

Part 1: Short Answer Questions (30 points)

1. Problem Definition (6 points)

Hypothetical AI Problem:

Predicting student dropout rates in universities.

- **Objectives:**
 1. Identify students at risk of dropping out early in the semester.
 2. Provide timely interventions to improve retention.
 3. Support university planning and resource allocation.
 - **Stakeholders:**
 1. University administration.
 2. At-risk students.
 - **KPI:**

Dropout Prediction Accuracy (%) — the percentage of correctly predicted dropouts.
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2. Data Collection & Preprocessing (8 points)

- **Two Data Sources:**
 1. Student academic records (grades, attendance).
 2. Learning Management System (LMS) activity logs.
 - **Potential Bias:**

Socioeconomic status may be underrepresented or misrepresented, leading to biased predictions favoring well-off students.
 - **Three Preprocessing Steps:**
 1. Handle missing values in attendance or grade columns using imputation.
 2. Normalize numerical features like GPA and hours studied.
 3. Encode categorical variables like course type and student major.
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3. Model Development (8 points)

- **Model Chosen:**

Random Forest — handles both numerical and categorical data well, is robust to outliers, and reduces overfitting through ensemble learning.
- **Data Splitting:**
 - 70% for training
 - 15% for validation
 - 15% for testing
- **Two Hyperparameters to Tune:**
 1. `n_estimators` — Number of trees; affects accuracy and stability.

2. `max_depth` — Controls tree complexity to prevent overfitting.
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4. Evaluation & Deployment (8 points)

- **Evaluation Metrics:**
 1. *Precision* — ensures the system doesn't flag students who aren't truly at risk.
 2. *Recall* — important to identify as many at-risk students as possible.
 - **Concept Drift:**

Changes in student behavior or curriculum over time that may reduce model accuracy.

 - *Monitoring:* Regularly retrain the model on fresh data; use performance tracking dashboards.
 - **Deployment Challenge:**

Scalability — Integrating and maintaining the system across different departments and campuses.
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Part 2: Case Study Application (40 points)

Problem Scope (5 points)

- **Problem:**

Predict if a patient will be readmitted within 30 days after discharge.
 - **Objectives:**
 1. Reduce avoidable readmissions.
 2. Optimize post-discharge care plans.
 - **Stakeholders:**
 1. Hospital administrators.
 2. Patients and their families.
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Data Strategy (10 points)

- **Data Sources:**
 1. Electronic Health Records (EHRs): diagnoses, medications, prior admissions.
 2. Demographics: age, gender, zip code, insurance type.
- **Two Ethical Concerns:**
 1. *Patient privacy* — sensitive health data must be protected.
 2. *Bias* — certain groups (e.g., minorities) might be unfairly flagged due to historical disparities.
- **Preprocessing Pipeline:**

1. **Missing Data Handling:** Fill gaps in medication/demographic data using median/mode.
 2. **Feature Engineering:**
 - Time since last admission
 - Number of chronic conditions
 3. **Encoding/Scaling:** One-hot encode categorical features; normalize numeric ones like lab results.
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Model Development (10 points)

- **Model Chosen:**
Gradient Boosting Machine (e.g., XGBoost) — Excellent at handling imbalanced classification problems and tabular healthcare data.
- **Confusion Matrix (Hypothetical):**

	Predicted Yes	Predicted No
Actual Yes	80	20
Actual No	30	170

- **Precision:**
 $= 80 / (80 + 30) = \mathbf{0.727}$ (72.7%)
 - **Recall:**
 $= 80 / (80 + 20) = \mathbf{0.80}$ (80%)
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Deployment (10 points)

- **Integration Steps:**
 1. Develop an API to serve the model.
 2. Connect API with hospital's EHR system.
 3. Display prediction results in the doctor's dashboard.
 - **HIPAA Compliance:**
 - Use encryption for data transmission.
 - Apply role-based access controls.
 - Maintain audit logs for model access and usage.
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Optimization (5 points)

- **Method to Address Overfitting:**
Use *cross-validation* and add *regularization* (L1/L2 penalties) to prevent the model from learning noise in training data.
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Part 3: Critical Thinking (20 points)

Ethics & Bias (10 points)

- **Impact of Bias:**
Biased training data may lead to higher readmission predictions for certain races or income groups, leading to discrimination in care.
 - **Bias Mitigation Strategy:**
Use *fairness-aware learning*, e.g., reweighing training samples or introducing constraints that enforce equal opportunity during training.
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Trade-offs (10 points)

- **Interpretability vs Accuracy:**
 - Complex models (e.g., XGBoost) offer high accuracy but are harder to explain.
 - Simpler models (e.g., Decision Trees or Logistic Regression) are more interpretable but might underperform.
 - In healthcare, *interpretability* is often prioritized to maintain clinician trust and meet regulatory standards.
 - **Limited Resources Impact:**
 - May need to choose lighter models (e.g., Logistic Regression) that consume less CPU/GPU.
 - Cloud deployment may be restricted; on-premise deployment becomes necessary.
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Part 4: Reflection & Workflow Diagram (10 points)

Reflection (5 points)

- **Most Challenging Part:**
Preprocessing medical data — due to complexity and irregular formats.
 - **Improvement with More Time/Resources:**
Would gather more labeled data and include domain experts (e.g., doctors) during feature selection.
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Diagram (5 points)

AI Development Workflow Flowchart:

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