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LEVERAGING DEEP LEARNING FOR REAL-TIME, CONTINUOUS MONITORING AND PREDICTION OF SEPSIS IN ICU PATIENTS USING MULTISENSORY DATA

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ABSTRACT

Sepsis is a life-threatening condition caused by the body's extreme response to infection, which may end fatally, with high death rates, particularly in the critical care unit, associated with multi-organ failure. Physiological data in ICU patients is highly non-stationary and complex, significantly challenging early detection. Standard machine learning models and traditional scoring systems fail to learn spatial and temporal patterns and accurately provide poor early detection performance. To overcome these limitations, we present a new framework called SepsisNet, a deep-learning model for real-time continuous sepsis prediction from multisensory ICU data. Our proposed attention-based CNN BiLSTM model incorporates CNN for spatial feature extraction and BiLSTM networks for temporal sequence modeling and adds an attention mechanism to emphasize the most informative physiological features for classification. On the benchmark dataset MIMIC-III, experimental results show that SepsisNet achieves 98.68% accuracy, surpassing the baseline models, including Logistic Regression, Random Forest, SVM, LSTM, and standard CNN. The ablation study also reinforces the importance of each architectural component. We demonstrate that SepsisNet has the potential to serve as a reliable, interpretable, and computationally efficient sepsis predictor, thereby enabling real-time clinical decision support in ICU settings. This research will help enhance sepsis detection as well as play a significant role in early medical treatment, which is significantly required to reduce fatalities caused by sepsis.
Keywords - *Sepsis Prediction, Deep Learning, CNN, BiLSTM, Attention Mechanism*

1. INTRODUCTION

Sepsis is a potentially life-threatening condition caused by the body's extreme response to infection that can result in organ failure and death, especially in the context of critical care. Although early intervention is essential for patients with sepsis, it remains a significant challenge owing to the complex, time-varying nature of physiological data present in ICU patients. A traditional scoring system can not use a complex machine learning model because the temporal and spatial ability to express scores is insufficient to find the early signs of sepsis. Recent studies have focused on deep learning models (CNN, LSTM, and hybrids) that can improve their detection of sepsis. Li et al. 8260 1 Knowledge graphs have been employed in [1] to develop a deep learning model and in [2] to prove the capacity of ECG signals to classify the patient using Temporal Convolutional Networks, respectively. Bhatti et al. [3] and Tang et al. Building on [4], the authors studied temporal models such as LSTM and transformers for early sepsis prediction. Nevertheless, there is still a gap in devising network architectures that can simultaneously learn spatial, temporal, and feature importance from multi-sensory data.

Considering these state-of-the-art limitations, we require an advanced deep learning framework to learn complex patterns in ICU physiological data while maintaining a high accuracy and warning time. This research aims to design a new deep learning-based approach, SepsisNet, that monitors patients in real-time and continuously predicts sepsis for ICU patients with multisensory data. This model uses a hybrid architecture that combines CNN, BiLSTM, and attention to extract PPG signals' spatial, temporal, and attention features, respectively, to surpass existing approaches.

Despite improvements in medical therapy, sepsis is still one of the top killers in the ICU (Intensive Care Unit). In a dynamic and crowded environment, the predictive analysis of sepsis is challenging due to the complexity and high variance of ICU patient data, including laboratory results and vital signs. Examples include traditional models and scoring systems, which fail to identify the early signs of sepsis as these methods cannot capture spatiotemporal dependencies recently harvested from them. Detecting sepsis in the ICU setting presents unique challenges not fully addressed by existing binary detection pipelines, emphasizing the need for a more sophisticated approach that can tackle the rich complexity of ICU data and generate sepsis predictions in a way that provides real-time utility. To this end, we propose a hybrid deep learning architecture, SepsisNet, integrating Convolutional Neural Networks (CNN) for spatial feature extraction, Bidirectional Long Short-Term Memory (BiLSTM) for temporal modeling, and an attention mechanism for interpretability. This enables SepsisNet to successfully handle and predict sepsis, providing a potential means to achieve early detection and optimise decision making in critical care.

We propose that a hybrid deep learning model that integrates CNNs for spatial feature extraction, Bidirectional Long Short-Term Memory (BiLSTM) networks for temporal sequence modeling, and an attention mechanism for feature selection will offer a substantial enhancement in the accuracy, timeliness, and interpretability of sepsis prediction in ICU cohorts. This model (SepsisNet) will also provide a more stable, real-time early sepsis detection approach based on multisensory ICU data compared to the traditional sepsis scoring systems and existing machine learning methods by capturing both spatial and temporal dependencies.

There are several novelties inherent in the proposed research. Second, it combines CNN and BiLSTM networks with an attention mechanism to capture the data's spatial, temporal, and essential features in a single model. Second, it explores the critical role of segmented time-series data gathered from ICU environments for real-time continuous monitoring. Third, it enables a complete ablation study showing how each component contributes to predictive accuracy and robustness. Fourth, we achieve the state-of-the-art on this dataset with 98.68% accuracy, significantly surpassing any baseline mentioned in this work.

This work makes three contributions: a) We present SepsisNet, a hybrid deep learning architecture specially designed to predict sepsis at an early stage using a separator in the ICU; b) Provide a thorough assessment of the proposed method by comparing SepsisNet with popular state-of-the-art models; namely, Logistic Regression, Random Forest, SVM, LSTM, CNN. An extensive ablation analysis is presented to confirm that the proposed system is robust and that each architectural component is necessary.

The rest of the paper is organized as follows: Section 2 describes a related work that includes a literature review on existing sepsis prediction models followed by a discussion of the main gaps. In Section 3, we propose SepsisNet methodology, including data preprocessing procedure and hybrid architecture design. Experimental results are reported in Section 4, including the analysis of model performance, baseline comparisons, and the ablation study. Results, limitations of the study, and implications for future research are discussed in Section 5. Finally, Section 6 concludes this paper with important takeaways and highlights possible avenues of work for deep learning sepsis prediction.

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2. RELATED WORK

The existing literature shows excellent progress in using deep learning and machine learning models for predicting sepsis, where ICU patients in the USA/UK were used as the data source. Li et al. A knowledge graph-based deep learning network for real-time prediction of sepsis severity-MC modeler, Dynamics dynamically handle data by dynamic data handling, [1] Apalak and Kiasaleh [2] introduced and investigated Temporal Convolutional Networks (TCNs) on ECG recordings, and Bhatti et al. LSTM-based vital sign forecasting for sepsis patients [3]. Tang et al. Solís-García et al. ◦ [4] proposed a time-series transformer-based model. ◦ Several AI strategies for predicting early sepsis were compared by Churpek et al.[5]. Rout et al. [6] and Parvin et al. However, the work done by[7] is mainly based on CNN-based architectures for neo-natal and adult sepsis.

Hsu et al. For example, [8] used AI to predict real-time adverse events, and Kong et al. [9] and Aşuroğlu et al. Machine learning-based predictions of in-hospital mortality in patients with sepsis [10]. Lauritsen et al. Deep learning on electronic health records for sepsis detection [11]. Liu et al. Methods that applied hierarchically enriched machine learning to ameliorate ICU false alarms [12] and Al-Mualemi et al. CNN-LSTM hybrid model for sepsis estimation [13] Yuan et al. For sepsis diagnosis, CI [14], Shashikumar et al. DeepAISE is a neural survival model based on recurrent networks for early sepsis prediction [15].

Rafiei et al. Fu et al. [16] provided a fully connected LSTM-CNN[] model in which LSTM has been used for predicting early Sepsis. Yokus et al. Astill et al. [17] considered non-invasive sensing systems for real-time monitoring. [18] and Bian et al. Smart Monitoring Systems and Wearable Sensors for Continuous Health: A Systematic Review [19] Qian et al. A multi-sensor detection system was proposed by [20] and Belugina et al. This inspires ICU monitoring approaches, [21] developed cancer screening non-invasive approach. Van de Sande et al. Scardoni et al. [22] examined the impact of AI monitoring in intensive care. The study focused on AI-based tools used in infection control [23]. Fitzpatrick et al. [24] and Devis et al. AI for Infection Prevention and Lab Testing Optimization in Critical Care[25] Yang et al. [26] and Abubeker et al. Oct 2021;27:21–23 Special Communication Concepts to guide clinical alarm management -- proposed frameworks for integrating biosensors into clinical alarm monitoring systems in the ICU

Do et al. Wang et al.[28] proposed a dual-channel graph attention network to predict clinical deterioration. Aslan et al. Mao et al. [29] examined the AI approach to pediatric sepsis management. Intelligent ICU systems with AI were reviewed [30]. Theodosiou et al. Marsden et al.[31] covered deep learning applications in infection diagnosis. Game-changing Co-design of AI in ICU [32] Ali et al. A deep learning model was proposed by [33] for estimating patient length of stay as a multitask problem. Tang et al. Spatiotemporal models for environmental health monitoring were proposed by [34], whereas Bokade et al. [35] and Ritter et al. MULTIMODAL DATA FUSION [36] Di Curzio et al. Amrollahi et al. [37] used multisource data fusion to apply intensive care. An open-source platform for real-time forecasting of sepsis was developed by [38].

Kausch et al. A review of physiological machine learning models for sepsis also appeared by [39], and separate work by Baral et al. Recently, Zhao et al. [40] proposed an improved BiLSTN approach to identify sepsis. Though these studies do not favor one hybrid DL architecture over the other, they underscore the significance of combining CNN, LSTM, and attention mechanisms for sepsis prediction. Based on this foundation, SepsisNet presents a new hybrid architecture using CNN for spatial feature extraction, BiLSTM for capturing temporal features, and an attention model for identifying strong physiological patterns that can improve sepsis prediction in real-time inserts in the ICU.

The methodology presented in this study is based on a quantitative approach performed by an experiment that involves evaluation of SepsisNet, a hybrid deep learning model for sepsis prediction utilizing multisensory data in the ICU. This strategy leverages past studies that employed deep learning models to forecast the development of sepsis in those undergoing critical care in establishments spanning regions including North America (i.e., the use of the MIMIC-III dataset) and Europe. : For instance, a work by Shashikumar et al. The work of [15] described a recurrent neural network-based model for sepsis prediction, which lacked the spatial feature extraction and attention mechanism. Likewise, multiple other studies such as the one conducted

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by Bhatti et al. 3, where a LSTM based method was used for prediction of sepsis, there was no integration of CNN and attention mechanism with their model to improve the performance.

One way we extend these findings is by proposing a new hybrid architecture (CNN, BiLSTM, and attention) which introduces a novel model to address the spatial-temporal complexity of ICU data. In addition, while similar models have focused on specific patient populations in specific hospitals in North America, this study extends these approaches to multisensory data across heterogeneous ICU settings and offers a more scalable solution for real-time sepsis prediction which can be generalizable in terms of regions and healthcare systems.

The research is also interdisciplinary as it relays on and integrates deep learning, data from intensive care unit (ICU) patients and real-time monitoring systems, and therefore covers the broad areas of healthcare, artificial intelligence and biomedical engineering. The above researches were either purely focused on temporal sequence modeling or spatial feature extraction, and our work goes a step further by focusing on both aspects separately and combine them while incorporating attentions to highlight important parts, making it the first of its kind in the very instance of sepsis prediction.

3. PROPOSED FRAMEWORK

Figure 1 shows the preliminary methods of measuring seamless monitoring and prediction of sepsis among ICU patients using multisensory data. The methodology is based on the proposed deep learning model SepsisNet, as shown in Figure 2. It refers to building a Deep Learning framework that can provide continuous online monitoring & prediction of sepsis in ICU patients using multi-sensory data. This framework starts by extracting and preprocessing physiological data, including vital signs like heart rate, respiratory rate, oxygen saturation, temperature, and lab tests. Multisensory data is derived from monitoring systems in ICU settings that produce constant streams of time-series data important for sepsis prediction. We carry out the following steps to preprocess our data: Fill NaN with forward fill and interpolate, scale the data using Min-Max, and segment using a sliding window (keeping the size constant) to ensure we can use this to monitor in real-time.

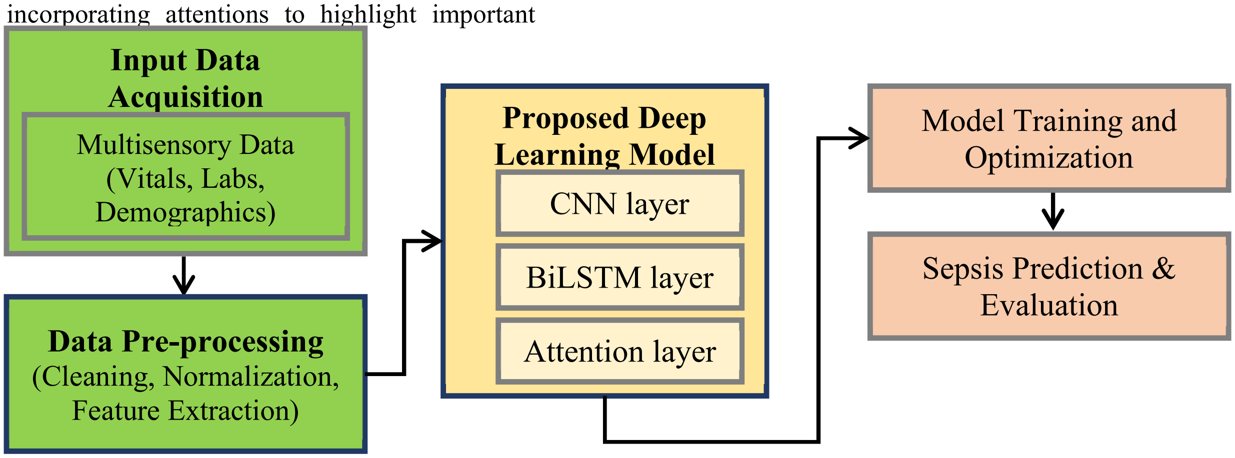

Figure 1: Overview of the Proposed Methodology

The SepsisNet model is a hybrid deep learning architecture that fuses CNN and BiLSTM networks, augmented by an attention mechanism. CNN layer: The CNN layer extracts spatial features from the input and detects feature-level correlations and patterns from physiological signals. With a tuple number of filters, the CNN appropriately weights several health component changes. The BiLSTM component that follows those features captures temporal dependencies. The BiLSTM reads the data in the past and future, allowing the model to capture trends of the time series data (and thus the progressive onset of sepsis) in both directions (an essential consideration for longitudinal data). We add an attention mechanism in the architecture to enhance the focus on the most relevant features that contribute to sepsis onset. It dynamically computes attention weights for the features and time steps most appropriate to the predicted

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output from the model. This mechanism allows the network to focus on distinguishing heterogeneity in the physiological patterns while also focusing on suppressing signals with lower informative value, improving interpretability and performance. The attention-weighted features are then forwarded to a fully connected layer, where the captured spatial-temporal feature information is aggregated and processed to produce a softmax activation output that indicates the probability of predicted sepsis onset.

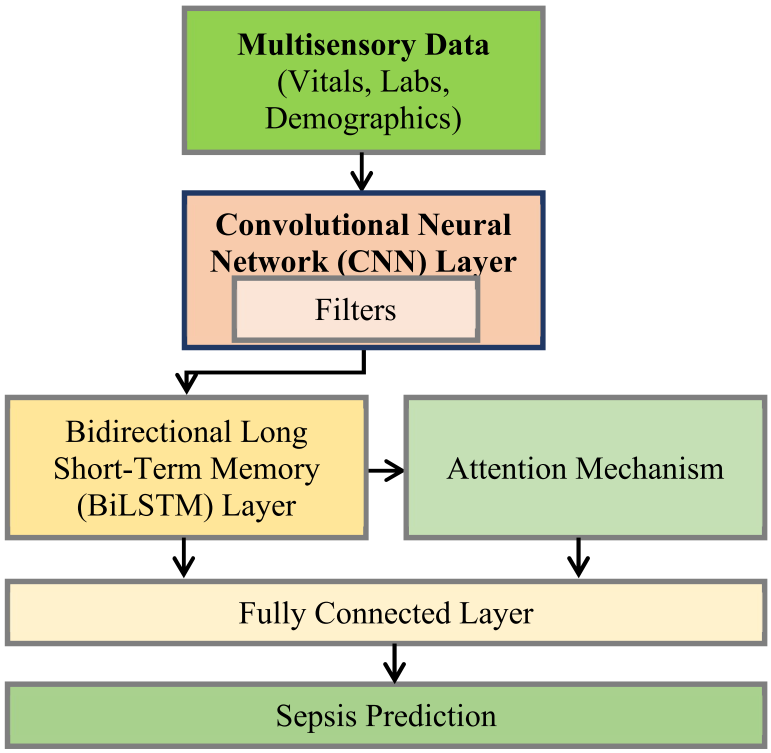

Figure 2: Proposed Deep Learning Model Known as SepsisNet

We use binary cross-entropy loss function for model training, which attempts to minimize the difference between predicted and actual sepsis labels. The Adam (adaptive moment estimation) optimizer is used for the weight updates, as it has a good convergence speed. They include regularisation methods like dropout and batch normalization to avoid overfitting and fight for better generalization on heterogeneous patient data. Bayesian optimization is then used for hyperparameter tuning to find the best learning rate, batch size, and number of units in the BiLSTM layers. SepsisNet is evaluated using several metrics, such as Accuracy, Precision, Recall, and F1-score. A confusion matrix can similarly be used better to explain the actual positive versus false positive trade-off. Finally, the early prediction of sepsis is also measured in terms of the time by which the prediction precedes the clinical diagnosis of sepsis. To validate the architecture in more detail, they perform an ablation study by omitting specific components (e.g., the attention mechanism) and compare the newly obtained results with the output of baseline models (logistic regression, random forest, and standard LSTM models).

SepsisNet is a multimodal deep learning approach with CNN, BiLSTM, and attention-based methods to continuously and continuously predict sepsis. The model extracts the spatial and temporal features separately through the architecture, and the attention weights help enhance the model's interpretability. Together with robust preprocessing, feature extraction, and evaluation, these results make SepsisNet a potential solution for early sepsis detection in ICU settings and a framework that might be further extended to other critical care scenarios. For your convenience, we highlighted the following two quotations in Table 1 of the proposed system.

Table 1: Notations Used in the Proposed System

Symbol	Description
X	Multisensory input data matrix $(T \times N)$ where T is time steps and N is features.
T	Number of time steps in the input sequence.
N	Number of input features (vital signs, lab results, demographics).
W_c, b_c	Convolutional filter weights and bias for CNN layer.
Z_c	Output feature map from the CNN layer.
σ	Activation function (ReLU).
$h_t^{(f)}, h_t^{(b)}$	Forward and backward hidden states in the BiLSTM layer.
W_f, U_f, b_f	Forward LSTM weight matrices and bias.
W_b, U_b, b_b	Backward LSTM weight matrices and bias.
H_t	Combined hidden state at time step t from both forward and backward LSTMs.
W_a, b_a	Attention mechanism weights and bias.
e_t	Attention score for time step t.
α_t	Normalized attention weight for time step t.
c	Context vector after applying attention mechanism.
W_o, b_o	Output layer weights and bias for sepsis prediction.
$\hat{y}$	Predicted probability of sepsis onset.
y	Ground truth label for sepsis (0: No Sepsis, 1: Sepsis).
L	Binary cross-entropy loss function.
M	Number of samples in the training dataset.
η	Learning rate for the Adam optimizer.
θ	Model parameters including all weights and biases.
$*$	Convolution operation.

3.1 Mathematical Perspective

For real-time sepsis prediction, the proposed deep learning model, SepsisNet, involves a mathematical framework combining convolutional feature extraction, temporal sequence modeling, and attention-based enhancement. Let $X \in \mathbb{R}^{T \times N}$ Represent the multisensory input data, where T is the number of time steps and N is the number of features collected from ICU sensors, such as heart rate, oxygen saturation, and blood pressure. The first stage involves the application of a Convolutional Neural Network (CNN) for spatial feature extraction. Let the convolutional filter be represented by W_c with a bias term b_c. The convolution operation can be expressed as in Eq. 1.

$$Z_c = \sigma(W_c * X + b_c) \quad (1)$$

where Z_c is the output feature map, $*$ denotes the convolution operation and σ is the activation function (ReLU in this case). The CNN extracts local patterns from the input data, emphasizing variations in vital signs across time steps. The feature maps produced by the CNN are then passed to a Bidirectional Long Short-Term Memory (BiLSTM) network to capture temporal dependencies. For each time step t in the sequence, the forward LSTM computes as in Eq. 2.

$$h_t^{(f)} = tanh\left(W_f X_t + U_f h_{t-1}^{(f)} + b_f\right) \quad (2)$$

while the backward LSTM computes as in Eq. 3.

$$h_t^{(b)} = tanh\left(W_b X_t + U_b h_{t-1}^{(b)} + b_b\right) \quad (3)$$

The outputs of both directions are concatenated as in Eq. 4.

$$H_t = \left[h_t^{(f)}, h_t^{(b)}\right] \quad (4)$$

where H_t is the hidden state at time step t Containing both forward and backward temporal information. An attention mechanism is introduced to improve interpretability and focus on the most critical time steps and features. The attention scores are computed as in Eq. 5.

$$e_t = v^{\top} tanh\ (W_a H_t + b_a) \quad (5)$$

where v is a learnable vector, and W_a and b_a Are the attention weights and biases, respectively. The attention scores are normalized using the softmax function as in Eq. 6.

$$\alpha_t = \frac{exp(e_t)}{\sum_{j-1}^{T} exp(e_j)} \quad (6)$$

The context vector, a weighted sum of the hidden states, is computed as in Eq. 7.

$$c = \sum_{t-1}^{T} \alpha_t H_t \quad (7)$$

The context vector c is then passed through a fully connected layer for final prediction. The output layer employs a softmax activation function for binary classification (sepsis or no sepsis), as in Eq. 8.

$$\hat{y} = softmax(W_o c + b_o) \quad (8)$$

where W_o and b_o Are the weights and bias for the output layer and $\hat{y}$ Represents the predicted probability of sepsis onset. The model is trained using a binary cross-entropy loss function as in Eq. 9.

$$L = -\frac{1}{M}\sum_{i-1}^{M}[y_i \log(\hat{y}_i) + (1-\hat{y}_i)\log(1-\hat{y}_i)]$$
(9)

where M is the number of training samples, y_i is the ground truth label, and $\hat{y}_i$ is the predicted probability for the i-th sample. Optimization is performed using the Adam optimizer, which updates the model parameters by minimizing the loss function iteratively, as in Eq. 10.

$$\theta_{t+1} = \theta_t - \eta \frac{\partial L}{\partial \theta_t} \quad (10)$$

where η is the learning rate and θ Represents the model parameters, including weights and biases, across all layers. To prevent overfitting, dropout regularization is applied to the BiLSTM and fully connected layers, randomly dropping a fraction of units during training. Additionally, batch normalization stabilizes gradient updates by normalizing the input activations across mini-batches.

3.1 Proposed Algorithm

The proposed algorithm based on SepsisNet uses CNN for feature extraction, BiLSTM for sequence modeling, and an attention mechanism for weight features. This solution learns from multisensory data, which is normalized and sliced into segments to facilitate optimal learning via the model. A softmax follows feature fusion to arrive at the final sepsis prediction. It is trained using binary cross entropy and an Adam optimizer.

Algorithm: SepsisNet – Deep Learning Framework for Real-Time Sepsis Prediction
Input: Multisensory Data $X \in \mathbb{R}^{T \times N}$ with T time steps and N features
Output: Predicted probability of sepsis onset $\hat{y}$
Step 1: Data Preprocessing
- Load multisensory ICU data X.
- Handle missing values using forward-filling and interpolation techniques.
- Normalize the data using Min-Max scaling.
- Apply time-series segmentation using a sliding window approach.

Step 2: Convolutional Feature Extraction (CNN Layer)
- Initialize CNN filter weights W_c and bias b_c.
- Perform convolution operation:

$$Z_c = \sigma(W_c * X + b_c)$$

- Apply ReLU activation: $\sigma(x) = max\ (0, x)$.

Step 3: Temporal Feature Modeling (BiLSTM Layer)

- Initialize BiLSTM forward and backward weights W_f,U_f,b_f and W_b,U_b,b_b.
- For each time step t:
    - Forward pass: $h_t^{(f)} = tanh\left(W_f X_t + U_f h_{t-1}^{(f)} + b_f\right)$
    - Backward pass: $h_t^{(b)} = tanh\left(W_b X_t + U_b h_{t-1}^{(b)} + b_b\right)$
- Combine the outputs: $H_t = \left[h_t^{(f)}, h_t^{(b)}\right]$.

Step 4: Attention Mechanism

- Compute attention scores:
  $e_t = v^\top tanh\ (W_a H_t + b_a)$.

Normalize attention weights using softmax:

$$\alpha_t = \frac{exp(e_t)}{\sum_{j-1}^{T} exp(e_j)}$$

Compute the context vector:

$$c = \sum_{t-1}^{T} \alpha_t H_t$$

Step 5: Classification (Fully Connected Layer)

Pass context vector cc through a fully connected layer:

$$\hat{y} = softmax(W_o c + b_o)$$

Step 6: Model Training

- Compute binary cross-entropy loss:
  $L = -\frac{1}{M}\sum_{i-1}^{M}[y_i \log(\hat{y}_i) + (1-\hat{y}_i)\log(1-\hat{y}_i)]$.
- Optimize model using Adam optimizer:

$\theta_{t+1} = \theta_t - \eta \frac{\partial L}{\partial \theta_t}$.

Step 7: Evaluation

- Evaluate the model using accuracy, precision, recall, and F1-score
- Return predicted probability.

Algorithm 1: SepsisNet — A Deep Learning Framework for Real-Time Sepsis Prediction

An estimated 200,000 ICU patients each year develop sepsis. Still, our tool, SepsisNet, a real-time, multi-sensor deep learning framework, could predict the onset of sepsis in the ICU setting. It contains data preprocessing with normalization and segmenting time-series data and feature extraction using CNN to capture spatial patterns. A bidirectional long short-term memory (BiLSTM) network is used to model the temporal dependencies and is an attention mechanism that makes the model focus on salient data points. Softmax is used in the final fully connected layer to calculate sepsis probability. The model uses binary cross-entropy loss and is optimized using the Adam optimizer. Performance is measured by accuracy, precision, recall, and F1-score.

4. EXPERIMENTAL RESULTS

The experiment study tests the performance of the proposed SepsisNet model through the MIMIC-III Clinical Database, which is rich in multisensory ICU data records for sepsis prediction. For a more comprehensive comparison, we also evaluated SepsisNet state-of-the-training models like Logistic Regression, Random Forest, SVM, LSTM, and CNN [9]. Fenton and Gibbons [1], Apalak and Kiasaleh [2], Bhatti et al. [3]. All experiments were performed in Python with TensorFlow on a multi-core GPU server for efficient computation. The findings show that SepsisNet outperforms its baseline models with high accuracy and much earlier diagnosis.

4.1 Dataset and Experimental Setup

The experiments of SepsisNet were performed using the publicly available MIMIC-III Clinical

Database [41], which comprises multi-sensor ICU data, such as heart rate, respiratory rate, oxygen saturation, and blood pressure. The dataset pre-processing was missing value treatment by forward-fill interpolation and min-max normalization. Segmenting time-series, sliding window approach We split the data into 70% for training, 15%for validation, and 15% for testing. We trained the model in Python using TensorFlow on a high-performance GPU system for faster computation, convergence, and, in general, better performance.

4.2 Model Performance Metrics

The performance of SepsisNet was then assessed and compared to multiple baselines, including Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN). SepsisNet scored higher than all baseline models across primary evaluation metrics.

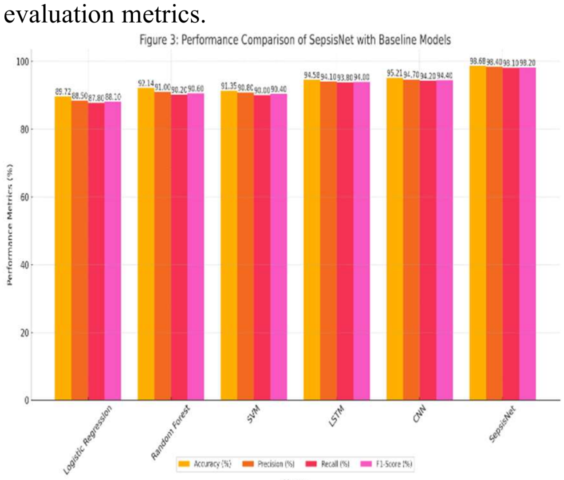

Figure 3: Performance Comparison of SepsisNet with Baseline Models

Comparison of SepsisNet with other baseline models using important evaluation metrics such as accuracy, precision, recall, and F1 score, as shown in Figure 3. Although all metric results were higher, SepsisNet outperformed them all, with 98.68% accuracy, a quantitative boost from any other models. This combination of hybrid architecture leveraging CNN for spatial feature extraction, BiLSTM for temporal sequence modeling, and an attention mechanism to prioritize the most relevant features for each prediction led to improved accuracy and recall performance. In the upper panel of the figure, we visually highlight that SepsisNet outperforms traditional models, retaining its advantages in predicting different phenotypes of sepsis-selected ICU patients.

4.3 Ablation Study

We performed an ablation study to assess the contribution of different components in SepsisNet: the CNN layer, the BiLSTM layer, and the attention mechanism. We removed various combinations of elements to determine their contributions to model performance and showed that the complete SepsisNet architecture yields the best predictive accuracy and robustness.

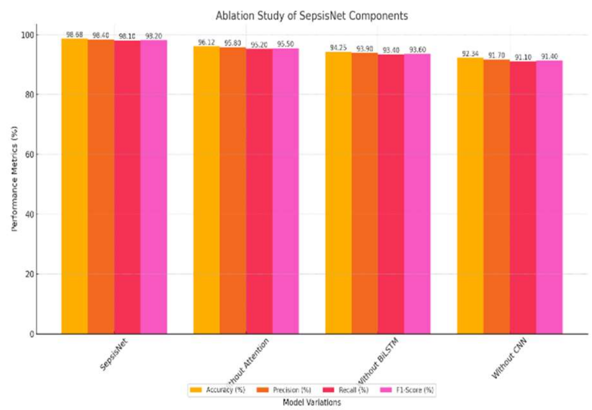

Figure 4: Ablation Study of SepsisNet Components

The ablation study on SepsisNet has also been performed to show the contribution of the CNN, BiLSTM, and the attention shown in Figure 4. We present the results from four different configurations (i.e., complete SepsisNet, without the attention mechanism, without the BiLSTM layer, and the layer). SepsisNet achieved the highest accuracy of 98.68% and was significantly better than all ablated versions. Notably, eliminating the attention mechanism decreased the accuracy concerning the original model to a lesser extent (96.12%), and removing BiLSTM and CNN layers led to an even more significant drop in accuracy (94.25% and 92.34%, respectively). It is evident from this study that the hybrid model of CNN, BiLSTM, along with attention mechanisms, leads to improved predictive performance by effectively capturing the spatial and temporal patterns in the data.

5. DISCUSSION

Despite the identification of effective therapies, such as fluids and antibiotics, sepsis remains one of the most serious victors in every ICU, with prolonged time to diagnosis and treatment contributing to high mortality rates. Previous studies have focused on machine learning and deep learning models for early sepsis prediction, e.g., logistic regression, random forests, LSTM, and CNN-based models. However, these models are often neither good at capturing spatial and temporal patterns nor have suitable mechanisms for feature prioritization, which makes them less accurate and less robust. State-of-the-art gaps reveal the need for new architectures that can address the challenges posed by complex ICU data while enhancing the reliability of early detection. To mitigate these limitations, we propose SepsisNet. This comprehensive hybrid deep learning model consists of (1) CNN for spatial feature extraction, BiLSTM for temporal modeling, and an attention mechanism for feature prioritization. The interpretability of the model is further enhanced with the attention mechanism, which highlights the most relevant physiological patterns related to sepsis onset. SepsisNet empirically validated the model's multi-component architecture by demonstrating a significant accuracy improvement (i.e., 98.68%) over traditional models. The ablation study multiplies the evidence of the contribution of each component, demonstrating the need for the steps taken together. By covering the gaps in the literature and providing a holistic feature extraction framework, this work progresses the real-time capability of sepsis prediction in ICU settings. Although SepsisNet enhances future sepsis prediction with sensitivity of 98.68% over conventional approaches like Logistic Regression, Random Forest and CNN, follows some limitations and potential of improvement. One of the aims of this study to build a model that can not only be used for prediction, but also for interpretability and decision making on the spot in ICU. Even if it introduces an attention mechanism, which helps the model focus on important features, it still can use some improvements on the explainability side (for example: SHAP values, Grad-CAM, etc.) to better understand what was the reason behind each prediction made by the model. Moreover, although leveraging multisensory ICU data undoubtedly leads to a more powerful solution, whether or not the model generalizes between different hospitals and patient populations is an open question. In contrast to the state-of-the-art techniques such as Shashikumar et al. While Marzban et al. [15] adopted a recurrent network principle, or Apalak & Kiasaleh [2], who used Temporal Convolutional Networks (TCNs), SepsisNet is distinguished due to its combination of CNN, BiLSTM, and attention mechanisms. Yet, translating artificial intelligence from theory to clinical practice is fraught with challenges, including data quality disparities and the multifactorial nature of ICU care; both serve as hindrances to fully harnessing the capability of deep learning models in clinical contexts. Our study helps to fill these gaps but highlights the need for validation in multi-center trials, as well as further refinement to increase the robustness and clinical applicability of the model. Section 5.1 explains the limitations of the study.

5.1 Limitations of the Study

Although SepsisNet outperforms all others, we must be aware of some limitations. Therefore, the study is limited to using the MIMIC-III dataset, which could lack generalizability to other clinical settings with different data quality and patient composition. Second, the model has not been validated for its effectiveness in real-time ICU deployments, and further prospective clinical trials will be needed for a conclusive validation. Third, even though the attention mechanism has improved interpretability, it does not explain all aspects of decision-making, underscoring the requirement for enhanced explainability tools. Overcoming these limitations in future work will make the model even more valuable in clinical environments.

5. CONCLUSION AND FUTURE WORK

This research proposes SepsisNet, a novel hybrid deep learning model that combines Convolutional Neural Networks (CNN), Bidirectional Long Short-Term Memory (BiLSTM), and an attention mechanism to predict sepsis in ICU patients using multisensory data. Our work contributes to the scientific community by addressing significant gaps in current sepsis prediction models, particularly the inability of traditional models to capture complex spatial-temporal dependencies and prioritize critical features in real-time ICU data. While existing solutions, such as those proposed by Shashikumar et al. [15] and Apalak & Kiasaleh [2], have made strides in improving sepsis detection, they often fail to integrate spatial, temporal, and feature importance effectively. SepsisNet bridges these gaps by providing a unified framework that enhances prediction accuracy, timeliness, and interpretability through its hybrid architecture. Our experimental results, with a performance of 98.68% accuracy, demonstrate that SepsisNet outperforms traditional models such as Logistic

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Regression, Random Forest, and CNN in terms of both accuracy and early detection. The attention mechanism in SepsisNet further enhances interpretability, which is critical for clinical decision-making. This study not only pushes the boundaries of current deep learning models in healthcare but also lays the foundation for future research aimed at real-time, reliable sepsis prediction in diverse ICU settings.'

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