AI Development Workflow Assignment

Week 5 Assignment: 10/11/2025

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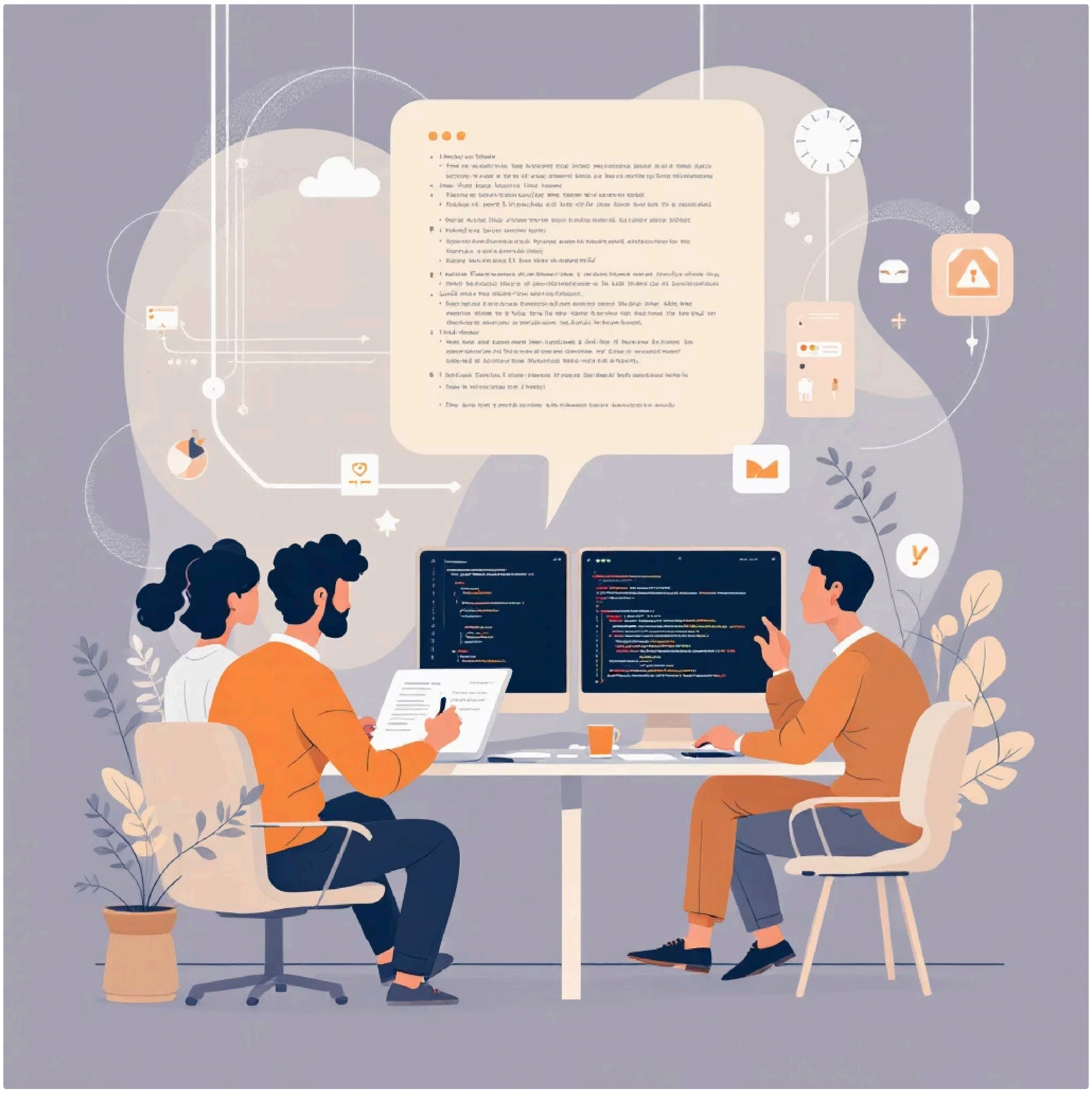


Part 1: Short Answer Questions (30 points)

Comprehensive examination of AI model development through practical scenarios, covering problem definition, data handling, model selection, and deployment strategies.

Question 1

Problem Definition (6 points)

Hypothetical Problem: Predicting Student Dropout Rates in a University

Objectives:

- Identify at-risk students early using demographic and academic data.
- Provide data-driven insights to guide targeted interventions.
- Reduce overall dropout rates and improve student retention.

Key Performance Indicator (KPI):

Retention Rate Improvement (%) — percentage reduction in student dropouts after model implementation.

Stakeholders:

- University administration (decision-makers)
- Academic advisors and student support officers

Data Collection & Preprocessing (8 points)

Data Sources:

- University information system (student grades, attendance, demographics).
- Online learning platform logs (engagement metrics, submission timestamps).

Potential Bias:

Socioeconomic bias — students from low-income backgrounds may have incomplete or misrepresented data, leading to unfair predictions.

Preprocessing Steps:

- Handle missing data through imputation (e.g., median grades).
- Normalize numeric features (grades, attendance %) to ensure consistent scaling.
- Encode categorical variables (e.g., gender, department) using one-hot encoding.

Model Development (8 points)

1	2	3
Chosen Model: **Random Forest Classifier** — balances interpretability and predictive power, handles non-linear relationships, and mitigates overfitting.	**Data Split:** 70% training, 15% validation, 15% test sets using stratified sampling to preserve dropout class proportions.	**Hyperparameters to Tune:** • `n_estimators` – number of trees (controls model complexity). • `max_depth` – limits tree depth to prevent overfitting.

Evaluation & Deployment (8 points)

Evaluation Metrics:

- **Precision** – measures correctness of predicted dropouts (reduces false alarms).
- **Recall** – measures how many true dropouts were detected (important for intervention coverage).

Concept Drift:

Change in the relationship between predictors and dropout outcome over time (e.g., new grading policies).

Monitor via periodic re-training and performance tracking on recent data.

Technical Deployment Challenge:

Scalability — model must handle increasing student data each semester while maintaining real-time predictions.

Part 2: Case Study Application (40 points)

Problem Scope (5 points)

Scenario: A hospital wants an AI system to predict patient readmission risk within 30 days of discharge.

Objectives:

- Identify patients at high risk of readmission.
- Enable proactive post-discharge care.
- Reduce healthcare costs and improve patient outcomes.

Stakeholders:

- Hospital management and clinical staff.
- Patients and healthcare insurers.

Data Strategy (10 points)

Data Sources:

- **Electronic Health Records (EHRs):** diagnosis codes, lab results, medications.
- Patient demographics and prior hospitalization history.

Ethical Concerns:

- **Patient privacy** — sensitive health data must be anonymized.
- **Algorithmic fairness** — model must not discriminate by age, gender, or ethnicity.

Preprocessing Pipeline:

- Remove identifiers (names, IDs) to maintain privacy.
- Handle missing lab results with domain-specific imputation.
- Feature engineering:
  - Calculate "days since last admission."
  - Aggregate lab trends (mean, variance).
  - Encode diagnosis categories.

Model Development (10 points)

Chosen Model:

Logistic Regression — interpretable and suitable for healthcare contexts where transparency is critical.

Hypothetical Confusion Matrix (100 patients):

	Predicted Readmit	Predicted Not Readmit
Actual Readmit	30	10
Actual Not Readmit	5	55

0.857

Precision

TP / (TP + FP) = 30 / (30 + 5) = 0.857

0.75

Recall

TP / (TP + FN) = 30 / (30 + 10) = 0.75

Deployment (10 points)

01

Integration Steps:

- Deploy model as a REST API in the hospital's EHR system.
- Automate nightly data refresh and prediction generation.
- Provide dashboard alerts for clinicians.

02

Regulatory Compliance:

- Adhere to HIPAA by encrypting all PHI (Protected Health Information) in transit and at rest.
- Maintain audit logs for model predictions and data access.

Optimization (5 points)

> ### Addressing Overfitting:
>
> Use regularization (L2) and cross-validation to ensure generalization to unseen patient data.

Part 3: Critical Thinking (20 points)

Ethics & Bias (10 points)

Impact of Biased Data:

If training data underrepresents certain groups (e.g., older patients or minorities), the model may underpredict their readmission risk, worsening healthcare inequities.

Mitigation Strategy:

- Apply re-sampling or re-weighting to balance underrepresented groups.
- Include fairness metrics (e.g., demographic parity).

Trade-offs (10 points)

Interpretability vs. Accuracy:

Highly complex models (e.g., deep neural networks) may outperform interpretable ones but are less explainable.

In healthcare, **interpretability is crucial** to gain clinician trust, even if slight accuracy is sacrificed.

Limited Computational Resources:

Resource constraints favor lightweight models (e.g., logistic regression, decision trees) over deep learning solutions requiring GPUs.

Part 4: Reflection & Workflow Diagram (10 points)

Reflection (5 points)

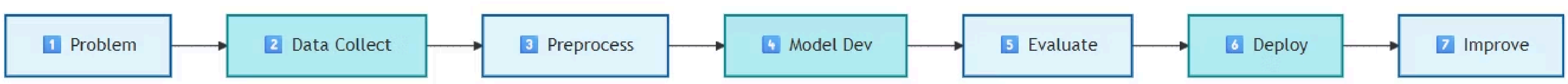
Most Challenging Part:

Data preprocessing — ensuring data quality and privacy compliance required the most effort.

Improvement with More Time:

- Gather more diverse data to enhance generalizability.
- Experiment with explainable AI methods for better clinician trust.

AI Development Workflow Diagram (5 points)



Textual Flowchart:

1. **Problem Definition**
2. **Data Collection & Understanding**
3. **Data Preprocessing & Feature Engineering**
4. **Model Development (Training, Validation)**
5. **Evaluation & Optimization**
6. **Deployment & Monitoring**
7. **Feedback Loop for Continuous Improvement**

(Based on CRISP-DM methodology)