AI Development Workflow Assignment Report

Title: Predicting Student Dropout Rates Using Machine Learning
Author: Caren Rayon
Date: July 2025

Part 1: Short Answer Questions (30 points)

1. Problem Definition (6 points)

Problem: Predicting the likelihood of a student dropping out before completing their academic program.
Objectives:

- Identify at-risk students early.
- Enable targeted interventions by educators.
- Improve overall retention rates.
  Stakeholders:
- School administrators
- Students and their families
  KPI: Model accuracy or F1-score in identifying dropouts correctly.

---

2. Data Collection & Preprocessing (8 points)

Data Sources:

- Student Information Systems (SIS)
- Learning Management Systems (LMS) like Moodle or Canvas

Potential Bias:

- Students from low-income backgrounds may be underrepresented or inaccurately labeled.

Preprocessing Steps:

1. Handle missing attendance/grade entries (e.g., fill or remove).
2. Normalize continuous variables like GPA and login hours.

3. Encode categorical variables (e.g., program type).

---

3. Model Development (8 points)

Chosen Model: Random Forest – It's interpretable and performs well on tabular data.

Data Splitting:

- 70% training
- 15% validation
- 15% testing

Hyperparameters to Tune:

- n_estimators: Number of trees in the forest
- max_depth: Prevents overfitting by limiting tree growth

---

4. Evaluation & Deployment (8 points)

Evaluation Metrics:

- Accuracy: Overall correct predictions.
- F1-Score: Balance between precision and recall for dropout prediction.

Concept Drift:
When model accuracy degrades due to changes in student behavior or academic policies.
Monitoring: Compare recent predictions vs real outcomes regularly.

Deployment Challenge:
Scalability — Ensuring the model performs across various departments and programs.

Part 2: Case Study Application (40 points)

Problem Scope (5 points)

Problem: Predict 30-day readmission risk after hospital discharge.
Objectives:

- Reduce hospital costs.

- Improve patient care and follow-up.
  Stakeholders:
- Hospital IT team
- Doctors and healthcare planners

Data Strategy (10 points)

Data Sources:

- Electronic Health Records (EHRs)
- Demographic data

Ethical Concerns:

- Privacy of patient data
- Biased treatment recommendations for minority groups

Preprocessing Pipeline:

- Fill missing lab values
- Encode gender, diagnosis
- Normalize age, time in hospital
- Feature engineering: e.g., count of past readmissions

Model Development (10 points)

Model: Gradient Boosting Classifier – balances accuracy and interpretability.

Confusion Matrix (Hypothetical):

	Predicted Yes	**Predicted No**
Actual Yes	80	20
Actual No	10	90

Precision: 80 / (80 + 10) = 0.89
Recall: 80 / (80 + 20) = 0.80

Deployment (10 points)

Integration Steps:

- Connect model to EHR via API
- Trigger predictions at discharge

Compliance:

- Use data encryption and de-identification
- Adhere to HIPAA laws

Optimization:
Use cross-validation or dropout regularization to avoid overfitting.

Part 3: Critical Thinking (20 points)

Ethics & Bias (10 points)

Risk: Biased data may mislabel vulnerable patients, denying them follow-up care.

Mitigation:

- Use IBM AI Fairness 360 to test for bias
- Adjust thresholds or resample training data

Trade-offs (10 points)

Interpretability vs Accuracy:
Doctors may prefer simpler models they can understand, even if slightly less accurate.

Resource Constraints:
Low compute may force use of logistic regression over deep neural nets.

Part 4: Reflection & Workflow Diagram (10 points)

Reflection (5 points)

Challenge: Balancing model performance with fairness.
Improvement: With more time, I would collect more diverse and recent data.

Workflow Diagram (5 points)

plaintext

CopyEdit

Problem Definition → Data Collection → Preprocessing → Model Training →

Evaluation → Deployment → Monitoring & Maintenance

References

- IBM AI Fairness 360 Toolkit
- Kaggle: Breast Cancer Dataset
- Scikit-learn Documentation
