Model: Gradient Boosting (XGBoost)

- **Justification:** Handles mixed data types, captures non-linear relationships, and provides feature importance for interpretability.

Hypothetical Confusion Matrix (for 1,000 patients):

	Predicted Readmit	Predicted No Readmit
Actual Readmit	80 (TP)	20 (FN)
Actual No Readmit	50 (FP)	850 (TN)

- **Precision:** TP / (TP + FP) = 80 / 130 ≈ **61.5%**
- **Recall:** TP / (TP + FN) = 80 / 100 = **80%**

Integration Steps:

1. **API Development:** Wrap the model in a REST API (e.g., Flask/FastAPI).
2. **EHR Integration:** Push predictions to EHR dashboards via HL7/FHIR standards.
3. **Clinician Alerts:** Flag high-risk patients in real-time during discharge planning.

Regulatory Compliance (HIPAA):

- **Data Encryption:** Use AES-256 for data at rest/transit.
- **Access Controls:** Role-based permissions (e.g., only clinicians can view predictions).
- **Audit Logs:** Track all model interactions for accountability.

Method to Address Overfitting:

- **Regularization (L1/L2):** Penalize complex models in XGBoost (e.g., `lambda=1.0`).
- **Cross-Validation:** Use 5-fold CV to ensure generalization.

Summary

This solution balances accuracy, ethics, and compliance, enabling the hospital to reduce readmissions while maintaining patient trust. XGBoost's interpretability aids clinician buy-in, and robust preprocessing ensures reliable predictions.