

Predictive Sepsis Detection and Post-Op Health Report Automation

PBL Review Report – I

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**Introduction**

Sepsis is a life-threatening condition affecting over 50 million patients globally with 11 million deaths annually, representing 20% of global mortality. Traditional sepsis detection methods like qSOFA and SOFA scores often fail in early identification, particularly in non-ICU settings where monitoring frequency is limited. Machine learning approaches have emerged as promising solutions, achieving superior performance with AUCs ranging from 0.87 to 0.99 across various studies.

Post-operative complications, including sepsis, affect millions of surgical patients worldwide with significant morbidity and mortality implications. Current postoperative monitoring relies heavily on manual processes with vital signs checked every 4-8 hours on surgical wards, leading to delayed detection of deteriorating conditions. Remote patient monitoring and automated health reporting systems offer potential solutions to bridge these gaps in care delivery.

**Problem Statement**

**Primary Problems:**

• **Late sepsis detection** - Traditional scoring systems achieve AUCs of only 0.17-0.73 compared to ML models achieving 0.87-0.99  
• **Manual monitoring limitations** - Vital signs monitored only every 4-8 hours postoperatively with no continuous surveillance after discharge  
• **High false alarm rates** - Existing sepsis alert systems suffer from alarm fatigue among clinicians  
• **Limited interpretability** - Current ML models lack clinical explainability for practical adoption  
• **Fragmented care** - No integrated system connecting sepsis prediction with postoperative health monitoring

**Clinical Impact:**

• Every hour of delayed sepsis treatment increases mortality risk by 4-9%  
• Approximately 350,000 sepsis-related deaths annually in the US alone  
• Substantial proportion of postoperative deaths occur after discharge

**Objectives**

**Primary Objective:**

Develop a scalable machine learning system for early sepsis prediction integrated with automated postoperative health monitoring

**Specific Objectives:**

• **Early Detection**: Predict sepsis onset 6-48 hours before clinical manifestation with >85% sensitivity  
• **Real-time Monitoring**: Implement continuous postoperative vital sign tracking and automated reporting  
• **Clinical Integration**: Create interpretable models using SHAP/LIME for clinical decision support  
• **Scalability**: Design web-based platform capable of handling multiple healthcare facilities  
• **Risk Stratification**: Identify high-risk surgical patients for targeted monitoring

**Engineering Systems, Tools and Key Parameters**

**Technology Stack (Revised):**

**Frontend**

* **Framework:** React with TypeScript  
  Stable, widely used, excellent for scalable web apps
* **Data Visualization:** D3.js or Chart.js  
  Powerful and flexible for clinical charts and dashboards
* **Progressive Web App (PWA) (optional):** Service Workers for offline support

**Backend**

* **Framework:** FastAPI (Python)  
  Lightweight, fast, async-ready, ideal for ML model serving
* **Model Training & Serving:**
  + XGBoost / LightGBM for model building (open source)
  + MLflow for experiment tracking and model versioning (open source)
* **Streaming:** Apache Kafka or Redis Streams (self-hosted, open source) for real-time vital signs ingestion
* **Caching:** Redis (open source)
* **Authentication & Security:** OAuth 2.0 with FastAPI Security utilities

**Databases**

* **Relational DB:** PostgreSQL (open source) for structured clinical data
* **Time-series DB:** InfluxDB (open source) for continuous vital signs data

**Cloud & Deployment**

* **Containerization:** Docker
* **Orchestration:** Kubernetes
* **Cloud Providers:**
  + AWS
  + Google Cloud Platform
  + Microsoft Azure
* **Monitoring:** Prometheus + Grafana (self-hosted)

**Development Tools**

* **ETL & Workflow:** Apache Airflow (open source)
* **Version Control:** Git and GitHub
* **API Gateway (optional):** Kong (open source) or cloud-native gateways within free tiers

**Key Clinical Parameters:**

**Sepsis Prediction Features:**  
• Vital signs: Heart rate, blood pressure, temperature, respiratory rate, oxygen saturation  
• Laboratory values: Lactate, white blood cell count, prothrombin time, creatinine  
• Clinical scores: SOFA, qSOFA components  
• Demographics: Age, gender, comorbidities

**Postoperative Monitoring:**  
• Wound healing indicators  
• Pain assessment scores  
• Functional status measures  
• Medication adherence tracking  
• Early warning signs of complications

**Existing Methods**

**Traditional Sepsis Detection:**

• **qSOFA Score**: AUC 0.76, limited sensitivity for early detection  
• **SOFA Score**: AUC 0.17-0.73, requires ICU-level monitoring  
• **SIRS Criteria**: High false positive rates, poor specificity

**Current ML Approaches:**

• **XGBoost Models**: Achieving AUCs 0.82-0.91 across multiple studies  
• **Deep Learning**: LSTM networks with AUCs 0.94-0.99 but limited interpretability  
• **Random Forest**: Consistent performance with AUC 0.87, good feature importance  
• **Gradient Boosting**: Strong performance in MIMIC-IV studies with AUCs 0.83-0.91

**Postoperative Monitoring Systems:**

• **Manual Vital Signs**: Every 4-8 hours, prone to human error  
• **Remote Patient Monitoring**: Limited adoption, mixed results in reducing readmissions  
• **Wearable Devices**: Emerging technology with promising results for continuous monitoring

**Comparative Analysis**

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| **Approach** | **Advantages** | **Disadvantages** | **AUC Performance** |
| **Traditional Scoring** | Established clinical use, Simple calculation | Poor sensitivity, Late detection | 0.17-0.76 |
| **Machine Learning** | High accuracy, Early prediction | Requires validation, Black box models(SHAP/LIME) | 0.87-0.99 |
| **Deep Learning** | Excellent performance, Pattern recognition | Limited interpretability, High complexity | 0.94-0.99 |
| **Hybrid Approach** | Combines accuracy with interpretability | Implementation complexity | 0.85-0.95 |

**Performance Comparison from Literature:**

• **LGBM (Lin et al.)**: AUC 0.90 using CBC data only  
• **Random Forest (Zhou et al.)**: AUC 0.87 with balanced datasets  
• **XGBoost (Multiple studies)**: Consistent AUCs 0.82-0.91  
• **Traditional Scores**: qSOFA (0.76), SOFA (0.73) significantly lower

**Recommended Solution**: Hybrid ML approach using XGBoost with SHAP interpretability, achieving optimal balance between performance and clinical usability.

**Future Trends**

**Emerging Technologies:**

• **Federated Learning**: Multi-hospital model training while preserving privacy  
• **Edge Computing**: Real-time inference on wearable devices for immediate alerts  
• **Multimodal Integration**: Combining clinical notes, imaging, and sensor data  
• **Conformal Prediction**: Uncertainty quantification for safer clinical deployment

**Clinical Integration:**

• **EHR Integration**: Seamless integration with existing hospital information systems  
• **Mobile Applications**: Point-of-care decision support on smartphones and tablets  
• **Regulatory Compliance**: FDA approval pathways for AI-based medical devices  
• **Continuous Learning**: Models that adapt and improve with new clinical data

**Refrences**

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