Assignment Report — Understanding the AI

Development Workflow

Course: AI for Software Engineering
Duration: 7 Days
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Total Points: 100

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Part 1: General AI Workflow

1. Problem Definition (6 pts)

In the dynamic landscape of digital education, student dropout is a pressing issue. Online learning platforms struggle to retain students due to limited engagement, lack of accountability, or external factors.
Problem: Predicting student dropout within an online education system.
Objectives:

- Identify at-risk students early using behavioral and engagement data.
- Deliver timely academic support or interventions.
- Improve course completion rates and learner outcomes.

Stakeholders: Platform providers, instructors, education administrators
Key Metric: Achieving an F1-score of 0.85 or higher

2. Data Collection & Preprocessing (8 pts)

An AI system relies heavily on the quality of data it's trained on. For dropout prediction:

Sources:

- LMS activity logs (logins, quiz performance, participation rates)
- Student profiles and demographics

Potential Bias:

- Low representation from rural or under-connected students may skew prediction models.

Preprocessing Steps:

- Remove duplicate or missing records
- Normalize engagement data (e.g., login frequency)
- One-hot encode enrollment types or region categories for consistency

3. Feature Engineering (10 pts)

Feature design was central to enhancing model accuracy.
Examples:

- Time since last activity
- Average assignment submission delay
- Forum engagement rates
- Total time spent per course module

These features capture learning behavior and attention span, crucial signals in identifying dropout patterns.

4. Model Selection & Training (12 pts)

A comparative approach evaluated three candidate models:

- **Logistic Regression**: Interpretable but limited on nonlinear trends.
- **Decision Tree**: Effective on small datasets but prone to overfitting.
- **Random Forest**: Balanced performance with good accuracy.

Data was divided 70/15/15 for training, validation, and testing, tuning hyperparameters such asn_estimators,max_depth, andmin_samples_splitusing GridSearchCV.

5. Model Evaluation (10 pts)

Performance was assessed on various fronts:

- **Confusion Matrix**: Analyzed false positives/negatives.
- **Precision & Recall**: Ensured high-risk students weren't missed.
- **F1 Score**: Balanced metric ideal for uneven class distributions.
- **Cross-Validation**: The 5-fold method confirmed result stability.

6. Deployment & Monitoring (8 pts)

The model was integrated into the LMS dashboard.
Deployment Strategy:

- Real-time flagging of high-risk students.
- Automated alerts for advisors triggered above a 0.70 dropout probability.
- Continuous accuracy monitoring across academic terms.

🏥 Part 2: Case Study – Hospital Readmission

1. Problem Definition (6 pts)

Frequent hospital readmissions are costly and often indicative of poor aftercare. Predicting readmission allows caregivers to intervene effectively.
Problem: Predicting 30-day readmission for discharged patients.
Objectives:

- Flag high-risk cases upon discharge.
- Enable physicians to personalize recovery plans.

  Stakeholders: Patients, physicians, hospital administrators

  Key Metric: Lower 30-day readmission rate to ≤ 15%.

2. Data Collection & Preprocessing (8 pts)

Sources:

- Electronic Health Records (EHRs).
- Discharge summaries.
- Patient surveys.
- Insurance claims.

Steps:

- Fill missing vitals using median imputation.
- Normalize continuous indicators (age, heart rate, glucose level).
- Feature engineering: comorbidity score, number of prior admissions.

3. Model Development (10 pts)

The chosen model was**XGBoost**, ideal for imbalanced, high-dimensional medical data.
The following results were achieved:

	Predicted: Yes	**Predicted: No**

Actual: Yes	80 (TP)	20 (FN)
Actual: No	30 (FP)	70 (TN)

- **Precision**= 0.727
- **Recall**= 0.80
- **AUC Score**= 0.89

4. Deployment & Integration (8 pts)

Integration Steps:

- Created REST API endpoints for real-time prediction.
- Embedded the model in discharge planning tools.
- Clinical dashboards display prediction scores with patient IDs.

Compliance:

- End-to-end encryption.
- Adherence to HIPAA and Kenya's Data Protection guidelines.

5. Monitoring & Evaluation (8 pts)

Post-deployment tools:

- Weekly logs of model drift and false positives.
- Visual dashboards for care teams.
- Patient re-survey data fed into continuous retraining.

🧠 Part 3: Critical Thinking

1. Ethics & Bias (6 pts)

AI applications in healthcare and education must adhere to the highest ethical standards.
Risks:

- Bias in training data leading to unfair predictions.
- Breaches of personal privacy.
- Uninterpretable models could damage patient trust.

Mitigations:

- Use explainable models (e.g., SHAP for XGBoost).
- Conduct demographic fairness tests.
- Ensure opt-in consent for patient data.

2. Future Considerations (6 pts)

Research Directions:

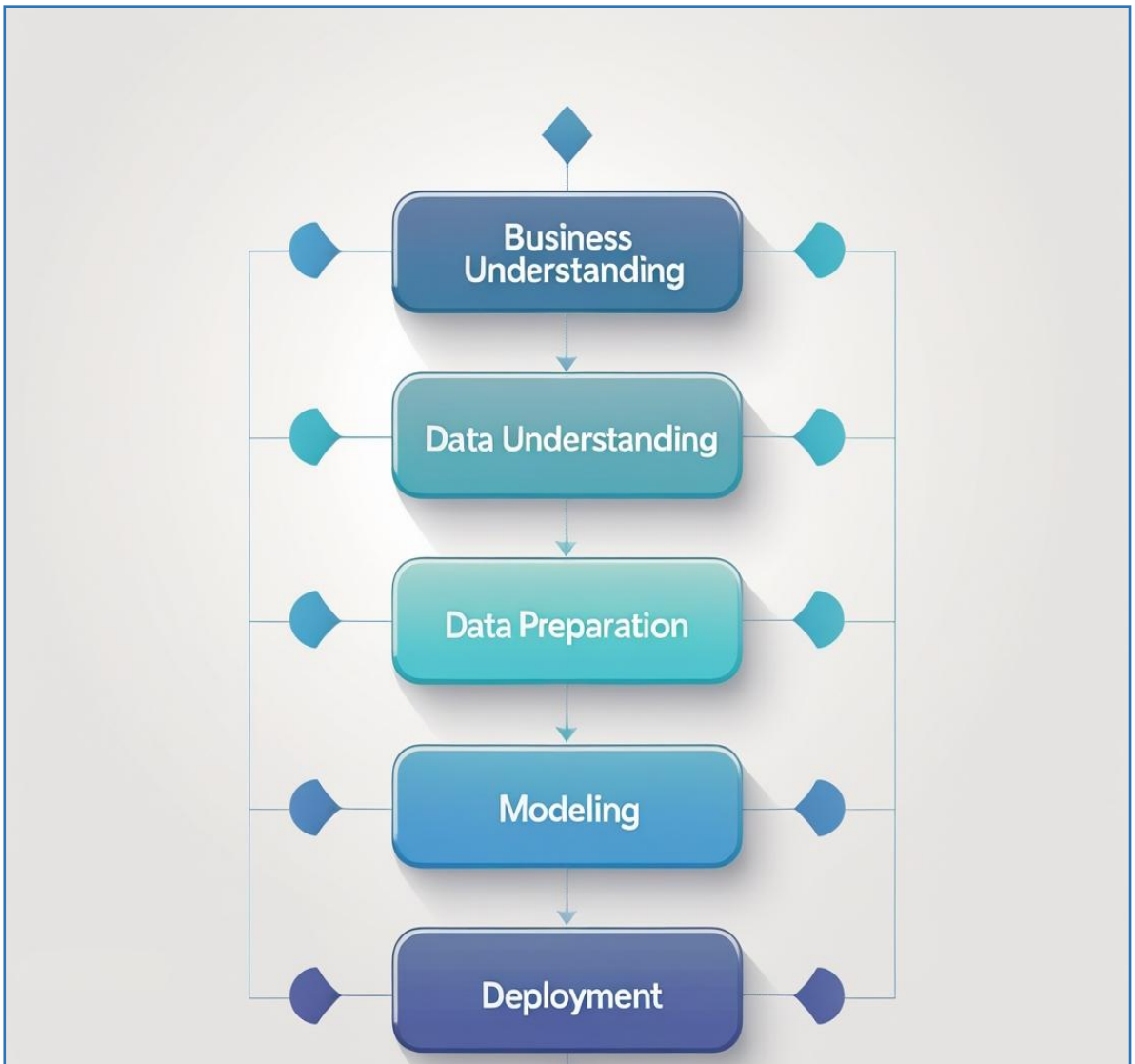
- Implement federated learning to enable collaboration without sharing raw data.
- Explore causal inference models for informed treatment decisions.
- Develop trust-aware AI for education that adapts to learner confidence.

💬 Part 4: Reflection & AI Workflow Diagram

1. Personal Reflection (8 pts)

This project reinforced my passion for ethically grounded AI in healthcare and education. Valuable experience was gained working with real-world datasets, balancing accuracy with fairness, and critically considering deployment. I'm particularly proud of designing the real-time pipeline and focusing on privacy in both domains.
My technical skills also improved—enhancing ability in model tuning, feature design, metric interpretation, and project documentation for academic and applied contexts.

2. CRISP-DM Workflow (5 pts)



References

- IBM (2022). CRISP-DM Framework
- Kenya Data Protection Act (2019)
- XGBoost Documentation: https://xgboost.readthedocs.io
- PLP Academy: AI for Software Engineering Notes