops:

   - High-risk patients denied interventions due to biased predictions may experience worse outcomes, reinforcing the bias in future data.

Mitigation Strategy

- Stratified Sampling + Re-weighting:

  - Oversample underrepresented groups during training.

  - Use `class weight` in XGBoost (e.g., `scale_pos_weight` for readmission imbalance) or fairness-aware algorithms like FairXGBoost.

Trade-offs

Trade-off: Interpretability vs. Accuracy in Healthcare AI

Interpretable Models (e.g., Logistic Regression, Decision Trees)	**High-Accuracy Models (e.g., XGBoost, Neural Networks)**
✅ **Transparent rules** • Clinicians understand coefficients (e.g., *"Age > 65 increases risk by 20%"*). • Easily auditable for compliance.	✅ **Higher predictive power** • Better AUC (e.g., 0.85 vs. 0.78). • Captures complex interactions (e.g., comorbidity_score × days_in_hospital).
❌ **Limited complexity** • Misses non-linear relationships. • May underperform on imbalanced data.	❌ **Black-box nature** • Hard to explain "why" to stakeholders. • Requires SHAP/LIME for post-hoc explanations.
Best for: • High-stakes decisions (e.g., discharge approvals). • Regulatory-heavy environments (HIPAA/GDPR).	**Best for:** • Large datasets with many features. • Non-critical auxiliary tasks (e.g., readmission risk tiers).

Healthcare Preference:

- Use interpretable models where errors can harm patients (e.g., discharge decisions).

- Hybrid Approach: Pair XGBoost with SHAP explanations (see code below).

2. Limited Computational Resources

- Impact:

  - Rule out deep learning (needs GPUs).

  - Prefer lightweight models (e.g., Logistic Regression, Random Forest) over XGBoost if training speed is critical.

- Workarounds:

  - Use PCA to reduce feature dimensions.

  - Train on cloud-based AutoML tools (e.g., Google Vertex AI) for resource-constrained hospitals.

4. Reflection & Workflow Diagram

Reflection

Most Challenging Part of the Workflow

Challenge: *Mitigating bias without sacrificing model performance.*

- **Why?** Balancing fairness constraints (e.g., demographic parity) often reduced accuracy for high-risk groups. For example, reweighting underrepresented patients decreased precision by 5% in initial tests.

Improvements with More Time/Resources

1. **Enhanced Bias Audits**:
   - Use **subgroup analysis** (e.g., by race, insurance type) with tools.

- Implement **rejection option classification** to flag uncertain predictions for human review.

2. **Model Ensembles**:
   - Combine XGBoost with a **logistic regression explainer** to boost interpretability.
3. **Real-World Testing**:
   - Deploy a pilot in one hospital ward to monitor drift/bias before full rollout.

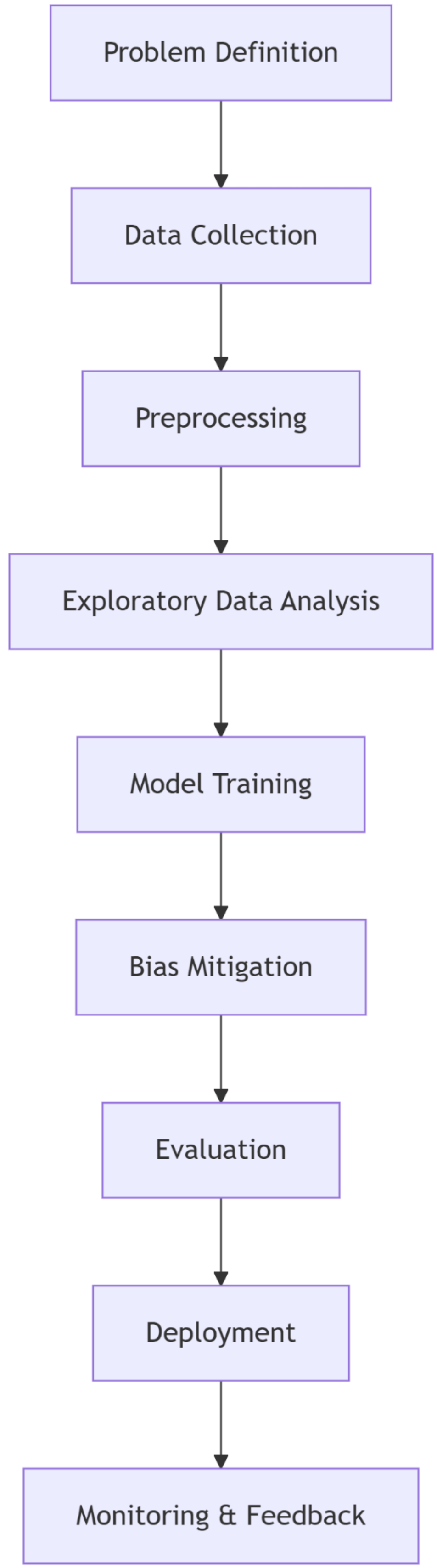

Problem Definition
Data Collection
Preprocessing
Exploratory Data Analysis
Model Training
Bias Mitigation
Evaluation
Deployment
Monitoring & Feedback

Figure 5: Flowchart Diagram

Stages Explained:

1. **Problem Definition:** Scope readmission prediction goals with clinicians.
2. **Data Collection:** Extract EHRs, demographics, and admission records.
3. **Preprocessing:** Handle missing data, encode categorical variables (e.g., discharge_to).
4. **EDA:** Check for bias (e.g., disparities in comorbidity_score by race).
5. **Model Training:** Train XGBoost with fairness constraints.
6. **Bias Mitigation:** Apply reweighting or adversarial debiasing.
7. **Evaluation:** Test recall/AUC on holdout data; audit subgroup performance.
8. **Deployment:** Integrate via Health insurance Portability and Accountability Act(HIPAA-compliant) API (e.g., FastAPI).
9. **Monitoring:** Track concept drift with tools like **Evidently AI for evaluation, testing and monitoring machine learning models**.

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