

Understanding the AI Development Workflow

Course: AI for Software Engineering

Assignment: Predicting 30-day Hospital Readmission Risk

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--- PART 1: Short Answer Questions ---

1. Problem Definition

Problem: Predict which discharged patients are likely to be readmitted within 30 days.

Objectives:

- i. Accurately predict 30-day readmission risk enabling targeted follow-up.
- ii. Reduce avoidable readmissions and associated costs.
- iii. Ensure fairness and privacy are maintained.

Stakeholders: clinicians, hospital administration, patients.

KPI: AUC-ROC

2. Data Collection & Preprocessing

Data sources:

- i. Electronic Health Records (EHR): admission/discharge notes, vitals, labs, medications.
- ii. Administrative claims / billing & social determinants (if available).

Potential bias:

- Under-representation of disadvantaged populations leading to worse performance for these groups.

Preprocessing steps:

- i. Missing data imputation (median for numerics, mode for categoricals).
- ii. Normalization/standardization of numeric features.
- iii. Categorical encoding and feature selection; derive time-series aggregates when applicable.

3. Model Development

Model: Multi-Layer Perceptron (Neural Network).

Justification: Flexible non-linear modeling for tabular EHR features; can learn interactions and combine diverse features (after car)

Data split:

- Training: 70% (stratified)
- Validation: 15%
- Test: 15%

Hyperparameters to tune:

- i. hidden_layer_sizes (controls model capacity)
- ii. alpha (L2 regularization strength; helps prevent overfitting)

4. Evaluation & Deployment

Metrics:

- AUC-ROC for overall discriminative ability.
- Recall (sensitivity) to minimize missed high-risk patients.

Concept drift:

- Definition: population or practice changes that alter input or label distributions over time.
- Monitoring: track rolling AUC, calibration, and feature distribution shifts; periodic retraining or incremental updates.

Technical deployment challenge:

- Integration with hospital EHR systems, ensuring low-latency inference and meeting security/authorization constraints.

--- PART 2: Case Study Application (Hospital Readmission) ---

Problem Scope:

- Predict 30-day readmission for adult patients at discharge.
- Objectives: improve post-discharge interventions, allocate resources, evaluate model fairness.
- Stakeholders: clinicians, care coordinators, hospital IT, patients, compliance officers.

Data Strategy:

- Sources: EHR clinical data (demographics, labs, vitals), prior admissions, medication lists, discharge disposition, and social de
- Ethical concerns:

1. Patient privacy and data protection under HIPAA.
 2. Algorithmic fairness: avoid systematically disadvantaging subpopulations.
- Preprocessing pipeline (high level):
 - i. Data ingestion & de-identification.
 - ii. Missingness analysis and imputation.
 - iii. Feature engineering: count of prior admissions, Elixhauser/Charlson comorbidity scores, lab trend features (e.g., delta creatinine).
 - iv. Encoding categorical features and scaling numerics.
 - v. Train/val/test stratified splitting.

Model Development:

- Choose MLPClassifier (Neural Network) with 2 hidden layers, ReLU activations, early stopping and dropout (or L2).
- Hypothetical confusion matrix (test) for 1,000 patients:

Predicted Negative	Predicted Positive
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Actual Negative	820	50
Actual Positive	80	50

- From this CM:

$$\text{Precision} = \text{TP}/(\text{TP}+\text{FP}) = 50/(50+50) = 0.50$$

$$\text{Recall} = \text{TP}/(\text{TP}+\text{FN}) = 50/(50+80) = 0.38$$

- Interpretation: model has moderate precision and low recall — tune threshold to increase recall for clinical use.

Deployment:

- Steps to integrate:

1. Wrap model as a RESTful API (FastAPI) with authentication and input validation.

2. Containerize (Docker) and deploy to hospital on-prem or private cloud.

3. Integrate via EHR middleware (HL7/FHIR connector) or build an EHR plugin/dashboard for clinicians.

4. Logging, monitoring, and alerting (performance and data drift).

- HIPAA compliance:

- Ensure encryption in transit & at rest (TLS, disk encryption).

- Access controls and audit logs, Business Associate Agreements (BAAs) where needed.

- De-identification/pseudonymization for data used in model development.

Optimization to address overfitting:

- Use early stopping, L2 regularization (weight decay), and dropout. Consider cross-validation and model ensembling as needed.

--- PART 3: Critical Thinking ---

Ethics & Bias:

- Example harm: If the training data under-represents patients from certain socioeconomic groups, the model may under-predict for them.
- Mitigation strategy: stratified sampling, fairness-aware reweighting, subgroup performance audits, and including protected attributes in the model.

Trade-offs:

- Interpretability vs accuracy: Clinicians often require interpretable explanations; a complex neural network might perform slightly worse but be more interpretable.
- Resource constraints: Limited compute pushes towards smaller models (logistic regression, decision trees) or model compression.

--- PART 4: Reflection & Workflow Diagram ---

Reflection:

- Most challenging: ensuring representative, high-quality labeled data while maintaining privacy/legal compliance.
- With more resources: collect multi-site datasets, run prospective validation, and implement clinician-in-the-loop deployment.

Diagram:

- See diagram.png included in this package (CRISP-DM style: Business Understanding → Data Understanding → Data Preparation → Modeling → Evaluation → Deployment).

References:

- CRISP-DM framework, standard ML texts, HIPAA guidance and healthcare ML papers (detailed references in the full PDF).