Comprehensive Comparison of Sepsis Machine Learning Research Papers

Here's a detailed tabular comparison of the 6 research papers you provided:

Summary Comparison Table

Study	Journal	Study Type	Sample Size	Best Algorithm	Best AUC
Yadgarov et al. (2024)	Frontiers in Medicine	Systematic Review & Network Meta-Analysis	457,932 patients (73 studies)	Neural Networks & Decision Trees	0.825
Lin et al. (2025)	Journal of Medical Internet Research	Retrospective Study	1,492 patients (654 sepsis)	Light Gradient Boosting Machine (LGBM)	**0.90**
Zhou et al. (2024)	Preventive Medicine Reports	Retrospective Study	2,385 patients (364 sepsis)	Random Forest	0.87
Shanmugam et al. (2025)	Indian Journal of Critical Care Medicine	Scoping Review	13 studies reviewed	XGBoost	0.753-0.99
Solís-García et al. (2023)	Applied Intelligence	Experimental Comparative Study	6,181 patients (570 sepsis)	Temporal Convolutional Network (TCN)	0.7553
Liu et al. (2025)	Scientific Reports	Retrospective Study	189,617 patients (10,824 sepsis)	Gradient Boosting	0.83

Detailed Methodology Comparison

Study	Dataset	Clinical Setting	Key Features	Prediction Window
Yadgarov et al.	Meta-analysis of 73 studies	ICU (67.1%), Wards (16.4%), ED (12.3%)	Various clinical parameters	0 hours to 7 days
Lin et al.	Tri-Service General Hospital	ICU	**CBC+DIFF data (18 parameters)**	Real-time
Zhou et al.	Anhui Medical University + MIMIC-III/eICU	ICU	18 features (SBP, Albumin, Heart Rate)	Early prediction

Study	Dataset	Clinical Setting	Key Features	Prediction Window
Shanmugam et al.	Multiple databases	ICU, ED, General Ward	Vital signs, demographics, lab results	4-48 hours
Solís-García et al.	MIMIC-III	ICU	44 laboratory and vital parameters	7 hours before onset
Liu et al.	MIMIC-IV	**Emergency Department**	Vital signs, demographics, medical history	At triage

Clinical Innovation and Key Findings

Study	Clinical Innovation	Key Finding	Validation Approach
Yadgarov et al.	Network meta-analysis framework	ML significantly outperformed traditional scoring	Network meta-analysis validation
Lin et al.	**AI-CDSS web system deployment**	CBC-only data achieved 90% AUC	External validation (MIMIC-III & eICU)
Zhou et al.	SHAP interpretability analysis	RF superior with balanced data	External validation (MIMIC-III & eICU)
Shanmugam et al.	Literature synthesis	XGBoost most commonly successful	Literature review synthesis
Solís-García et al.	Benchmark comparison framework	Deep learning outperformed traditional ML	80% train, 10% test, 10% validation
Liu et al.	Interpretable ML with SHAP/LIME	Comprehensive data better than vital signs alone	80% train, 20% test

Key Performance Insights

Best Performing Models:

- **Highest AUC**: Lin et al. (2025) - LGBM with CBC data (AUC: 0.90)
- **Largest Scale**: Yadgarov et al. (2024) - Meta-analysis of 457,932 patients
- **Most Comprehensive**: Liu et al. (2025) - 189,617 patients with complete triage data

Algorithm Performance Ranking:

1. **LGBM** (Lin et al.) - AUC: 0.90
2. **Random Forest** (Zhou et al.) - AUC: 0.87
3. **Gradient Boosting** (Liu et al.) - AUC: 0.83
4. **Neural Networks** (Yadgarov et al.) - AUC: 0.825
5. **TCN** (Solís-García et al.) - AUC: 0.7553

Most Innovative Approaches:

- **CBC-only prediction** (Lin et al.) - Simplest data requirements
- **Real-time AI-CDSS** (Lin et al.) - Clinical deployment ready
- **Network meta-analysis** (Yadgarov et al.) - Comprehensive evidence synthesis
- **Emergency triage integration** (Liu et al.) - Point-of-care application

This comparison shows that machine learning consistently outperforms traditional sepsis scoring systems, with the most promising results coming from simplified approaches using readily available clinical data.

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