Statistical Signal Processing Assisted by Artificial Intelligence for Early Sepsis Detection Using Multimodal ICU Data

A comprehensive review of AI approaches for early detection and prediction of sepsis in intensive care units

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Introduction to Sepsis

Definition

2016 Definition: Life-threatening organ dysfunction caused by a dysregulated host response to infection

Dysregulated response: Immune system releases excessive inflammatory chemicals → widespread vasodilation → hypotension → reduced organ perfusion

Assessment Tools

SOFA Score: Measures organ dysfunction in 6 systems:

- Respiration, Coagulation, Liver
- Cardiovascular, Kidneys, Nervous system

qSOFA: Rapid assessment of 3 parameters:

- Respiration, Blood pressure, Consciousness

Evolution of Definitions

1991: Based on SIRS criteria (2+ of: temp, HR, RR, WBC)

2001: Added severe sepsis and septic shock classifications

2016: Focus on organ dysfunction rather than inflammation

Challenges

Early Detection Critical: Each hour of delay increases mortality by 4-8%

• Current diagnostic tools are slow (e.g., blood cultures take 48 hours)

• Massive multimodal ICU data overwhelms manual analysis capacity

• Symptoms resemble other conditions, making diagnosis difficult

• Need for advanced statistical signal processing and AI

Research Methodology

Approach

Directed Narrative Review methodology to select studies relevant to early sepsis detection using biosignal processing and AI techniques

Selection Criteria

Time Frame: 2017-2021 and beyond (up to 2025)

Methodological Value: Innovative/pioneering approaches

Accessibility & Reliability: Peer-reviewed journals/conferences

Key Studies Reviewed

1. **Futoma et al.**
   2017
   First RNN with Gaussian Processes for early sepsis prediction
2. **Moor et al.**
   2021
   Large-scale international study validating DL models
3. **Kwon et al.**
   2021
   Deep learning model using ECG only
4. **Gupta et al.**
   2020
   Multiple physiological signals with machine learning
5. **Yamanashi et al.**
   2021
   EEG (BSEEG score) as early indicator of sepsis mortality

Study 1: Learning to Detect Sepsis Using Multi-Task Gaussian Process with RNN

Data Collection

51,697 cases over 18 months

8 medications, 29 diseases

6 vital signs, 28 laboratory values

3 demographic variables

Data Preprocessing

Multi-Output Gaussian Process algorithm:

- Estimates missing values with confidence intervals
- Filters out random disturbances (noise removal)
- Converts data into structured time grid (hourly)

Modeling & Training

LSTM Model for complex temporal relationships

- Handles correlations between variables across time
- Training window: 2 hours before to 6 hours after onset

Preventing Overfitting:

- L2 regularization: Penalizes large weights
- Early stopping: Halts training before overfitting

Results

Evaluated using **Matched Lookback Validation**

4 hours

Early prediction of sepsis onset

1.4 false alarms per true alarm (80% sensitivity)

Outperformed traditional RNNs, MWES, NWES, logistic regression, and random forest

Study 2: Predicting Sepsis Using Deep Learning Across International Sites

Data Collection

136,478 ICU admissions

4 databases from 3 countries (USA, Netherlands, Switzerland)

Period: 2001-2016

59 variables from vital signs and laboratory tests

Data Preprocessing

Standardized data and handled missing values

Note: Medications were excluded to avoid misleading the model with treatment indicators

Modeling

Self-Attention Deep Network

- Models short- and long-term temporal relationships
- Captures correlations between variables across time
- Superior to traditional methods (SOFA, qSOFA, SIRS)

Results

Validation Approach:

- Internal: Train and test on same hospital database
- External: Train on one database, test on another

Internal Validation	External Validation
0.846	**0.76**
Accuracy	Accuracy
3.7 hours early prediction	1.7 hours early prediction

Improvements: Ensemble strategy and fine-tuning enhanced generalization across hospitals

Study 3: Deep Learning Model for Sepsis Screening Using ECG

Data Collection

- **46,017** patients across two hospitals
- ECG data with 2 demographic variables (age, sex)
- ECG advantages: non-invasive, inexpensive, continuous

Data Preprocessing

- **Band-pass filter** to reduce noise
- Removed unstable segments (first/last seconds)
- **Normalization** to ensure consistent scale
- **Data augmentation** with synthetic noise

Modeling

Residual Convolutional Neural Network (ResNet-like CNN)

- Learns complex, high-dimensional patterns from ECG waveforms
- **Skip connections** solve vanishing gradient problem
- Enables efficient learning in deep networks

Results

Trained on one hospital, tested on another (generalizable)

Sepsis Detection (Internal)	Sepsis Detection (External)
0.901 Accuracy	**0.863** Accuracy

Septic Shock (Internal)	Septic Shock (External)
0.906 Accuracy	**0.899** Accuracy

0.845

Single-lead ECG Accuracy

Enables wearable-based sepsis screening

Study 4: Early Detection of Sepsis-Induced Deterioration Using Machine Learning

Data Collection

132 patients suspected of sepsis

First 48 hours of hospital admission

Continuous Signals:

- ECG (500 Hz)
- Plethysmography/SpO_2 (125 Hz)
- Respiratory rate (62.5 Hz)

Data Preprocessing

Segmented signals into **5-minute windows** with precise heartbeat detection

Feature Extraction Strategies:

1. Histogram of Derivatives
Rate of change & acceleration of signals

2. Temporal Comparison
Detect evolving pattern instability

3. Wavelet + Autoregressive
ECG morphology analysis (QRS, T waves)

Modeling & Training

Machine Learning Models:

- SVM, Random Forest, GBM
- kNN, MLP, Naïve Bayes
- Logistic Regression

90% training, 10% testing with cross-validation

Focus on generalization across patients

Results

First two strategies: **56%** accuracy

62.4%

Best Accuracy with SVM

Wavelet + Autoregressive strategy

Challenges: Limited signal diversity, small dataset

Key insight: ECG morphological features provide effective predictive power

Study 5: Mortality among patients with sepsis associated with a bispectral electroencephalography

Data Collection

628 patients at same hospital

EEG recordings: 3-10 minutes each

Demographic data: age, sex, comorbidities

Feature Engineering

BSEEG Score: Ratio of low-frequency to high-frequency brainwave power

Increased ratio = abnormal brain slowing = marker of encephalopathy

Normalized into standardized score for objective assessment

Patient Stratification

Patients grouped by two factors:

- Clinical sepsis status from medical records
- BSEEG score (high or low)

Four distinct groups:

- Sepsis + High BSEEG
- Sepsis + Low BSEEG
- Non-sepsis + High BSEEG
- Non-sepsis + Low BSEEG

Results

Data Analysis: Cox regression adjusting for age, sex, comorbidities

Diagnostic Accuracy	Prognostic Value
Low	**High**
Not accurate for confirming sepsis	Excellent for mortality prediction

46.3%

"Sepsis + High BSEEG" survival rate at one year

BSEEG is an **independent predictor** of mortality, even after adjusting for traditional risk factors

Key Findings and Conclusions

Early Detection

AI and statistical signal processing can detect sepsis **3-4 hours earlier** than traditional methods

Multimodal Data

Different data modalities effectively used: vital signs, lab values, **ECG**, and **EEG**

Generalization

Models can generalize across hospitals and countries with proper validation techniques

Time Sensitivity

Each hour of delay increases mortality by **4-8%**, making early detection critical

Some models (like BSEEG) are better for prognosis than diagnosis, highlighting the need for specialized approaches in sepsis management

Future Directions

Model Integration

Combine multiple AI models for **improved accuracy** and robustness

Real-time Implementation

Deploy models in **clinical settings** for immediate decision support

Wearable Devices

Develop **continuous monitoring** solutions for at-home and remote care

Beyond Sepsis

Expand approaches to other **critical conditions** and diseases

Interpretability

Focus on **explainable AI** for clinical adoption and trust

The integration of statistical signal processing with AI represents a paradigm shift in early detection of critical conditions, with potential to save lives through timely intervention