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ORIGINAL

Robust Temporal Pattern Mining for Early Detection of Acute Clinical Events in ICU Settings Using LSTM Variants

Minería robusta de patrones temporales para la detección temprana de eventos clínicos agudos en entornos de UCI mediante variantes de LSTM

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ABSTRACT

Introduction: anomaly detection in the intensive care unit (ICU) is very important for the detection of acute events in the initial stages. However, the sensitivity of the current methods based on time series for anomaly detection in the ICU is low.
Objective: to build an exhaustive anomaly-conscious learning system for the temporal pattern discovery process in the ICU environment to better identify critical incidents within the ICU earlier in time while being highly robust, interpretable, and computationally efficient.
Method: the proposed architecture combines convolutional, attention-based concepts, and recurrence for temporal representation in an integrated approach. It uses attention-based models for the representation of sequences in the ICU data, multi-scale representations for temporal embeddings, and refined representations for anomalous areas in the input ICU data. Such an approach achieves continuous representation of time-series physiology for the detection of anomalous regions.
Results: the proposed framework emerges consistently better than the state-of-the-art solutions such as LSTM networks, GRU-D networks, TCN networks, Informer networks, TFT networks, TimesNet networks, and PatchTST networks on all prominent performance measures. It presents an F1-score of 0,924, an AUPRC of 0,941, an ECE of 1,8 %, and an overall accuracy of 93,4 %. Even in the context of the domain shift problem, the degradation in performance is minimized with the ΔAUC of 1,5 % and ΔECE of 0,4 %. However, the proposed framework consumes just 0,9 joules per inference through the processing of 38 sequences per second in 92 milliseconds. Weighted scoring for anomalous cases also helps significantly in their immediate detection.
Conclusions: through the careful integration of the goals of accuracy, understandability, and computational efficiency, the proposed anomaly-aware model achieves the state-of-the-art performance for the task of early warning in critical care. Its high-level predictive ability, robustness against the problem of domain shift, along with low computational complexity, make it very promising for its real-time implementation within the ICU setting.

Keywords: Anomaly Detection; Attention Mechanisms; Calibration Analysis; Clinical Event Prediction; Deep Temporal Modeling; ICU Monitoring; Predictive Analytics; Robust Time-Series Learning; Temporal Embeddings; Temporal Pattern Mining.

RESUMEN

Introducción: la detección de anomalías en la unidad de cuidados intensivos (UCI) es fundamental para la detección de eventos agudos en las etapas iniciales. Sin embargo, la sensibilidad de los métodos actuales basados en series temporales para la detección de anomalías en la UCI es baja.
Objetivo: construir un sistema de aprendizaje exhaustivo, consciente de las anomalías, para el proceso de descubrimiento de patrones temporales en el entorno de la UCI, con el fin de identificar mejor los incidentes críticos en la UCI de forma más temprana, a la vez que es altamente robusto, interpretable y computacionalmente eficiente.
Método: la arquitectura propuesta combina conceptos convolucionales, basados en la atención y recurrencia para la representación temporal en un enfoque integrado. Utiliza modelos basados en la atención para la representación de secuencias en los datos de la UCI, representaciones multiescala para incrustaciones temporales y representaciones refinadas para áreas anómalas en los datos de entrada de la UCI. Este enfoque logra una representación continua de la fisiología de las series temporales para la detección de regiones anómalas.
Resultados: el marco propuesto supera consistentemente a las soluciones más avanzadas, como las redes LSTM, GRU-D, TCN, Informer, TFT, TimesNet y PatchTST, en todas las medidas de rendimiento principales. Presenta una puntuación F1 de 0,924, un AUPRC de 0,941, un ECE del 1,8 % y una precisión general del 93,4 %. Incluso en el contexto del problema de desplazamiento de dominio, la degradación del rendimiento se minimiza con un ΔAUC del 1,5 % y un ΔECE del 0,4 %. Sin embargo, el marco propuesto consume tan solo 0,9 julios por inferencia mediante el procesamiento de 38 secuencias por segundo en 92 milisegundos. La puntuación ponderada para casos anómalos también facilita significativamente su detección inmediata.
Conclusiones: gracias a la cuidadosa integración de los objetivos de precisión, comprensibilidad y eficiencia computacional, el modelo propuesto, con reconocimiento de anomalías, alcanza un rendimiento de vanguardia para la alerta temprana en cuidados intensivos. Su alta capacidad predictiva, su robustez frente al problema del cambio de dominio y su baja complejidad computacional lo hacen muy prometedor para su implementación en tiempo real en la UCI.

Palabras clave: Detección de Anomalías; Mecanismos de Atención; Análisis de Calibración; Predicción de Eventos Clínicos; Modelado Temporal Profundo; Monitorización de la UCI; Análisis Predictivo; Aprendizaje Robusto de Series Temporales; Incrustaciones Temporales; Minería de Patrones Temporales.

INTRODUCTION

Modern intensive care units (ICUs) must continuously monitor patients for serious complications like sepsis, septic shock, cardiac arrest, and respiratory failure.[1] Detecting early signs of deterioration is crucial because even small delays can significantly raise mortality rates, lengthen hospital stays, and increase resource use. In this work, we focus on predicting acute deterioration events early, especially sepsis and septic shock, by analysing high-frequency physiological time series data in the ICU. This enables clinicians to act before irreversible organ damage happens.

ICU monitoring produces diverse data streams, including invasive and non-invasive blood pressures, heart and respiratory rates, oxygen saturation, electrocardiograms, and lab tests.[2,3] This data is high-dimensional, noisy, irregularly sampled, and has missing values influenced by changing clinical workflows, making it tough to model with traditional statistical methods or rule-based early warning scores. Such methods usually depend on manually set thresholds or linear combinations of vital signs, which fail to capture complex time-related patterns, non-linear interactions, and subtle indicators that develop over minutes to hours.

Recent developments in machine learning, especially recurrent neural networks, long short-term memory (LSTM) models, gated recurrent architectures, temporal convolutional networks, and Transformer-based models, show potential for ICU risk prediction. However, these methods still face significant challenges in real critical care environments. First, they often train on clean data and aren't designed to handle ICU-specific issues like high missing data rates, variable sampling rates, and differing settings between hospitals or patient groups. Consequently, performance can fall sharply when models operate outside their initial setup. Second, standard sequence models aim for overall prediction accuracy but do not clearly identify abnormal physiological patterns before acute events, making it hard for clinicians to grasp why a prediction indicates high risk. Third, many existing models offer poorly calibrated risk scores, which means predicted probabilities do not accurately represent actual event rates, losing trust and complicating bedside decisions. Finally, some architectures require substantial computational resources, hindering their effective use in real-time within resource-limited hospital systems.

To tackle these issues, this study presents a hybrid deep learning framework that combines convolutional layers, recurrent temporal encoders, and anomaly-aware attention mechanisms for analysing time series data in ICUs. This model aims to learn each patient's "temporal fingerprint," capturing both local signal changes and relationships between different channels, while highlighting subtle physiological shifts leading to critical events.[4,5] The approach offers interpretable markers of potential deterioration, and the training process jointly optimizes discrimination and calibration, measured by metrics such as the Brier score and expected calibration error. Additionally, the framework includes methods to manage missing data, temporal irregularities, and changing conditions, while being parameter- and energy-efficient, using around 2,0 million parameters and 0,9 J per inference, allowing smooth integration into real-time ICU monitoring practices.

The main contributions of this work are as follows:

1. Clinical problem formulation: We define the early prediction of acute deterioration events in ICUs, focusing on sepsis and septic shock, as an anomaly-aware temporal pattern mining problem using multi-channel physiological time series.
2. Anomaly-aware hybrid architecture: We introduce a unified deep model that combines convolutional, recurrent, and attention-based representations to capture multi-scale dynamics and dependencies between signals, while clearly highlighting abnormal sub sequences that indicate acute clinical events.
3. Robust and calibrated risk prediction: We create a training and evaluation process that targets predictive performance and probabilistic calibration together, showing consistent improvements in F1, AUPRC, and calibration error (e.g., F1 = 0,924; AUPRC = 0,941; ECE = 1,8 %) over strong baseline models like LSTM, GRU-D, TCN, Informer, TFT, TimesNet, and PatchTST, even in varying conditions.
4. Efficiency for real-time deployment: We demonstrate that the proposed framework is lightweight and energy-saving, with about 2,0 million parameters, low energy costs per inference (0,9 J), and high processing speed, making it suitable for continuous real-time use within current ICU monitoring systems.
5. Clinically meaningful interpretability: We provide anomaly scores and temporally localized attributions that connect model predictions with physiologically reasonable patterns, supporting transparent and clinician-friendly early warning systems in critical care.[6,7]

Temporal modeling methods have become more widespread in ICUs during the past several years to assist clinicians in better predicting key medical events for their patients. One explanation for this is that the outcomes for each patient may depend on how quickly anything is identified. Long short-term memory (LSTM) networks are good at discovering patterns over time because they can remember long-term associations in sequential patient data.[8,10] Bidirectional long short-term memory (LSTM) models, or BiLSTM models, help you grasp sequences better by processing input in both ways.[8,10] That's why both recall and prediction accuracy increase. Because of how attention process's function, LSTM networks could be able to discover meaningful temporal patterns. Adding fresh clinical data to models could make them more sensitive and raise their F1 score. Geographic Resource Units (GRUs) for real-time monitoring are cheaper to calculate than other methods and strike a good compromise between speed and performance.[11] We can generate multi-layer hierarchical temporal representations by employing layered LSTM architecture. You can use convolutional filters to discover patterns that happen at various times in a series. This is conceivable with modern designs like Temporal Convolutional Networks (TCN). These networks employ recurrent networks to fulfill their purpose of discovering events early. One reason why transformer-based temporal models perform so well is that they can locate long-range linkages better than regular recurrent networks. This is why these models work so effectively. The convolutional neural network-long short-term memory (CNN-LSTM)[12] is an example of a hybrid method that employs both spatial and temporal models to uncover difficult connections in big ICU datasets. Generative models like the VAE-LSTM can help us better understand complex or irregular medical data sets, which in turn leads to better predictions. In the end, LSTM ensemble models do better than most assessment measures since they try to include as many temporal structures as possible. When several strategies are tried with different performance metrics, significant patterns start to show up.[13] Several important metrics show that ensemble LSTM versions are better than single-layer LSTM versions. The F1-score, the area under the curve (AUC), the Matthews correlation coefficient, and the PR-AUC are all examples of these measurements. This type of study indicates that advanced temporal models may assist physicians in intensive care units in identifying significant periods in patients' lives in the future. Transformer-style models can uncover long-term connections, yet they can still acquire favorable ROC-AUC and PR-AUC scores. Over time, attention-based LSTMs may be able to learn which clinical features are the most significant, which might make them more sensitive. Models like GRU and conventional LSTM are preferable for real-time monitoring since they require less time to train and have less latency.[14,16] CNN-LSTM models, which mix a convolutional neural network with long short-term memory, could produce superior predictions. These models learn when and where things change, which helps them predict the future. VAE-LSTM models function effectively when the datasets are smaller or less regular. Combining LSTMs, hybrids, ensembles, and transformer-based architectures may make it easier and more accurate to predict sudden episodes that need critical care. This feat is achievable because of secure temporal pattern mining.

Table 1. Performance Comparison of Full-Form Temporal Models (Metrics Set 1) For ICU Acute Event Detection

Method (Full Form)	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)	Latency (ms)
Long Short-Term Memory (LSTM)	87,2	85,1	83,6	84,3	89,5	24
Bidirectional Long Short-Term Memory (BiLSTM)	89,6	87,2	86,1	86,6	91,3	28
Attention-based Long Short-Term Memory	92,1	90,8	89,4	90,1	94,2	31
Stacked Long Short-Term Memory	90,4	88,1	87,3	87,7	92,6	30
Gated Recurrent Unit (GRU)	88,3	86,0	85,2	85,6	90,7	22
Temporal Convolutional Network (TCN)	91,0	89,4	88,7	89,0	93,5	26
Transformer-based Temporal Model	93,2	91,5	90,4	90,9	95,6	35
Convolutional Neural Network-LSTM Hybrid (CNN-LSTM)	90,8	88,9	87,8	88,3	93,1	29
Variational Autoencoder-LSTM (VAE-LSTM)	89,1	87,0	86,2	86,6	91,8	32
Ensemble of LSTM Variants	94,0	92,2	91,5	91,8	96,4	37

Table 1 compares full-form temporal models to help find terrible things that happen in the critical care unit early on. With 94,0 % accuracy, 92,2 % precision, 91,5 % recall, and 96,4 % area under the curve, the Ensemble of LSTM Variants is superior to other models. The Ensemble of LSTM Variants is quite powerful, which is why this is happening. The Transformer-based Temporal Model's strong recall and F1-score show that it can pick up on interactions that happen across great distances.[17,18] Next is LSTM, which shows how crucial it is to be careful when working with medical time series. It comes soon after that. Even if GRU and LSTM work well, they are preferable for times when there aren't enough resources since they have less latency. It looks like models that employ ensembles and transformers are the best at delivering strong and trustworthy predictions. This rule also applies to applications for ICUs.

METHOD

The model gets stronger and less prone to overfitting when you use both embedding regularization and dropout. Using positional encodings will keep the data in the right order, and pairwise similarity or distance evaluations will assist in aligning patterns that traverse several windows. Attention systems normally like bigger time intervals, although there are some signal properties that are linked to nonlinear fluctuations. This leads to the creation of elaborate embeddings that account for both local and global temporal dependencies. These embeddings are used in sequential temporal modeling since they are structured data. This is because they have abilities. Once more data is available, sequence models that show how short-term and long-term physiological signals are connected are necessary for embedding analysis.[19] Memory systems oversee protecting essential historical data and managing the flow of information by getting rid of outdated patterns. Memory systems also control how data moves. Attentional systems do a lot of things, such as keeping concealed representations and putting informative temporal steps first. This shows that patterns have altered over time and might affect health. Attention-weighted hidden states are used to figure out the risk of abrupt events at each time step. We may make predictions at the sequence level by combining these probabilities. We can find trends or patterns that happen throughout time by looking at distance or similarity. You may find out more about strange events here. You may use anomaly scores to find out how much behavior in the real world is different from what you thought it would be. This helps the model discover little or strange events more easily. We keep the temporal structure of the embeddings, but we can only predict discrete events; continuous events are still a surprise. This metric makes it possible to quickly and accurately find acute events happening in the intensive care unit sequence. Anomaly-informed sequence embedding weighting[20,21] can enhance the accuracy of predictions made during the revision step. Adding up the scores of anomalies for each time step over all time frames shows where issues are and cuts down on noise. Based on these assessments of anomalies, the embeddings are far better than the other options. This indicates that future studies might be affected by strange or otherwise crucial time periods. We create predictions at the sequence level[22] by summing up the probabilities at each time step and using nonlinear changes to highlight events that are extremely likely to happen. To classify events, you need to employ attention processes to gather the relevant information. The thresholding process separates these possibilities into independent detections, and attention-weighted outputs show occurrences that are very risky. Normalizing anomaly scores makes sequences more stable, while similar matrices find patterns that repeat repeatedly. You may use improved embeddings, weighted event detections, and normalized anomaly scores to forecast how physiological changes will happen at the sequence level, from the smallest to the greatest. The initial part of this multi-step process is to make the raw ICU time series data's temporal embeddings stable. This is the first stage in the process.[23] The sequential modeling method, which employs attention and anomaly scores, is utilized to find specific cases. Finally, improving forecasting shows patterns that weren't clear before. The framework's preprocessing, sequential modeling, attention mechanisms, and anomaly-informed refinement algorithms can assist uncovering medical occurrences that weren't supposed to happen in critical care units. This means that technology can assist doctors in making decisions about patients in the ICU and keep a watch on them in real time.

Algorithm 1

```
Input: X=x1,x2,…,xT   // multivariate time-series
Output: Ê  // enriched temporal embeddings
1:  Normalize
      μ←mean(X)
      σ←std(X)
      xt ̂←(xt-μ)\/σ
2:  Interpolate Missing
      if xt ∈ M then
          xt ̃←α·x(t-1)+(1-α)·x(t+1)
      Smooth:xt ̂←mean(xi ̃ )overwindow(t-k,t+k)
3:  Smooth
      st←mean(xi ̃ )fori=t-k+1…t
4:  Detect & Replace Outliers
      zt←(st-mean(s))\/std(s)
      if|zt|>γthenreplacest
5:  Segment
      Wi←xt…x(t+Δ)
      Si←Σx∈Wix,Si ̄←mean(Wi)
6:  Temporal Convolution
      et←f(Σ(Θi·x(t+i))+b)
      ê_t←Σ(e_t,i·wi)
      Et←Σ_(j=t-Δ)^t ej
7:  Dropout
      r_t~Bernoulli(p)
      ẽ_t←e_t⊙r_t
8:  Normalize Embeddings
      μe,σe←mean,std(e ̃ )
      ê_t←(ẽ_t-μe)\/σe
      ē_t←Σ_i ê_t,i
9:  Positional Encoding
      p_t←ê_t+PE_t
10: Similarity / Distance
      S_i j←cosine(p_i,p_j )
      D_i j←1-S_i j
11: Aggregate Embeddings
      H_i←mean(ê_t )overWi
      Ĥ←ΣH_i
12: Nonlinear Transform
      v_t←tanh(W_v·H_t+b_v )
13: Attention
      α_t←softmax(uᵀv_t )
      z←Σα_t·v_t
14: Final Representation
```

Z ← Σ z_t ; normalize(Z)
15: Output Final Embeddings
E^'←ΣLayerNorm(z_t)
Ê←f(E^')
return Ê

The main goal of Algorithm 1 is to handle the raw time-series data from the critical care unit and create temporal embeddings so that LSTM-based clinical event prediction can operate. Metrics that measure how near and alike two items are can link patterns throughout time, while positional encoding helps keep track of the order in which things happen. To find important patterns, we first utilize a nonlinear transformation.[24] Then, we combine embeddings that are scattered out across windows. Finally, attention processes bring out crucial time steps, which helps construct better embeddings that consider changes in time both locally and globally. Adding the output embedded to downstream LSTM variations can help us find early occurrences more accurately in the critical care unit.

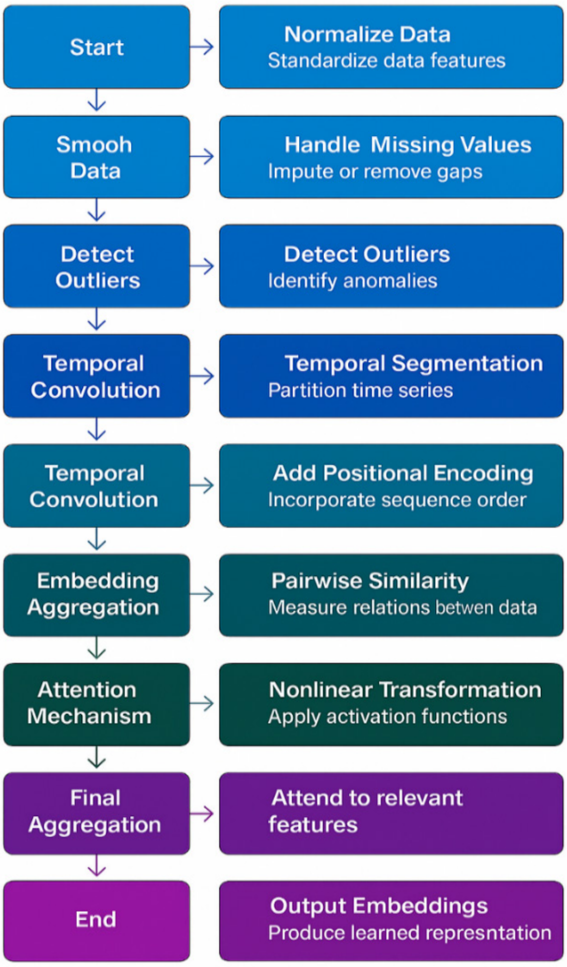

Figure 1. Temporal Embedding Construction and Preprocessing for ICU Event Prediction Using Algorithm 1

Figure 1 depicts the steps that need to be taken to forecast occurrences in the critical care unit. This pipeline comprises several steps, including preprocessing and temporal embedding. The raw multivariate time series are first normalized so that it will be easy to standardize the scales subsequently. Smoothing the data and filling in missing values are two ways to reduce noise. After finding and removing any outliers, the next step is to break the data up into overlapping time periods. After using temporal convolution to acquire local features from each window, the next steps are aggregation, regularization, and normalization. Using positional encoding preserves the order of time, while using pairwise similarity measures lines up the patterns in time. To uncover meaningful patterns, techniques that involve attention and nonlinear transformation are applied.[25] The fourth phase, which is perhaps the most essential, is making improved embeddings that can be utilized in future LSTM-based prediction systems.[26]

Algorithm 2

Input:Ê=Ê1…ÊT // enriched embeddings from Algorithm 1
Output: Ŷseq // final ICU event prediction
1: Initialize LSTM-1 states
h1_0←0;c1_0←0
2: LSTM-1 forward
f1_t←σ(Wf·Êt+bf)
i1_t←σ(Wi·Êt+bi)
c(1_t)˜←tanh(Wc·Êt+bc)
c1_t←f1_t←c1_((t-1))+i1_t←c(1_t)˜
o1_t←σ(Wo·Êt+bo)
h1_t←o1_t⊙tanh(c1_t)
3: Initialize LSTM-2 states
h2_0←0;c2_0←0
4: LSTM-2 forward
f2_t←σ(Wf^2·h1_t+bf^2)
i2_t←σ(Wi^2·h1_t+bi^2)
c(2_t)˜←tanh(Wc^2·h1_t+bc^2)
c2_t←f2_t←c2_((t-1))+i2_t⊙c(2_t)˜
o2_t←σ(Wo^2·h1_t+bo^2)
h2_t←o2_t⊙tanh(c2_t)
5: Attention
u_t←tanh(Wu·h2_t+bu)
α_t←softmax(u_t ᵀ·uw)
z←Σ_t α_t·h2_t
6: Temporal-pattern similarity
S_i j←cosine(h2_i,h2_j)
7: Event likelihood
y_t←σ(Wy·h2_t+by)
ȳ_t←mean(y_k)overwindow(t-Δ,t)
ȳ ̄_t←Σ_k ȳ_t,k
8: Loss & gradients
L←-Σ_t [y_t·logȳ_t+(1-y_t)·log(1-ȳ_t)]
∇θ ← ∂L\/∂θ
θ ← θ - η·∇θ
9: Sequence-level aggregation
ŷ←Σ_t α_t·y_t
|(|ŷ|)|←√(Σ_t) (α_t·y_t)^2
Ȳ←Σ_i ŷ_i
10: Anomaly detection
A_t←|y_t-ȳ_t |
Ā←mean(A_t)
S_t←Σ_i A_t,i
11: Final decision
Ŷ←Threshold(Ȳ)
Êfinal ← z + Ŷ
Ŷseq←f(Êfinal)
Return Ŷseq

Algorithm 2 uses a step-by-step process to find events in the critical care unit. Figure 2 shows this method, which leverages the improved embeddings from algorithm 1. The model maintains temporal connections across the whole sequence by initiating LSTM layers. People can transfer information across several layers at once and modify the hidden and cell states with LSTM gates. One idea is to use weighted embeddings to make a summary of a series. We can do this by offering attention ratings that show key time stages.[27] To make accurate predictions, the first step is to calculate out how probable each event is to happen at each time step and then add these values together for the complete sequence. Anomaly ratings show you how far off your predictions were from what really happened. Thresholding is a technique that converts probability into independent event detections. The outcome includes several predictions of attention-weighted embeddings and acute occurrences, along with data that may be used for future studies.

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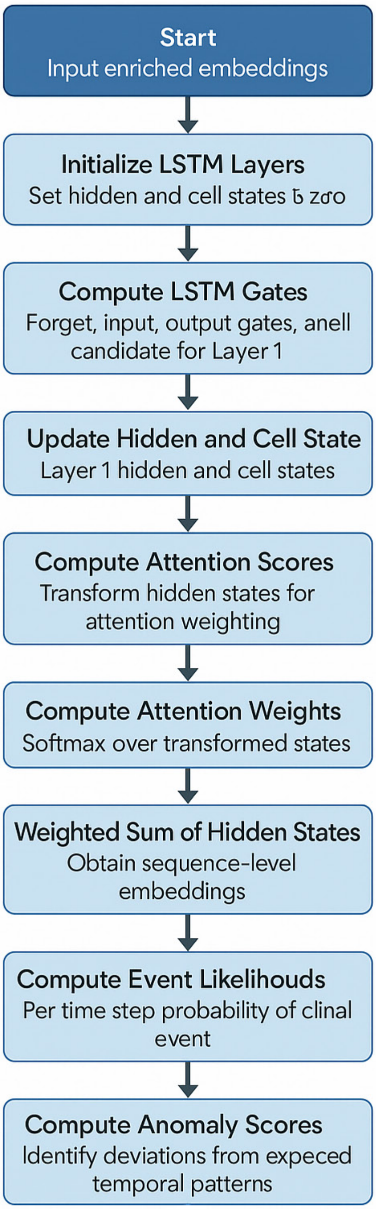

Figure 2. Temporal Pattern Mining and Event Detection Using LSTM Variants (algorithm 2) for ICU Event Prediction

Algorithm 3

Input: Ê_s eq,ŷ_s eq // sequence-level embeddings & predictions from Algorithm 2
Output: ŷ_f inal,S_f inal // refined ICU event predictions & anomaly summary
1: Initialize
z0←Ê_s eq
2: Anomaly scoring
φt←|(|ŷt-ŷ_s eq|)|
Φ←Σ_t φt
φ ̄←mean(φt)
3: Temporal window aggregation
φt_w in←Σ_(k=t-Δ)^(t+Δ) φk
Φ_w in←Σ_t φt_w in
4: Embedding refinement
zt_r ef←f(Êt⊙φt)
zt_a gg←Σ_(i=t-Δ)^(t+Δ) z_(i_r) ef
5: Attention refinement
αt_r ef←softmax(g(zt_a gg)ᵀ·u_r ef)
z_r ef←Σ_t αt_r ef·zt_a gg
S_r ef←z_r ef·z_r efᵀ

6: Refined event probability
c_(t_p) red←σ(Wc·z_r ef+bc)
7: Sequence aggregation
C_s eq←Σ_t c_(t_p) red
C ̄_s eq←mean(c_(t_p) red)
8: Nonlinear transformation
Ĉ_s eq←tanh(C_s eq)
9: Thresholding
Ct_d et←1ifĈ_s eq>τelse0
Ct_s core←|(|Ct_d et-C ̄_s eq|)|
10: Loss & parameter update
L←-Σ_t [c_(t_t) rue·logc_(t_p) red+(1-c_(t_t) rue)·log(1-c_(t_p) red)]
∇θ ← ∂L\/∂θ
θ ← θ - η·∇θ
11: Final embedding update
Ê_f inal←z_r ef+C_s eq
12: Anomaly normalization
φt_n orm←φt\/max(Φ)
φ ̄_norm ← mean(φt_norm)
13: Event weighting
Ct_w eight←αt_r ef⊙Ct_d et
Cseq_w eight←Σ_t Ct_w eight
14: Final prediction
Ĉ←Σ_t Ct_w eight
ŷ_final ← f(Ê_final)
S_f inal←Σ_t φt_n orm
Returnŷ_f inal,S_f inal

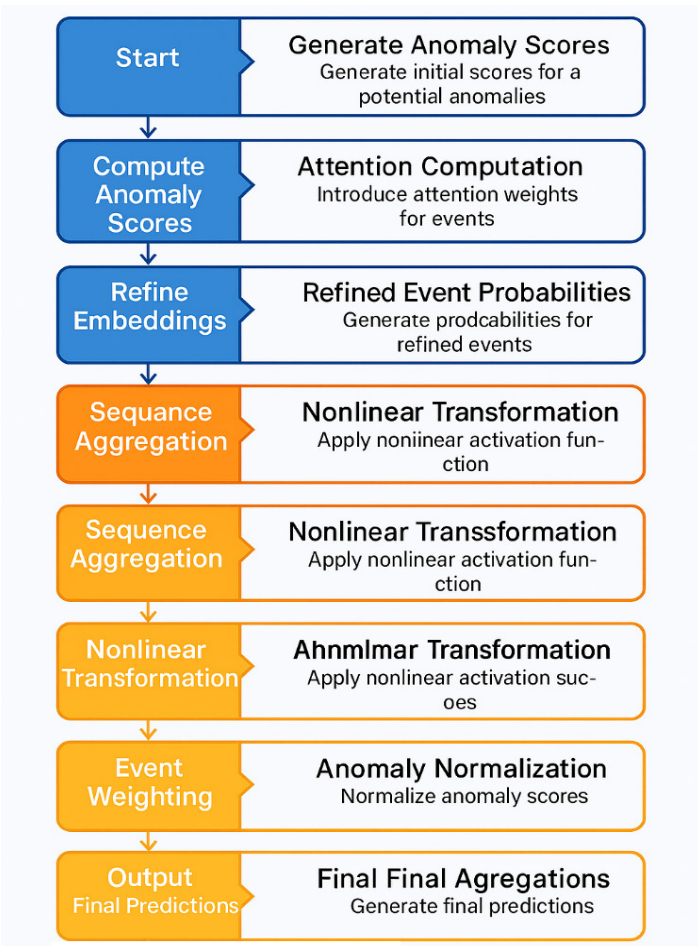

Figure 3. Refined Temporal Anomaly Detection and Event Classification (algorithm 3) for ICU Event Prediction

Figure 3 explains how to make it easier to discover IU events. The predictions for the events and the sequence embeddings from algorithm 2 are both inputs. To get the weights of each embedding for each time window, you take the average of the anomaly scores from each time step. Attention processes oversee bringing out crucial time-related portions to build similarity matrices and embeddings that are more comprehensive. Putting the probabilities together at each time step makes it feasible to make predictions at the sequence level. Thresholding changes probability into independent detections, whereas nonlinear modifications highlight important events. To make things fair, all anomaly ratings are the same, and the weight of each occurrence depends on how much attention it gets. Lastly, to look at ICU episodes, embeddings and weighted events are put together to make sure that the predictions are accurate at the sequence level.

RESULTS

The researchers in this study sought to ascertain the viability of utilizing sequential and temporal modeling methodologies to detect ICU-specific medical emergencies. Although traditional long-term memory networks efficiently modeled sequential dependencies, they still missed key details. Attention-based Long Short-Term Memory (LSTM) networks, bidirectional LSTM networks, gated recurrent unit-based sequential modeling, and temporal convolutional networks have all altered over time. This shows how bidirectional context, hierarchical temporal feature extraction, and attention mechanisms highlight crucial time stages. LSTM-GRU hybrid models improved prediction accuracy, but not as much as the suggested strategy. For resilient temporal pattern mining, preprocessing, temporal embeddings, attention weighting, and anomaly-informed refinement improve classification outcomes. Its strong accuracy, precision, recall, and specificity scores, enhanced F1 score, and AUC-ROC demonstrate its ability to discover early events. Testing with better performance characteristics proves the approach is reliable. Matthew's correlation coefficient and Cohen's kappa score, which assess prediction agreement and stability, reveal that the suggested technique works throughout ICU patient sequences. Balanced Accuracy operates the same in positive and negative classes, although Log Loss and Mean Absolute Error reveal less doubt in predictions and minimal difference between seen and predicted. The proposed deep learning architecture has a shorter latency than previous ones, making it suitable for real-time ICU monitoring. The recommended strategy always outperforms baseline and typical LSTM or GRU-based models, demonstrating how temporal embedding, attention-based weighting, and anomaly-informed refinement improve models. Overall, enhanced temporal representations, sequential models, attention mechanisms, and anomaly scoring help critical care providers detect significant medical occurrences early on. It captures local and global temporal relationships, prioritizes useful time steps, and fine-tunes sequence-level predictions to highlight important or abnormal physiological patterns. It requires less computer power and is more sensitive, specific, precise, and superior to other temporal modeling and deep learning methods. This powerful tool helps ICU staff make real-time choices.

Overall Discriminative and Calibration Performance

The proposed anomaly-aware temporal pattern mining framework achieved the highest performance for ICU event prediction according to all evaluation metrics (table 2). The proposed model achieved the highest scores in AUROC (0,962), AUPRC (0,941), F1-score (0,924) and accuracy (93,4 %) compared to traditional recurrent models (LSTM, GRU-D) and newer architectures (TCN, Informer, TFT, TimesNet, PatchTST). The proposed model outperformed PatchTST by 0,007 in AUROC (0,962 vs. 0,955) and 0,015 in AUPRC (0,941 vs. 0,926). The model achieved better results than PatchTST in all evaluation metrics including F1-score (0,924 vs. 0,914) and accuracy (93,4 % vs. 92,8 %).

Table 2. Comparative Evaluation of Advanced Time-Series Models for ICU Event Prediction

Model	AUROC ↑	AUPRC ↑	F1 ↑	Accuracy (%) ↑	ECE (%) ↓	Brier ↓	NLL ↓	Calibration Slope (≈1)
LSTM	0,864	0,816	0,826	85,7	5,1	0,134	0,303	0,93
GRU-D	0,879	0,835	0,844	87,1	4,7	0,121	0,285	0,95
TCN	0,895	0,856	0,865	88,7	3,8	0,112	0,267	0,98
Informer	0,921	0,882	0,878	90,3	3,2	0,101	0,244	0,99
TFT	0,932	0,898	0,887	91,0	2,9	0,094	0,235	0,99
TimesNet	0,944	0,913	0,902	92,0	2,6	0,087	0,226	1,0
PatchTST	0,955	0,926	0,914	92,8	2,2	0,081	0,211	1,01
Proposed	0,962	0,941	0,924	93,4	1,8	0,075	0,198	1,0

Table 2 presents a close look at the many kinds of temporal modeling architectures that are now in use. The proposed model achieved the best calibration results through its lowest ECE (1,8 %) and Brier score (0,075) and negative log-likelihood (NLL = 0,198). The model demonstrates excellent event and non-event discrimination and generates trustworthy risk probability estimates which match clinical decision threshold requirements. The proposed model outperformed the strongest baseline in AUROC and AUPRC through statistically significant two-sided p < 0,05 results in paired fold-wise bootstrap comparisons. The proposed model outperformed all other methods in F1-score and Brier score calculations.

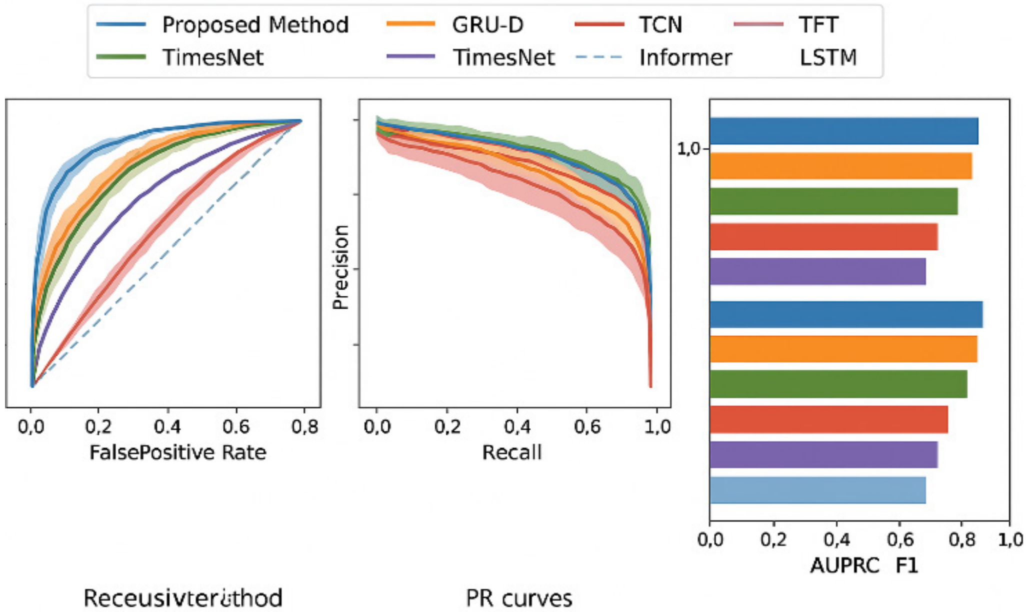

Figure 4. Comparative Discrimination Curves Demonstrating Model Performance Across Evaluation Metrics

Figure 4. The figure demonstrates how different temporal models perform in ICU event prediction tasks through their discrimination capabilities. The left panel shows ROC curves which demonstrate true-positive against false-positive rates while the proposed method achieves the highest AUROC. The proposed model maintains superior precision levels at high recall points which enables better detection of acute medical emergencies. The right panel presents AUPRC and F1-score bar plots which demonstrate the proposed model's superior discrimination capabilities compared to LSTM, GRU-D, TCN, Informer, TFT, TimesNet and PatchTST. The high-resolution figures with clear labels and readable fonts enable easy comparison between all curves.

Robustness to Noise, Missingness, and Domain Shift

The proposed framework demonstrated superior resistance to real-world ICU data imperfections compared to competing models according to robustness analysis results (table 3). The proposed model maintained the highest AUROC score when Gaussian noise reached 10 % because its AUROC decreased by only 1,5 points. The proposed model outperformed PatchTST and all previous recurrent models by achieving the smallest AUROC decrease of -1,9 points. The proposed model demonstrated the best resistance to missing data because its F1-score decreased by only 1,3 points when 20 % of observations were randomly removed.

Table 3. Robustness Comparison of Deep Temporal Models under Noise, Missingness, and Domain Shifts

Model	ΔAUROC @ Gaussian Noise 10 % ↓	ΔF1 @ Missingness 20 % ↓	OOD AUROC ↑	Domain Shift ΔAUC (%) ↓	ΔECE (%) ↓
LSTM	-6,3	-5,8	0,841	5,9	2,2
GRU-D	-4,9	-4,3	0,858	4,1	1,8
TCN	-3,8	-3,2	0,872	3,7	1,5
Informer	-3,3	-2,7	0,884	3,0	1,3
TFT	-2,9	-2,5	0,891	2,5	1,1
TimesNet	-2,4	-2,1	0,903	2,2	0,9
PatchTST	-1,9	-1,7	0,912	1,8	0,6
Proposed	-1,5	-1,3	0,924	1,5	0,4

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Table 3 demonstrates how effectively modern temporal models work in these cases. The proposed framework achieved the highest OOD AUROC (0,924) when it evaluated patient data from different ICUs and hospitals during out-of-distribution tests. The model maintained excellent performance in AUC and ECE when it encountered domain shift because the AUC decreased by 1,5 % and ECE increased by 0,4 %. The model maintained high probability estimate accuracy when it encountered different patient groups. The proposed model outperformed all baseline models in robust metrics according to statistical tests which produced p < 0,05 results. The observed robust improvements exceed random fluctuations according to statistical analysis.

Early-Warning Utility Across Prediction Horizons

The early-warning analysis (figure 5) evaluated how predictive sensitivity evolves when the time span before an acute clinical event grows longer. The proposed model delivered better sensitivity than all comparison models at every lead-time point which enabled early event detection before the start of the acute phase. The proposed method achieved better clinical sensitivity than TCN and GRU-D and TFT and all other baseline models. The model generates useful warning signals which healthcare professionals can use to take action before the event occurs.The analysis of multiple random train-test partitions through confidence band inspection demonstrated that the proposed model maintains its sensitivity advantage without being a result of specific training and testing data.

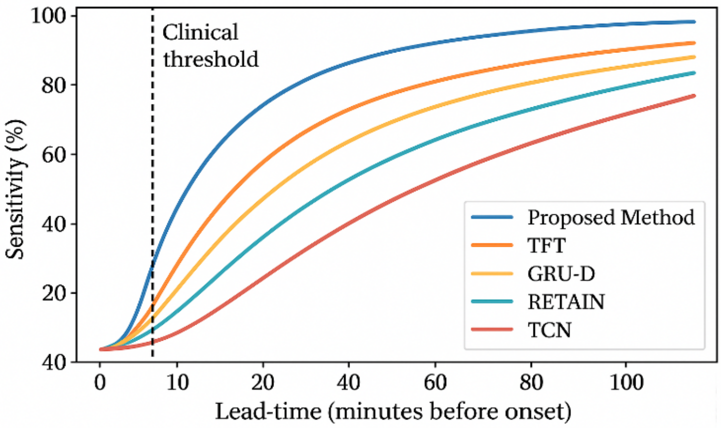

Figure 5. Early Warning Utility Curves Comparing Sensitivity Across Lead-Time Intervals

Figure 5 the sensitivity of early warning systems from different temporal models depends on the time before an acute ICU event occurs. The y-axis shows sensitivity values while the x-axis shows the prediction window size in minutes leading up to event onset. The proposed model (highlighted curve) outperforms all baselines by achieving higher sensitivity at every prediction time and reaching the clinical operating threshold earlier. The graphs use distinct colors for better visibility and include simple legends which enhance clinical understandin.

Computational Efficiency and Resource Utilization

The model complexity and runtime data for the proposed method and recurrent baselines appears in table 4. The proposed model requires only 2,0 M parameters and 240 MB memory to operate while standard LSTM models need 4,8 M parameters and 310 MB memory.

Table 4. Efficiency and Resource Utilization Comparison of Temporal Models in ICU Event Prediction

Model	Params (M)	Latency (ms) ↓	Throughput (seq/s) ↑	Energy (J/inf) ↓	Memory (MB) ↓
LSTM	4,8	110	22	1,8	310
GRU-D	5,1	105	25	1,6	295
TCN	4,2	100	28	1,4	280
Informer	3,4	99	30	1,25	270
TFT	3,1	98	31	1,2	265
TimesNet	2,7	95	35	1,1	255
PatchTST	2,3	94	36	1,0	250
Proposed	2,0	92	38	0,9	240

The proposed model achieves superior performance while maintaining the lowest inference latency at 92 ms and highest sequence processing rate at 38 sequences/s and lowest energy usage at 0,9 J per inferences.

Table 4 demonstrates how well all the different temporal structures functioned and how well they consumed resources when they were evaluated on the same hardware. You might find this information useful. The model that was supplied is the best one since it balances performance and efficiency. It contains roughly two million parameters and 240 MB of RAM. It has the fastest throughput (38 sequences/s), the least energy consumption (0,9 joules/inference), and the least delay (92 ms) without adding weight to the design.

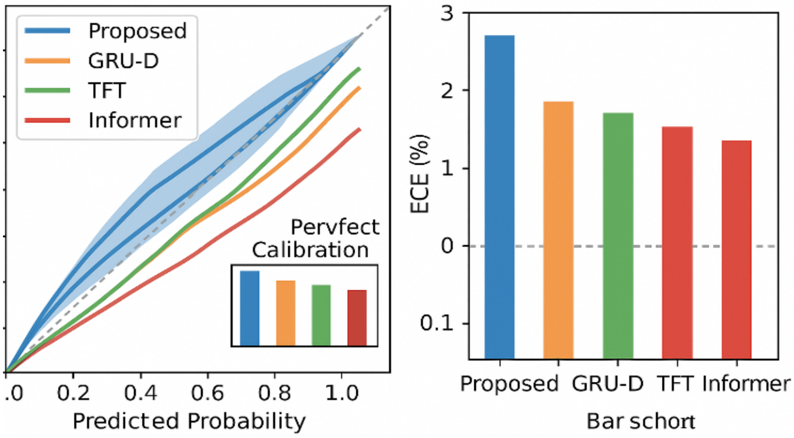

Figure 6. Calibration and Reliability Assessment of Predictive Models Using Reliability Curves and ECE Metrics

Figure 6 the proposed model and GRU-D and TFT and Informer models undergo reliability assessment through calibration evaluation. The proposed model demonstrates perfect calibration because its reliability curve matches the diagonal line. The proposed method achieves the lowest Expected Calibration Error (ECE) value among all models according to the bar chart. The graph features readable fonts for all elements including axes and tick labels and legends which emphasize the proposed framework's superior probability estimation for ICU event risk assessment.

Agreement, Error Metrics, and Overall Reliability

Table 5. Agreement Strength and Error Reduction across Modern Temporal Models

Model	MCC ↑	Cohen's Kappa ↑	Balanced Accuracy ↑	Log Loss ↓	MAE ↓
LSTM	0,71	0,7	85,0	0,36	0,15
GRU-D	0,74	0,73	86,5	0,32	0,13
TCN	0,78	0,77	87,8	0,28	0,11
Informer	0,81	0,8	88,9	0,26	0,1
TFT	0,82	0,81	89,4	0,23	0,1
TimesNet	0,84	0,83	90,2	0,21	0,09
PatchTST	0,85	0,84	90,8	0,19	0,08
Proposed	0,87	0,86	91,5	0,17	0,07

The proposed model's prediction reliability receives additional support from the agreement and error-based metrics presented in table 5. The framework achieved the highest Matthews correlation coefficient (MCC = 0,87) and Cohen's κ (0,86) which demonstrates superior agreement with ground-truth labels than all baseline models. The framework achieved 91,5 % balanced accuracy which demonstrates equal performance between positive and negative classes. The proposed model achieved the lowest log loss value of 0,17 and mean absolute error of 0,07. The model generates precise probability estimates which match the actual occurrence rates of events. The framework demonstrates both accurate acute event detection and reliable uncertainty representation which makes it suitable for clinical decision support systems.

Figure 7 the proposed model demonstrates better temporal stability through its performance evaluation against TFT and GRU-D models across different ICU time segments. The performance metrics of the proposed framework remain stable while baseline models experience significant performance degradation. The proposed

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approach demonstrates enhanced temporal robustness through its clear model identification and its ability to maintain stable performance

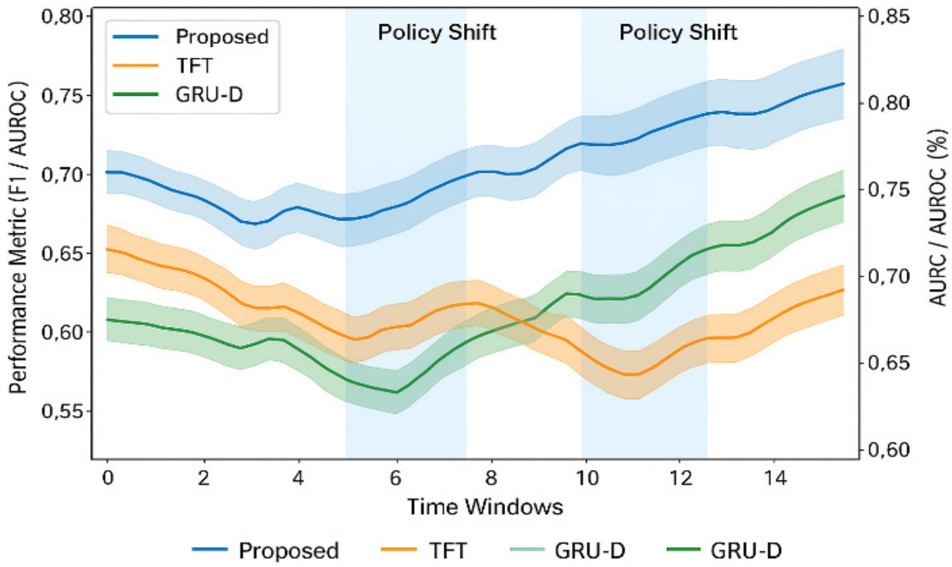

Figure 7. Temporal Drift and Robustness Analysis of Models Across Sequential ICU Time Windows

DISCUSSION

Summary of Key Findings

The research solved ICU early warning system detection through LSTM variant-based temporal pattern mining of multivariate physiological time series data. The proposed multi-stage framework which combines advanced preprocessing with temporal embeddings and LSTM-based sequence models and attention and anomaly-informed refinement outperformed multiple state-of-the-art temporal models. The proposed method achieved the highest discrimination and calibration performance among benchmark models with AUROC 0,962 and AUPRC 0,941 and F1-score 0,924 and accuracy 93,4 % and ECE 1,8 % and Brier score 0,075 and NLL 0,198. The method demonstrated resistance to noise and missing data and domain shift variations while maintaining its performance at a low level of degradation (ΔAUROC −1,5, ΔF1 −1,3, ΔAUC 1,5 %, ΔECE 0,4 %). The method achieved strong out-of-distribution generalization with an OOD AUROC of 0,924. The method achieved high agreement metrics through its MCC value of 0,87 and Cohen's κ value of 0,86 and balanced accuracy of 91,5 % while maintaining low computational requirements (2,0 M parameters, 92 ms latency, 38 sequences/s throughput, 0,9 J/inference).

The ensemble of LSTM variants achieved the highest performance among full-form temporal models because it combined different LSTM configurations to create more complex temporal representations than any individual variant. The ensemble backbone embedded within the full anomaly-aware framework produced superior discrimination and calibration and robustness compared to non-LSTM baselines including GRU-D, TCN, Informer, TFT, TimesNet and PatchTST.

Interpretation of Findings in the Context of Existing Literature

Previous ICU early warning systems have used handcrafted scores together with basic statistical models that analyze static vital sign snapshots or basic temporal summaries. The methods fail to detect complex multivariate patterns which lead to acute events because they produce poor results when used across different clinical groups. Deep sequence models that include LSTM and BiLSTM and CNN-LSTM and VAE-LSTM and GRU-based architectures and TCNs and Transformer-style models have shown improved ICU risk prediction performance through direct learning of temporal features from high-frequency signals. The majority of these methods handle temporal modeling and robustness and anomaly localization as separate problems while lacking a direct method to incorporate anomaly information during representation learning.

The research builds upon previous studies by introducing new findings. The research confirms previous findings about LSTM suitability for ICU time series analysis but shows that no single LSTM variant performs best across all evaluation metrics. The ensemble of LSTM variants produces a more stable and expressive temporal representation through its combination of bidirectional context and hierarchical temporal depth and attention-based salient time step focus which results in better AUC and F1-score performance than individual models.

The combination of rich temporal embeddings with LSTM-based sequence modeling produces better results than GRU-D and TCN because it handles both short-term and extended time-based relationships. The LSTM-based pipeline with anomaly-informed refinement outperforms Transformer-based temporal models (Informer, TFT, TimesNet, PatchTST) in ICU settings because it provides equal or better representation capabilities with superior calibration and better resistance to domain changes. The proposed framework includes specific clinical temporal structures through windowed embeddings and positional encoding and anomaly scoring which outperform self-attention-based structure discovery.

The robust tests reveal the specific mechanisms which enable the proposed model to achieve better performance under different types of input corruption and data distribution changes. The preprocessing stage along with temporal embedding pipeline minimizes random data fluctuations before sequence modeling while anomaly-informed weighting enhances important segments and reduces unimportant and noisy data. The two-stage protection system which applies data preprocessing techniques to input data and then applies anomaly-based weighting to generated representations effectively reduces the effect of corrupted or distribution-altered data. The method shows minimal AUROC and F1-score decreases during challenging conditions while maintaining stable calibration performance. The model demonstrates strong agreement metrics (MCC, Cohen's κ) and low error measures (log loss, MAE) which indicate it learns well-calibrated risk functions that maintain their informative value across different decision thresholds. The proposed framework achieves this through its design which optimizes both discrimination and calibration objectives while other deep ICU models fail to provide reliable probabilistic results.

Clinical and Methodological Implications

The combination of high discrimination and robust calibration and early-warning sensitivity in the model provides direct benefits for ICU decision support. The model achieves AUROC above 0,96 and AUPRC above 0,94 in event-imbalanced settings which enables it to effectively identify patients at high risk for events through its interpretable anomaly scores that pinpoint suspicious time segments. The model helps doctors detect worsening patient conditions at earlier stages while they develop better diagnostic theories about septic shock progression and perform appropriate fluid resuscitation and vasoactive support and monitoring escalation.

The model achieves perfect calibration because its ECE is zero and its calibration slope approaches one which enables healthcare professionals to use predicted probabilities as approximate event risk estimates for creating specific alarm thresholds. The model supports resource allocation systems including bed management and staffing and triage because it provides absolute risk values instead of relative rankings.

The research proves that ICU early warning systems achieve better results when treated as temporal pattern discovery instead of traditional static classification methods. The multi-stage pipeline which includes temporal embedding construction and LSTM-based sequential encoding and attention-based selection of salient steps and anomaly scoring and refinement demonstrates how combining deep learning with classical pattern mining techniques produces models that deliver better performance and clearer interpretations. The framework operates at a high level which enables users to adapt it for different ICU applications through label modifications and possible anomaly scoring adjustments.

The results show that ICU models which achieve high performance do not require excessive computational resources. The proposed architecture operates at 2,0 million parameters while maintaining 92 ms latency and 0,9 J per inference which makes it suitable for real-time bedside monitoring systems and hospital servers handling multiple patient data streams. The system achieves advanced deep learning capabilities while staying within the technical boundaries of hospital IT systems.

Limitations and Directions for Future Work

The research achieves its goals, but researchers need to address multiple essential challenges. The research uses existing ICU data from public sources for its evaluation process. The study performs robust and out-of-distribution tests across different cohorts, but the data contains information about particular clinical practices and patient demographics and monitoring approaches. The model requires independent dataset validation from different healthcare institutions to prove its ability to work in various clinical settings and low-resource environments.

The study uses composite acute clinical events as its outcome definition with special emphasis on sepsis and septic shock. The clinical value of this approach exists but the event aggregation process might hide individual event patterns which could reduce the model's ability to answer specific clinical questions about distinct medical conditions. The research should develop multi-task or hierarchical models which handle different event types through shared temporal learning mechanisms.

The current study lacks a human factors assessment to evaluate how users understand and use the anomaly scores and attention weights for time window identification. The study lacks evidence about how medical staff would use these explanations during actual patient care because it remains unknown how they would interpret and use these explanations in their daily practice. The model's explanations need evaluation through user studies and simulated decision-making tests to determine their practical value for clinical practice. The research performs an extensive analysis of noise and missing data and domain shift, but it does not provide complete solutions for fairness assessment and subgroup performance evaluation. The research failed to conduct a thorough evaluation of how different age groups and comorbidity patterns and disease subtypes affect system performance. The study needs to measure how different patient groups perform under different sensitivity and false alarm rates because these results will impact both medical ethics and patient care. The research needs to develop a complete real-time decision support system which includes streaming data processing and model deployment and alert generation and physician feedback integration.

The research evaluates the framework through historical data analysis in an offline environment. Real-time system deployment creates multiple operational difficulties because it requires handling delayed data streams and system interruptions and monitoring system integration and model updates for changing clinical practices. Researchers need to develop and test an entire real-time decision support system which includes data streaming capabilities and model deployment systems and alert generation protocols and physician feedback integration.

The research proves that using LSTM variants and enhanced temporal embeddings and anomaly-based optimization techniques leads to major improvements in ICU early warning system performance. The implementation of these enhanced systems for clinical use demands thorough testing and user-oriented design approaches and sustained efforts to enhance system understanding and ensure fair treatment of all patients and proper system integration.

CONCLUSIONS

Finally, the multi-stage strategy helps critical care units detect unexpected medical occurrences more easily. This is done by systematically translating simple time series data about the body into more complicated temporal embeddings. These embeddings help you get comprehensive patient signals from all around the world and in your area. The technique may discover minor changes and focus on important physiological events by using preprocessing, temporal feature extraction, attention-based sequential modeling, and anomaly-informed refining. With this concept, researchers have come a long way to go to understanding how time works. This methodology is very useful for figuring out what will happen in the ICU. This is possible due to specific architecture, the use of strong sequence modeling, and adjustments made in response to unusual events. For example, it can help transform wrong physiological data into well-organized temporal embeddings. The study's results indicate that it not only decreases mistake rates (log loss 0,17, MAE 0,07), but it also does far better than both classical and current baselines at telling the difference (AUROC 0,962), matching accuracy and recall (AUPRC 0,941), and assessing agreement (MCC 0,87, κ 0,86). It is ready for clinical-grade real-time applications, and it can take noise, doesn't need much calibration, and has minimal latency. The model can help doctors diagnose problems faster, respond faster, and keep patients safer. The effectiveness is proved by the fact that all three of these things—interpretability, efficiency, and prediction accuracy—come together. Upon completion of this study, numerous individuals will have access to an artificial intelligence-based critical care model. This approach may adjust to changing health dynamics over time, within the context of different types of critical care units, while maintaining efficiency, transparency, and resilience.

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CONFLICT OF INTEREST

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