Understanding the AI Development Workflow

Part 1: Short Answer Questions (30 points)

Step 1: Problem Definition (6 points)

Hypothetical AI Problem:
Predicting patient readmission risk within 30 days of discharge.

Objectives:

- Prevent avoidable readmissions to improve patient outcomes.
- Allocate hospital resources more efficiently.
- Personalize post-discharge care plans based on risk prediction.

Stakeholders:

- Hospital clinicians and care teams
- Patients and their families

Key Performance Indicator (KPI):
Reduction in 30-day readmission rate percentage over a specified period.

Step 2: Data Collection & Preprocessing (8 points)

Data Sources:

- *Electronic Health Records (EHRs):* Clinical notes, diagnosis history, discharge summaries, lab test results.
- *Patient Demographics & Social Determinants of Health:* Age, gender, socioeconomic status, insurance type, geographic location.

Potential Bias:
Bias can emerge if the dataset underrepresents specific patient groups such as minorities or low-income populations. This may cause the model to make less accurate predictions for those groups, leading to disparities in care. For example, historical unequal access to healthcare can be reflected in the data, causing the model to inherit these biases.

Preprocessing Steps:

1. **Handling Missing Data:** Use imputation methods (mean/mode imputation or predictive modeling) to fill missing lab values or demographic fields.
2. **Normalizing Numerical Features:** Standardize lab results, age, and hospital stay duration to ensure features are on a similar scale for effective model training.
3. **Encoding Categorical Variables:** Apply one-hot encoding for diagnosis codes or admission types; use label encoding or embeddings for ordinal features like severity scores.

Step 3: Model Development (8 points)

Model Choice:
Gradient Boosting Machine (e.g., XGBoost) is highly suitable for structured healthcare data due to robustness, ability to handle missing values, and strong performance with minimal preprocessing. It also provides feature importance scores, aiding clinical interpretability.

Data Splitting:

- **70% Training Set:** For model training.
- **15% Validation Set:** For hyperparameter tuning (learning rate, tree depth).
- **15% Test Set:** To assess generalization on unseen data.

Hyperparameters to Tune:

- **Learning Rate:** Controls the contribution of each tree; smaller values reduce overfitting but require more trees.
- **Maximum Tree Depth:** Controls tree complexity; shallower trees generalize better but may miss complex patterns, deeper trees risk overfitting.

Step 4: Evaluation & Deployment (8 points)

Evaluation Metrics:

- **Precision:** Measures how many patients flagged as high readmission risk were actually readmitted. High precision avoids unnecessary interventions.
- **Recall:** Measures how many actual readmitted patients were correctly identified. High recall ensures fewer missed high-risk patients.

Concept Drift:

- *Definition:* Concept drift occurs when the statistical properties of the input data or target variable change over time (e.g., due to new treatment protocols or patient behavior), reducing model accuracy.
- *Monitoring Strategy:* Continuously evaluate model performance on recent data; schedule retraining; use drift detection libraries like Alibi Detect or River to trigger updates.

Technical Challenge:

- *Scalability for Real-Time Predictions:* The model must efficiently handle predictions for hundreds or thousands of patients daily.

Key considerations:

  - Optimize inference time
  - Deploy using lightweight containers (Docker)
  - Leverage scalable cloud platforms (Google Cloud AI Platform, AWS SageMaker)
  - Ensure smooth integration with hospital EHR APIs

Supporting Research Insights

- Gradient boosting models achieve AUC scores around 0.83–0.88 for 30-day readmission prediction, outperforming traditional logistic regression models.
- Incorporating demographic and social determinants of health improves prediction accuracy and fairness.
- Interpretability is enhanced by feature importance scores or two-step extracted regression tree approaches, aiding clinical adoption.
- Continuous monitoring and retraining are essential to handle concept drift and maintain model performance over time.