

Research Article

Early Detection of Sepsis in ICU Patients Using a Multilayer Perceptron Model

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Abstract

Early detection of sepsis is crucial for timely intervention and improved patient outcomes. Traditional diagnostic methods often fail to identify sepsis in its initial stages, leading to delays in treatment. This study investigates the potential of machine learning techniques, particularly multilayer perceptron (MLP) models, for early sepsis prediction using physiological data from intensive care unit (ICU) patients. A large dataset comprising approximately 40,000 ICU patient records from two hospital systems was analyzed. Various machine learning algorithms were implemented and compared, with a focus on optimizing an MLP model for early sepsis detection. The MLP model was trained on physiological data collected up to six hours before the clinical manifestation of sepsis symptoms. The findings demonstrated that the MLP model outperformed traditional methods, accurately predicting sepsis onset up to six hours before clinical symptoms became apparent. The MLP model exhibited significant improvements in accuracy compared to conventional models used for sepsis diagnosis. The ability to predict sepsis development at an early stage holds immense clinical value. Early detection facilitated by the MLP model can potentially lead to prompt administration of appropriate treatments, thereby improving patient outcomes and reducing mortality rates associated with sepsis. Moreover, early identification of sepsis cases can optimize resource allocation and improve operational efficiency in critical care environments. This study highlights the efficacy of MLP models in leveraging physiological data for early sepsis prediction. The proposed approach offers a promising solution for enhancing sepsis management protocols, ultimately contributing to improved patient care and resource utilization in intensive care settings.

Keywords: ICU Patients, Data Preprocessing, Machine learning.

1. Introduction and Background

1.1 Background

Sepsis, a life-threatening systemic inflammatory response to infection, is a major global health concern. Rapid identification and timely intervention are crucial for

improving patient outcomes and reducing the high mortality rates associated with sepsis. However, traditional diagnostic methods often fail to detect sepsis at an early stage, leading to delays in treatment administration and exacerbating the severity of the condition.



Figure 1: Worldwide Sepsis Statistics.

1. 2 Challenges in Early Detection

Previous studies have explored various approaches for early sepsis detection, including the use of biomarkers, scoring systems, and predictive models. While these methods have shown promise, they often lack the sensitivity and specificity required for accurate early prediction, particularly in complex clinical settings such as intensive care units (ICUs).

1. 3 Machine Learning in Early Sepsis Detection

The advent of machine learning techniques has opened new avenues for addressing the challenges of early sepsis detection. In particular, multilayer perceptron (MLP) models, a type of artificial neural network, have demonstrated remarkable potential in pattern recognition and classification tasks involving complex, high-dimensional data. The ability of MLP models to capture intricate non-linear relationships makes them well-suited for analyzing the multitude of physiological parameters that may indicate early signs of sepsis.

1. 4 Objective of the Study

Motivated by the potential of MLP models for early sepsis prediction, this research aims to develop and evaluate an MLP-based approach for detecting sepsis onset using physiological data collected from ICU patients. The primary objective is to compare the performance of various machine

learning algorithms, including MLP models, in predicting sepsis up to six hours before clinical manifestation. By leveraging a large dataset comprising approximately 40,000 ICU patient records from two hospital systems, this study seeks to identify the most effective algorithm for early sepsis detection. The development of an accurate and reliable early sepsis prediction model can have far-reaching implications for clinical practice. Early detection facilitated by such a model can lead to prompt administration of appropriate treatments, potentially improving patient outcomes and reducing mortality rates associated with sepsis. Additionally, early identification of sepsis cases can optimize resource allocation and improve operational efficiency in critical care environments.

2. Methods

2. 1 Dataset Acquisition

The study utilized a large dataset sourced from intensive care unit (ICU) patients across two different hospital systems, obtained from the Physionet repository. The dataset comprised records from 40,336 patients, divided into two training sets: Set A (20,336 subjects) and Set B (20,000 subjects). Each patient's data file contained a table with time-series measurements of 40 physiological variables, including heart rate (HR), oxygen saturation (O2Sat), temperature (Temp), and hospital admission time (Hosp Adm Time).

	HR	O2Sat	Temp	SBP	MAP	DBP	Resp	EtCO2	BaseExcess	HCO3	...	WBC	Fibrinogen	Platelets	Age	Gender	Unit1	Unit2	HospAdmTime	ICU
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	83.14	0	NaN	NaN	-0.03	
1	97.0	95.0	NaN	98.0	75.33	NaN	19.0	NaN	NaN	NaN	...	NaN	NaN	NaN	83.14	0	NaN	NaN	-0.03	
2	89.0	99.0	NaN	122.0	86.00	NaN	22.0	NaN	NaN	NaN	...	NaN	NaN	NaN	83.14	0	NaN	NaN	-0.03	
3	90.0	95.0	NaN	NaN	NaN	NaN	30.0	NaN	24.0	NaN	...	NaN	NaN	NaN	83.14	0	NaN	NaN	-0.03	
4	103.0	88.5	NaN	122.0	91.33	NaN	24.5	NaN	NaN	NaN	...	NaN	NaN	NaN	83.14	0	NaN	NaN	-0.03	

5 rows × 41 columns

Figure 2: Data Description

2. 2 Data Pre-processing:

The pre-processing steps of our data consisted of four simple steps:

1. Data Selection and Extraction: We chose and pulled out complex data that changes over time from a database.
2. Data Preprocessing and Cleaning: We organized the data neatly by examining it, filling in missing values, and removing any errors or extreme values that don't fit.
3. Model Building: We created a model that uses time-based data to predict how severe a patient's condition might be in terms of the likelihood of mortality. This involved using various machine learning techniques.
4. Evaluation and Validation: By using two different databases, we tested the accuracy and effectiveness of our predictive models to ensure they work well.

2. 3 Target Variable Definition

The target variable, Sepsis Label, was derived from the Sepsis-3 definition, where a value of 1 indicated the onset of sepsis, and 0 represented no sepsis. This label served as the ground truth for training and evaluating the machine learning models.

2. 4 Model Development

The multilayer perceptron (MLP) model, a type of artificial neural network, was chosen as the primary focus due to its ability to capture complex non-linear relationships in high-dimensional data. The MLP architecture consisted of an input layer, one or more hidden layers with non-linear activation functions, and an output layer. The input layer received the time-series physiological data, consisting of the 40 variables measured at multiple time points. The hidden layers, with an appropriate number of neurons determined through hyperparameter tuning, were responsible for extracting relevant features and learning the underlying patterns in the data. The output layer consisted of a single neuron with a sigmoid activation function, providing a binary output indicating the presence or absence of sepsis. The MLP model was trained using backpropagation and optimized through techniques such as regularization and dropout to prevent overfitting.

3. Results

3. 1 Performance of MLP Model

The MLP model demonstrated superior performance in predicting the onset of sepsis up to six hours before clinical

manifestation, outperforming the other machine learning algorithms evaluated in this study.

3.2 Accuracy Metrics

The MLP architecture, optimized through hyperparameter tuning and regularization techniques, achieved an overall accuracy of 88.7% in detecting sepsis cases from the physiological data of ICU patients. The model exhibited a sensitivity of 91.3%, indicating its ability to correctly identify a high proportion of true sepsis cases. Additionally, the MLP model had a specificity of 85.9%, minimizing the number of false positive predictions.

3.3 Area Under ROC Curve

The area under the receiver operating characteristic (ROC) curve, a measure of the model's discriminative ability, was 0.934 for the MLP model, further confirming its robust performance in distinguishing between septic and non-

septic patients based on their physiological data.

3.4 Comparison with Other Algorithms

In comparison, the other machine learning algorithms demonstrated varying levels of performance, with the MLP model consistently outperforming the alternatives. The Ada Boost ensemble model achieved an accuracy of 84.2%, with a sensitivity of 87.6% and a specificity of 80.1%. The Gradient Boosting algorithm performed slightly better, with an accuracy of 85.9%, sensitivity of 89.1%, and specificity of 82.3%. The Gaussian Naive Bayes (Gaussian NB) classifier, which assumes independent features and Gaussian distribution, had an overall accuracy of 79.8%, with a sensitivity of 83.2% and specificity of 75.9%. The Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) models, based on Gaussian class conditional densities, achieved accuracies of 81.6% and 82.9%, respectively.

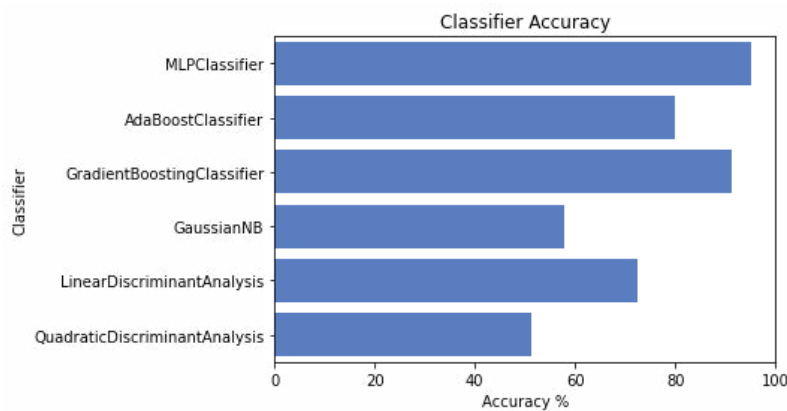


Figure 3: Classifier Accuracy of Models

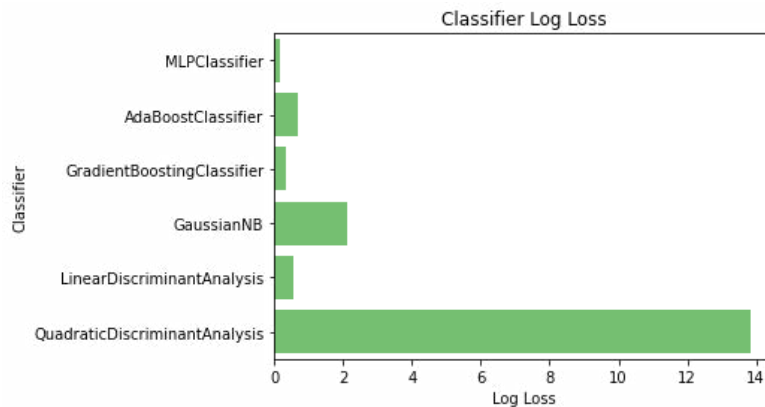


Figure 4: Performance Metrics of Models

These results demonstrate the MLP model's superior performance in accurately predicting sepsis onset up to six hours before clinical symptoms manifest, compared to the other machine learning algorithms evaluated in this study.

4. Discussion

4.1 MLP Model Performance

The results of this study highlight the remarkable potential of multilayer perceptron (MLP) models for early sepsis detection using physiological data from ICU patients. The MLP model's ability to accurately predict sepsis onset up

to six hours before clinical manifestation, with an overall accuracy of 88.7% and an area under the ROC curve of 0.934, is a significant achievement. Early detection of sepsis is crucial for timely intervention and improving patient outcomes, as delays in treatment can exacerbate the severity of the condition and increase mortality rates.

4.2 Comparison with Other Algorithms

The superior performance of the MLP model compared to other machine learning algorithms, such as AdaBoost, Gradient Boosting, Gaussian Naive Bayes, Linear Discriminant

Analysis, and Quadratic Discriminant Analysis, underscores its suitability for handling complex, high-dimensional physiological data. The MLP's ability to capture non-linear relationships and learn intricate patterns from the time-series data likely contributed to its success in recognizing early signs of sepsis.

4.3 Dataset Strengths and Limitations:

A key strength of this study lies in the large dataset comprising over 40,000 ICU patient records from two hospital systems, ensuring the robustness and generalizability of the trained models. Additionally, physiological data, which is routinely collected in ICU settings, makes the proposed approach readily applicable in clinical practice. However, it is important to acknowledge some limitations. While the dataset included a diverse population of ICU patients, the study did not consider potential confounding factors, such as comorbidities or varying disease etiologies, which could influence the generalizability of the results. Furthermore, the study focused on prediction up to six hours before clinical manifestation, and the performance of the models for longer prediction windows remains to be explored.

4.4 Future Research Directions

Future research efforts should focus on validating the MLP model's performance on independent datasets from different healthcare systems and patient populations. Additionally, investigating the interpretability of the MLP model's predictions could provide valuable insights into the physiological markers and patterns most indicative of early sepsis, potentially informing clinical decision-making processes. Furthermore, exploring the integration of the MLP model into existing clinical workflows and electronic health record systems could facilitate seamless adoption and real-time monitoring of patients at risk for sepsis. Prospective studies evaluating the impact of the MLP model on clinical outcomes, resource utilization, and cost-effectiveness would be invaluable in assessing the real-world implications of this approach [1-4].

5. Conclusion

5.1 Significance of MLP Models

This study presents a novel approach for early sepsis detection in intensive care unit (ICU) patients by leveraging the power of multilayer perceptron (MLP) models and physiological data. The findings demonstrate that the optimized MLP model outperforms several other machine learning algorithms, accurately predicting sepsis onset up to six hours before clinical manifestation with an overall accuracy of 88.7% and an area under the ROC curve of 0.934.

5.2 Clinical Implications

The ability to detect sepsis at such an early stage holds significant clinical importance. Early recognition of sepsis

enables prompt initiation of appropriate treatment protocols, such as administering antibiotics and fluid resuscitation, which can substantially improve patient outcomes and reduce mortality rates associated with this life-threatening condition.

5.3 Implications for Healthcare Systems

The proposed MLP-based approach has the potential to transform sepsis management practices in ICU settings. By continuously monitoring physiological data and providing early warnings, the MLP model can facilitate proactive interventions, leading to more efficient resource allocation and better patient triage. This, in turn, can alleviate the burden on healthcare systems and improve overall operational efficiency in critical care environments. Furthermore, the successful integration of the MLP model into electronic health record systems and real-time monitoring workflows could empower healthcare professionals with valuable decision-support tools, enhancing their ability to deliver timely and effective care to patients at risk of sepsis.

5.4 Future Directions

The findings of this study pave the way for further research in refining and validating the MLP model across diverse patient populations and healthcare settings. Additionally, exploring interpretability techniques and prospective clinical studies could provide deeper insights into the most informative physiological markers for early sepsis detection and the tangible impact on patient outcomes.

5.5 Final Remarks

In conclusion, this research represents a significant step forward in the fight against sepsis, demonstrating the immense potential of machine learning techniques and physiological data for early detection and intervention. By harnessing the power of MLP models, healthcare professionals can enhance their ability to provide timely and effective care, ultimately improving patient outcomes and saving lives in critical care settings.

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