AI Development Workflow Assignment

Course: AI for Software Engineering
Total Points: 100
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Part 1: Short Answer Questions (30 points)

1. Problem Definition (6 points)

AI Problem:
Predicting Student Dropout Rates at a University

Objectives:

- Identify at-risk students early for timely intervention.
- Reduce overall dropout rate by 10% within one academic year.
- Optimize allocation of student support resources.

Stakeholders:

- University administration and academic advisors.
- Students and their families.

KPI:
AUC-ROC (Area Under the Receiver Operating Characteristic Curve) for dropout prediction.

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2. Data Collection & Preprocessing (8 points)

Data Sources:

- Student Information System (SIS): Academic records, attendance, grades.
- Learning Management System (LMS): Login frequency, assignment submissions.

Potential Bias:
Underrepresentation of certain demographic groups (e.g., international students), leading to model bias.

Preprocessing Steps:

1. Impute missing data (e.g., fill missing grades with median).
2. Normalize numerical features (e.g., GPA, attendance).
3. Encode categorical variables (e.g., one-hot encoding for majors).

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3. Model Development (8 points)

Model:
Random Forest Classifier
Reason: Handles feature interactions, robust to noise, interpretable feature importance.

Train/Validation/Test Split:
70% training, 15% validation, 15% test.

Hyperparameters to Tune:

- n_estimators: Controls number of trees.
- max_depth: Controls complexity, prevents overfitting.

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4. Evaluation & Deployment (8 points)

Evaluation Metrics:

- Precision: Fraction of predicted dropouts who dropped out.
- Recall: Fraction of actual dropouts correctly identified.

Concept Drift:
Change in data distribution over time, reducing model accuracy.
Monitoring: Regularly re-evaluate model on new data.

Deployment Challenge:
Scalability: Ensuring system handles concurrent predictions during peak periods.

Part 2: Case Study Application (40 points)

Scenario: Predicting Patient Readmission Risk

1. Problem Scope (5 points)

- **Problem:** Predict 30-day hospital readmission risk.
- **Objectives:** Early identification for targeted care, reduce readmission rates/costs.
- **Stakeholders:** Hospital admin, care teams, patients.

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2. Data Strategy (10 points)

- **Data Sources:**
    - EHRs (diagnoses, meds, vitals)
    - Demographics (age, gender, socioeconomic status)
- **Ethical Concerns:**

i. Patient privacy, data security (HIPAA).

ii. Algorithmic bias.

- **Preprocessing Pipeline:**
    - Impute missing clinical values.
    - Feature engineering (e.g., number of prior admissions, comorbidity index).
    - Normalize continuous features.
    - One-hot encode categorical features.

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3. Model Development (10 points)

- **Model:**
  Gradient Boosted Trees (e.g., XGBoost)
  Reason: Excellent performance on tabular data, interpretable.
- **Hypothetical Confusion Matrix:**

	Predicted Readmit	**Predicted No Readmit**
Actual Readmit	40	20
Actual No Readmit	15	125

- **Precision:** 40 / (40+15) = **0.727**
- **Recall:** 40 / (40+20) = **0.667**

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4. Deployment (10 points)

- **Integration Steps:**
    i. Build REST API for predictions.
    ii. Integrate with EHR for real-time scoring.
    iii. Dashboard for flagged patients.
- **Regulatory Compliance:**
    - Encrypt data, secure APIs.

- User access controls & audit trails.
- HIPAA compliance reviews.

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5. Optimization (5 points)

- **Overfitting Mitigation:**
  Use cross-validation and regularization (early stopping, L1/L2 penalties).

Part 3: Critical Thinking (20 points)

1. Ethics & Bias (10 points)

- **Effect of Biased Data:**
  If the model is trained on biased data, it may overlook risk in underrepresented groups, exacerbating health disparities.
- **Mitigation:**
  Use stratified sampling and fairness-aware algorithms, monitor subgroup performance.

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2. Trade-offs (10 points)

- **Interpretability vs. Accuracy:**
  More accurate models (deep nets) can be black boxes, while simpler models (logistic regression) are more interpretable but may be less accurate. In healthcare, interpretability is often prioritized.
- **Limited Resources:**
  With limited compute, use lightweight models (e.g., logistic regression) or quantize models, even if predictive power drops.

Part 4: Reflection & Workflow Diagram (10 points)

1. Reflection (5 points)

- **Most Challenging Part:**
  Balancing data quality, fairness, and privacy concerns was most difficult.
- **Improvements:**
  With more resources, collect more diverse data, use explainable AI, and get more stakeholder feedback.

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2. Workflow Diagram (5 points)

Problem Definition

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Data Collection

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Data Preprocessing & Feature Engineering

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Model Development (Selection, Training, Tuning)

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Model Evaluation (Validation, Metrics)

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Deployment (Integration, Monitoring)

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Maintenance (Monitoring, Retraining)

References

1. CRISP-DM Framework: https://en.wikipedia.org/wiki/Cross-industry_standard_process_for_data_mining
2. HIPAA: https://www.hhs.gov/hipaa/index.html
3. Fairness in ML: https://fairmlbook.org/
4. XGBoost Docs: https://xgboost.readthedocs.io/
5. Scikit-learn: https://scikit-learn.org/stable/modules/model_evaluation.html

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End of Submission