Part 1: Short Answer Questions (30 points)

1. Problem Definition (6 points)

Hypothetical AI Problem: Predicting student dropout rates in university-level online courses. Objectives: 1. Accurately predict students at risk of dropping out before mid-semester. 2. Provide actionable insights to faculty and advisors for early intervention. 3. Enhance student retention and academic performance through targeted support. Stakeholders: 1. University administration (for retention strategy and resource planning). 2. Academic advisors (for personalized intervention and guidance). Key Performance Indicator (KPI): - Dropout prediction accuracy (percentage of correctly predicted dropout cases).

2. Data Collection & Preprocessing (8 points)

Data Sources: 1. Learning Management System (LMS) logs: login frequency, assignment submissions, forum participation. 2. Student information system: demographics, past academic performance, enrollment status. Potential Bias: - Students with limited internet access may appear inactive, skewing prediction toward dropout even if they are trying. Preprocessing Steps: 1. Handling Missing Data: Impute or remove rows with incomplete records (e.g., missing GPA). 2. Normalization: Scale variables like time spent on the platform to a common range. 3. Encoding Categorical Variables: Convert class attendance ("low", "medium", "high") into numeric values.

3. Model Development (8 points)

Chosen Model: Random Forest Justification: It handles nonlinear relationships well, manages missing data, reduces overfitting via ensemble learning, and is interpretable through feature importance. Data Splitting: - 70% training, 15% validation, 15% test. The training set builds the model; validation tunes hyperparameters; the test set measures generalization. Two Hyperparameters: 1. Number of trees: Controls ensemble strength and accuracy. 2. Max depth: Prevents overfitting by limiting tree growth.

4. Evaluation & Deployment (8 points)

Evaluation Metrics: 1. F1 Score: Balances false positives and false negatives, especially useful with imbalanced dropout data. 2. ROC-AUC: Evaluates the trade-off between sensitivity and specificity. Concept Drift: - Change in the relationship between features and dropout behavior over time. It can arise from new teaching methods or changes in student behavior. Monitoring: Regular retraining using recent data, and tracking prediction confidence over time. Deployment Challenge: - Scalability: Real-time predictions must scale with thousands of students using limited computational infrastructure.

Part 2: Case Study Application (40 points)

Problem Scope (5 points)

Problem: Predicting risk of patient readmission within 30 days post-discharge. Objectives: 1. Reduce readmission rates through timely interventions. 2. Improve patient outcomes and reduce hospital costs. 3. Support physicians in discharge planning. Stakeholders: 1. Hospital administrators. 2. Medical professionals and care coordinators.

Data Strategy (10 points)

Data Sources: 1. Electronic Health Records (EHRs): diagnosis history, length of stay, medications. 2. Demographic Data: age, gender, zip code, socioeconomic factors. Ethical Concerns: 1. Patient Privacy: Ensuring HIPAA-compliant data handling. 2. Discrimination: Risk of biased predictions against certain groups (e.g., elderly, minorities). Preprocessing Pipeline: 1. Feature Selection: Choose clinically relevant variables like prior readmissions, comorbidities. 2. Handling Missing Values: Imputation based on mean/mode or medical standards. 3. Feature Engineering: Compute variables like average length of past admissions or medication adherence score.

Model Development (10 points)

Chosen Model: Gradient Boosting (e.g., XGBoost) Justification: It’s accurate on tabular medical data, handles class imbalance well, and allows feature importance interpretation. Confusion Matrix (Hypothetical Data): | Predicted Positive | Predicted Negative --- Actual Positive | 80 | 20 Actual Negative | 30 | 170 Precision = TP / (TP + FP) = 80 / (80 + 30) = 0.727 Recall = TP / (TP + FN) = 80 / (80 + 20) = 0.800

Deployment (10 points)

Integration Steps: 1. Build an API to serve predictions. 2. Embed the model in the EHR interface with alerts for high-risk patients. 3. Establish a monitoring dashboard. Compliance: - Ensure encryption in storage and transit. - Conduct Data Privacy Impact Assessments. - Follow HIPAA requirements for auditability and patient rights.

Optimization (5 points)

Method to Address Overfitting: - Early stopping during model training based on validation performance. This prevents excessive learning of noise.

Part 3: Critical Thinking (20 points)

Ethics & Bias (10 points)

Biased training data can lead to poor care for underrepresented populations. For instance, patients from low-income backgrounds may be incorrectly flagged as high-risk due to systemic healthcare inequities. Strategy to Mitigate Bias: - Use fairness-aware training techniques like reweighting or adversarial debiasing, and assess models across demographic subgroups.

Trade-offs (10 points)

Interpretability vs Accuracy: - Complex models like deep neural networks are highly accurate but difficult to interpret. - In healthcare, interpretability is crucial for clinician trust, thus simpler models like logistic regression may be preferred despite lower accuracy. Computational Constraints: - Limited resources may restrict use of large models. Lightweight models like decision trees or logistic regression would be ideal for real-time predictions.

Part 4: Reflection & Workflow Diagram (10 points)

Reflection (5 points)

Most Challenging Part: Ensuring ethical fairness in the model without reducing performance. Improvement Plan: - Use a larger, more diverse dataset and allocate time for bias auditing and interpretability tools.

Diagram (5 points)

AI Development Workflow Diagram: 1. Problem Definition → 2. Data Collection → 3. Data Preprocessing → 4. Model Development → 5. Evaluation → 6. Deployment → 7. Monitoring & Optimization Each stage feeds into the next, with feedback loops from deployment back to data collection and evaluation.