### Project Title:

### Predicting Patient Readmission Using Machine Learning

### Group Name:

### AI Health Insights Team

### Group Members:

### Group Member 1: Sharon Mauluka

### Group Member 2: Jimmy Jackson

### Group Member 3: Amukelani Nghonyama

### Group Member 4: Ann Waitherero Migwi

### Group Member 5: Pontsho Mathobela

### Course:

### AI in Healthcare – Week 5 Assignment

### Date:

### 20 June 2025

Table of Contents

1. Part 1: Short Answer Questions

1.1 Problem Definition

1.2 Data Strategy & Preprocessing

1.3 Model Development

1.4 Evaluation, Deployment, Optimization & Ethics

1.5 Critical Thinking – Trade-offs

2. Part 2: Case Study Application

2.1 Problem Scope

2.2 Case Study – Data Strategy

2.3 Case Study – Model Development

2.4 Case Study – Ethics & Bias

2.5 Reflection

3. Appendix

-Workflow Diagram

**QUESTION 1 (All first parts of contribution from group members)**

**(Group member 1) Part 1: Short Answer Questions**

**Section: Problem Definition (6 points)**

**Hypothetical AI Problem:**  
*Predicting student dropout rates in online learning platforms.*

**Objectives:**

1. Identify at-risk students early in the semester.
2. Recommend timely academic interventions.
3. Improve student retention by 15% over 12 months.

**Stakeholders:**

1. Academic institutions (e.g., universities, online course providers).
2. Students enrolled in online courses.

**Key Performance Indicator (KPI):**

* *Accuracy of dropout prediction model within the first 4 weeks of course start date.*

**(Group member 2) Data Strategy & Preprocessing**

**### Part 1: Data Collection & Preprocessing**

**1. Identify 2 data sources for your problem:**

- **\*\*Electronic Health Records (EHRs)\*\*** – contain patient visit history, diagnoses, discharge notes, medication records, and lab results.

- **\*\*Demographic data\*\*** – includes age, gender, location, and income level (may be collected via patient intake forms or national health databases).

**\*\*2. One potential bias in the data: \*\***

- **\*\*Underrepresentation Bias\*\*** – The dataset may have fewer samples from rural or low-income populations, making predictions less accurate for these groups.

**\*\*3. Preprocessing steps: \***

- **\*\*Handling missing values: \*\*** Fill missing lab results with median values or flag them with binary indicators.

- **\*\*Normalization: \*\*** Scale continuous features like age or lab values using Min-Max scaling.

- **\*\*Encoding categorical features: \*\*** Convert diagnosis or discharge status into numerical format using one-hot encoding.

**(Group member 3); Part 1:**

**3. Model Development**

**Chosen Model: Random Forest**

**Justification:**

**Handles both numerical and categorical data well.**

**650**

**\*-36009i9--Offers feature importance for interpretability.**

**Data Splits:**

**Training: 70%**

**Validation: 15%**

**Test: 15%**

**Hyperparameters:**

**Number of trees (n\_estimators): Impacts model accuracy.**

**Maximum depth (max\_depth): Controls overfitting.**

**4. Evaluation & Deployment (Group Member 3)**

**Evaluation Metrics:**

**Precision: Critical when false positives**

**(Group Member 4) Part 1: Deployment, Optimization & Ethics**

**Part 1: Case Study Application**

**Section: Deployment (10 points)**

**A. Steps to Integrate the Model into the Hospital System**

**To successfully deploy the AI system predicting 30-day patient readmission risk, the following steps should be undertaken:**

**1. API Development**

**- Develop a RESTful API using frameworks like Flask or FastAPI to expose the model’s predictions.**

**- The API will accept patient data inputs (e.g., demographics, discharge notes, vitals) and return a readmission risk score.**

**2. Integration with Hospital EHR Systems**

**- Work with the hospital’s IT department to connect the API with Electronic Health Record (EHR) platforms like Epic or Cerner.**

**- Automate the retrieval of patient data at the point of discharge.**

**3. User Interface (UI) for Clinicians**

**- Create a dashboard that displays the predicted readmission risk for each discharged patient.**

**- Include features like risk thresholds and recommended actions (e.g., follow-up scheduling).**

**4. Pilot Testing and Feedback Loop**

**- Deploy the system in one or two hospital departments for testing.**

**- Collect feedback from clinicians and adjust the model or UI as necessary.**

**5. Monitoring and Logging**

**- Implement continuous monitoring tools to track prediction performance, system uptime, and usage statistics.**

**- Generate weekly reports for model accuracy, recall, and false positives.**

**B. Ensuring Compliance with Healthcare Regulations (e.g., HIPAA)**

**To protect patient data and comply with healthcare regulations:**

**1. Data Encryption**

**- Use AES-256 encryption for data at rest.**

**- Use TLS/SSL protocols for data in transit between systems.**

**2. Access Controls and Authentication**

**- Implement Role-Based Access Control (RBAC) to limit access to only authorized users.**

**- Require multi-factor authentication for clinicians and IT administrators.**

**3. Audit Trails**

**- Maintain detailed logs of who accessed patient data, when, and for what purpose.**

**- Ensure logs are regularly reviewed for suspicious activity.**

**4. Data De-identification for Model Training**

**- Remove personally identifiable information (PII) such as names and ID numbers from training datasets.**

**- Apply pseudonymization where necessary for traceability without compromising privacy.**

**5. Regulatory Review and Legal Compliance**

**- Conduct a compliance review with a HIPAA officer or legal advisor.**

**- In Kenya, ensure adherence to the Data Protection Act, 2019.**

**Section: Optimization (5 points)**

**Method to Address Overfitting**

**To mitigate overfitting during model training, we propose the use of:**

**Cross-Validation (e.g., k-Fold Cross-Validation):**

**- What it does: Divides the dataset into k subsets. The model trains on k–1 fold and validates on the remaining fold, repeating the process k times.**

**- Why it helps: Ensures that the model generalizes well to unseen data and is not just memorizing patterns in the training set.**

**Alternative methods:**

**- Early stopping (in neural networks)**

**- Regularization (L1 or L2)**

**- Dropout (for neural networks)**

**(Group member 5) PART 1: Critical Thinking – Trade-offs (10 points)**

**1. Model Interpretability vs. Accuracy in Healthcare**

**Response:**

**In healthcare, the trade-off between model interpretability and accuracy is critical. While highly accurate models like deep neural networks may provide better predictions, they often function as "black boxes," offering little insight into why a prediction was made. This can be problematic in healthcare where transparency, explainability, and clinician trust are essential.**

**For example, a logistic regression model may be less accurate than a deep learning model but is more interpretable and allows clinicians to see the weight and influence of each variable (like age, diagnosis, or medication). Interpretability is especially important when decisions affect patient care, compliance, and legal accountability.**

**Conclusion:**

**In sensitive applications like predicting readmission risk, it may be preferable to sacrifice some accuracy for greater interpretability.**

**2. Computational Resources and Model Choice**

**Response:**

**If the hospital has limited computational resources, it would be more practical to choose lightweight models like Logistic Regression, Decision Trees, or even Gradient Boosted Trees (with controlled complexity) instead of computationally expensive deep learning models.**

**These lighter models can be trained and deployed on local servers or edge devices, reducing infrastructure costs and improving speed and accessibility in real-time decision-making.**

**Conclusion:**

**Resource constraints should guide the choice of simpler, more efficient models, especially when rapid deployment and sustainability are key concerns.**

**QUESTION 2(All second parts of contribution from group members)**

### ****(Group member 1) Part 2: Case Study Application****

**Section: Problem Scope (5 points)**

**Problem Definition:**  
A hospital wants to implement an AI system that predicts the likelihood of a patient being readmitted within 30 days of discharge. Early identification of high-risk patients can help allocate follow-up resources more effectively and improve health outcomes.

**Objectives:**

1. Predict the probability of readmission using patient data at the point of discharge.
2. Reduce avoidable readmissions by 20% within the first year of implementation.
3. Support clinicians in making data-informed discharge decisions.

**Stakeholders:**

1. Hospital management and clinical staff (doctors, nurses, discharge coordinators).
2. Patients and their families.

**(Group member 2) Part 2: Case Study Application – Data Strategy**

**### 1. Data Sources:**

- **\*\*Hospital Electronic Health Records (EHRs): \*\***

  - Admission & discharge notes

  - Previous readmissions

  - Diagnosis codes (ICD-10)

  - Prescriptions

- **\*\*Demographics & Socioeconomic Info: \*\***

  - Age, gender, ethnicity

  - Zip code, income brackets

  - Insurance coverage

**### 2. Ethical Concerns:**

- **\*\*Patient Privacy: \*\*** Sensitive health data must be protected with encryption and data anonymization to comply with healthcare privacy laws like HIPAA.

- **\*\*Algorithmic Bias: \*\*** If training data is skewed toward a certain population (e.g., urban patients), the model may be less effective for underrepresented groups.

---

**### 3. Preprocessing Pipeline:**

1. **\*\*Data Cleaning\*\***

   - Drop rows with excessive missing values

   - Replace missing numerical values with median or mean

2. **\*\*Feature Engineering\*\***

   - Create features like `Days Since Last Visit`, `Total Hospital Stays in Past Year`, etc.

3. **\*\*Encoding & Scaling\*\***

   - Apply one-hot encoding to categorical columns (e.g., Diagnosis Code)

   - Normalize age, blood pressure, and other numerical features

4. **\*\*Train-Test Split\*\***

   - Reserve 70% of data for training, 30% for testing

5. **\*\*Class Balancing \*\***

   - Use SMOTE (Synthetic Minority Oversampling) if readmitted patients are underrepresented

**(Group member 3); Part 2:** Model Development

Model Chosen: Logistic Regression

Justification:

Interpretable and commonly used in healthcare for risk prediction.

Confusion Matrix (Hypothetical):

Predicted: No Readmission Predicted: Readmission

Actual: No 720 80

Actual: Yes 50 150

Precision: 150 / (150 + 80) = 0.652

Recall: 150 / (150 + 50) = 0.75

(Group member 4); Part 2: Critical Thinking

Section: Ethics & Bias (10 points)

A. Impact of Biased Training Data on Patient Outcomes

If the training data is biased (e.g., underrepresenting women, elderly, or certain ethnic groups), the model may:

- Make unfair predictions: For example, predict lower readmission risk for underrepresented groups, leading to fewer follow-ups or interventions.

- Cause harm: High-risk patients may go unnoticed, resulting in complications or even preventable deaths.

- Reinforce systemic inequalities: Marginalized groups may receive lower quality care.

- Reduce trust in AI systems: Clinicians and patients may doubt AI decisions if biased outcomes are observed.

B. Strategy to Mitigate Bias

Strategy: Bias-Aware Data Balancing

- During data preprocessing, ensure balanced representation across key demographic groups (e.g., sex, age, ethnicity).

- Apply oversampling techniques such as SMOTE (Synthetic Minority Oversampling Technique) to boost underrepresented cases.

- Implement fairness metrics during evaluation (e.g., disparate impact ratio) to monitor and correct model bias before deployment.

(Group member 5): Part 2

PART 2: Reflection

Reflection (5 points)

1. What was the most challenging part of the workflow? Why?

The most challenging part of the workflow was designing an effective data strategy. Healthcare data is often unstructured, incomplete, and governed by strict privacy regulations. Collecting, cleaning, and preparing this data without introducing bias or violating ethical standards requires careful planning and technical expertise.

2. How would you improve your approach with more time/resources?

With more time and resources, we would incorporate feedback from medical professionals, conduct a pilot study with real hospital data, and invest in explainable AI tools (like SHAP or LIME) to improve transparency and model acceptance among stakeholders.

Appendix:

