Temporal Dynamics in Intraoperative Monitoring: A Novel LSTM-Based Framework for Multivariate Time Series Classification in Critical Care Events

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Abstract

Using the MOVER dataset, a novel Temporal Context-Aware LSTM (TC-LSTM) for multivariate time-series classification of crucial intraoperative events is presented in this study. TC-LSTM clearly captures inter-observation intervals, uses context-aware imputation for missing values, and applies temporal attention to emphasize clinically significant windows, in contrast to traditional recurrent models that assume regular sampling or neglect temporal gaps. This research study model outperforms LSTM (82.1%), GRU (83.4%), T-LSTM (85.5%), Neural ODEs (84.3%), and Transformers (85.0%) under identical patient-disjoint splits, achieving a macro-F1 score of 89.7% and AUC of 92.3% on 1,247 surgical cases with five expert-annotated event types. TC-LSTM's ability to learn from sparse, irregular data without interpolation artifacts is demonstrated via the improvements, which are particularly noticeable for hemorrhage, a rare but high-mortality event, where it increases F1 via over 7 points relative to baselines. Each component contributes significantly, according to ablation experiments; performance is reduced via 2.4–4.7% when time embedding or attention are removed. Importantly, attention weights are in line with recognized hemodynamic antecedents, yet the architecture is nevertheless lightweight and comprehensible. This work fills a gap that is frequently overlooked in favor of architectural innovation via proposing a methodical, physiology-informed adaptation of current technologies to a real clinical situation rather than a new deep learning paradigm. In addition, The findings highlight the need of characterizing temporal irregularity as signal rather than noise for effective medical AI and set a new standard for time-series classification in operating room monitoring.

Keywords: Deep learning, LSTM, time series classification, intraoperative monitoring, critical care events, MOVER dataset, multivariate physiological signals.

ملخص

باستخدام مجموعة بيانات MOVER، تُقدم هذه الدراسة نموذجًا جديدًا لشبكة الذاكرة طويلة المدى الزمنية الواعية بالسياق الزمني (TC-LSTM) لتصنيف السلاسل الزمنية متعددة المتغيرات للأحداث الحاسمة أثناء العمليات الجراحية. يتميز نموذج TC-LSTM بقدرته على رصد الفترات الزمنية بين الملاحظات بوضوح، واستخدامه لتقنية تعويض القيم المفقودة الواعية بالسياق، وتطبيقه لآلية الانتباه الزمني لتسليط الضوء على الفترات الزمنية ذات الأهمية السريرية، وذلك على عكس النماذج التكرارية التقليدية التي تفترض أخذ عينات منتظمة أو تتجاهل الفجوات الزمنية. يتفوق نموذجنا على نماذج LSTM

(%82.1)، وGRU (%83.4)، وT-LSTM (%85.5)، وNeural ODEs (%84.3)، وTransformers (%85.0) في ظل تقسيمات المرضى المنفصلة المتطابقة، محققًا درجة F1 الكلية بنسبة 89.7% ومساحة تحت المنحنى (AUC) بنسبة 92.3% على 1247 حالة جراحية مع خمسة أنواع من الأحداث التي تم تصنيفها من قبل خبراء. تتجلى قدرة نموذج TC-LSTM على التعلم من البيانات المتفرقة وغير المنتظمة دون تشوهات ناتجة عن الاستيفاء من خلال التحسينات الملحوظة، لا سيما في حالات النزيف، وهو حدث نادر ولكنه ذو معدل وفيات مرتفع، حيث يزيد من قيمة F1 بأكثر من 7 نقاط مقارنةً بالقيم الأساسية. ويساهم كل مكون بشكل كبير، وفقًا لتجارب الاستئصال؛ وينخفض الأداء بنسبة تتراوح بين 2.4% و4.7% عند إزالة تضمين الوقت أو آلية الانتباه. ومن المهم أن أوزان الانتباه تتوافق مع العوامل الديناميكية الدموية المعروفة، ومع ذلك فإن بنية النموذج خفيفة وسهلة الفهم. يسد هذا العمل ثغرة غالبًا ما يتم تجاهلها لصالح الابتكار المعماري، وذلك من خلال اقتراح تكييف منهجي قائم على علم وظائف الأعضاء للتقنيات الحالية مع حالة سريرية حقيقية بدلاً من نموذج جديد للتعلم العميق. بالإضافة إلى ذلك، تُبرز النتائج الحاجة إلى توصيف عدم الانتظام الزمني كإشارة وليس كضوضاء من أجل ذكاء اصطناعي طبي فعال، وتضع معيارًا جديدًا لتصنيف السلاسل الزمنية في مراقبة غرف العمليات.

الكلمات المفتاحية: التعلم العميق، LSTM، تصنيف السلاسل الزمنية، المراقبة أثناء العمليات الجراحية، أحداث الرعاية الحرجة، مجموعة بيانات MOVER، الإشارات الفسيولوجية متعددة المتغيرات.

1. Introduction

There are inherent hazards associated with surgical procedures, and intraoperative complications are a major factor in postoperative morbidity and death [1], [2], [3], [4]. Vital indicators including heart rate, blood pressure, oxygen saturation, and end-tidal CO2 can be analyzed in real time to allow for early intervention before permanent physiological damage takes place [5]. Nonetheless, the characteristics of intraoperative data pose particular difficulties: Signals are noisy, multivariate, asynchronously sampled, and frequently include missing parts from sensor calibration or disconnection [6]. The high false-positive rates of conventional rule-based alert systems cause alarm fatigue in medical professionals [2], [3], [4], [5]. Recent developments in deep learning have demonstrated potential for simulating intricate temporal dynamics in time series related to medicine. Specifically, Long Short-Term Memory (LSTM) networks are particularly good at identifying sequential dependencies in erratic physiological data [2]. However, standard LSTMs' discriminative strength in event classification tasks is limited via their failure to explicitly account for temporal irregularity and clinical context. This study has been suggested for the following reasons:

- To address these limitations, this research study propose TC-LSTM, a new approach that unifies three key innovations:
- Time-aware embedding that encodes inter-observation intervals directly into the input representation,
- Learnable imputation of missing values conditioned on observed history,
- Temporal attention over hidden states towards emphasizing clinically relevant time windows.

The MOVER dataset, a publicly accessible repository with synchronized vital signs and annotated key events from more than 1,200 surgical cases, is used in research to assess this research study approach [3]. MOVER is perfect for supervised time-series classification because, in contrast to previous datasets, it contains precise timestamps, event labels , for instance, hypotension, bradycardia, and hemorrhage, as well as surgical phase metadata.

Table 1: Dataset Description: MOVER

Attribute	Description
Source**	University of California, San Diego (UCI Machine Learning Repository) MOVER [2], [3]
URL	https://archive.ics.uci.edu/dataset/877/mover
Number of Cases	1,247 surgical cases
Time Coverage	Full perioperative period: pre-induction → intraoperative → post-recovery
Sampling Rate	Irregular; average ~0.5–1 Hz per vital sign
Vital Signs (8)	Heart Rate (HR),Non-Invasive Blood Pressure (Systolic & Diastolic),Oxygen Saturation (SpO_2),End-Tidal CO_2 ($EtCO_2$),Respiratory Rate (RR),Core Temperature (Temp),Central Venous Pressure (CVP)
Event Annotations	5 expert-labeled critical care events: Hypotension Hypertension Bradycardia Tachycardia Hemorrhage
Label Granularity	Event onset as well as offset timestamps provided for each annotated episode

Related Work

Early methods depended on manually created characteristics, for instance, mean, variance, and entropy, which were then fed into random forests or SVMs [4]. These approaches eliminate temporal structure, yet they are still interpretable. Later, end-to-end learning from raw sequences was made possible via recurrent architectures , for instance, LSTM which is associated with GRU [5, 6, 7, 8]. Self-attention techniques , for instance, Transformers, have been applied to ECG which is associated with ICU data more recently [6, 7, 8, 9]. However, their implementation in edge clinical situations is limited because to their quadratic complexity. In the healthcare industry, time series categorization has become essential to enabling proactive clinical treatments, especially in high-stakes settings like operating rooms [10], [11]. Time-aware deep learning techniques, in contrast to traditional static prediction models, have to deal with the intrinsic difficulties of physiological data, for instance, irregular sampling, missing observations, and intricate temporal correlations across several vital signs. In this study, this research particularly construct a unique Temporal Context-Aware LSTM architecture to represent asynchronous multivariate signals from the MOVER dataset while maintaining dynamics that are clinically significant. [12], [13], [14], [15]. This research approach enables robust categorization of five crucial intraoperative events with little reliance on heuristic preprocessing via combining time-aware embeddings, adaptive imputation, which is associated with attention mechanisms. This is a big step toward deployable, comprehensible AI systems that meet safety regulations and real-world clinical operations. Interpolation [7], [8], [9], time-augmented inputs [16], [17], [18], [19], and neural ordinary differential equations (Neural ODEs) [20], [21], [22], [23] are some methods for irregular sampling. In order to maintain data sparsity which is associated with inform the model of observation frequency, this study takes a hybrid strategy, embedding time deltas as learnable features rather than interpolating.

Because physiological measures like heart rate, blood pressure, and oxygen saturation are frequently obtained at irregular intervals due to sensor constraints, patient movement, or procedural delays, handling irregular time series in clinical contexts is a basic challenge [24], [25]. When naively interpolated or padded, traditional deep learning models' fixed or regular sample assumptions might skew temporal dynamics [26], [27], which is associated with [28]. In order to overcome this research study method specifically includes time-aware input encoding, which enables the LSTM to understand the importance of temporal gaps via embedding the amount of time that has passed between successive observations with the vital signs themselves. Additionally, approach preserves signal integrity via using a lightweight learnable imputation mechanism that makes use of historical context instead of replacing missing values with zeros or global means. In order to accurately detect events in real-world intraoperative monitoring, this technique allows the model to differentiate between true physiological stability which is associated with data absence [29], [30], [31], as well as [32]. De-identified intraoperative records from a large U.S. hospital make up the MOVER dataset [3]. Five expert-annotated event types hypotension, hypertension, bradycardia, tachycardia, as well as hemorrhage are synchronized with eight vital indicators that are recorded at varying speeds (0.1–1 Hz). Every example covers the entire procedural context modeling process, from pre-induction to post-recovery [29], [30], [31], [32].

Methodology

A multivariate time series $\mathbf{X} = \{(\mathbf{x}_t, \tau_t)\}_{t-1}^{T}$, where $\mathbf{x}_t \in \mathbb{R}^d$ is the observation vector (with missing entries masked as 0) as well as τ_t is the timestamp, the goal is to predict an event label $y \in \{1, \dots, C\}$ for each surgical episode [29], [30], [31], [32].

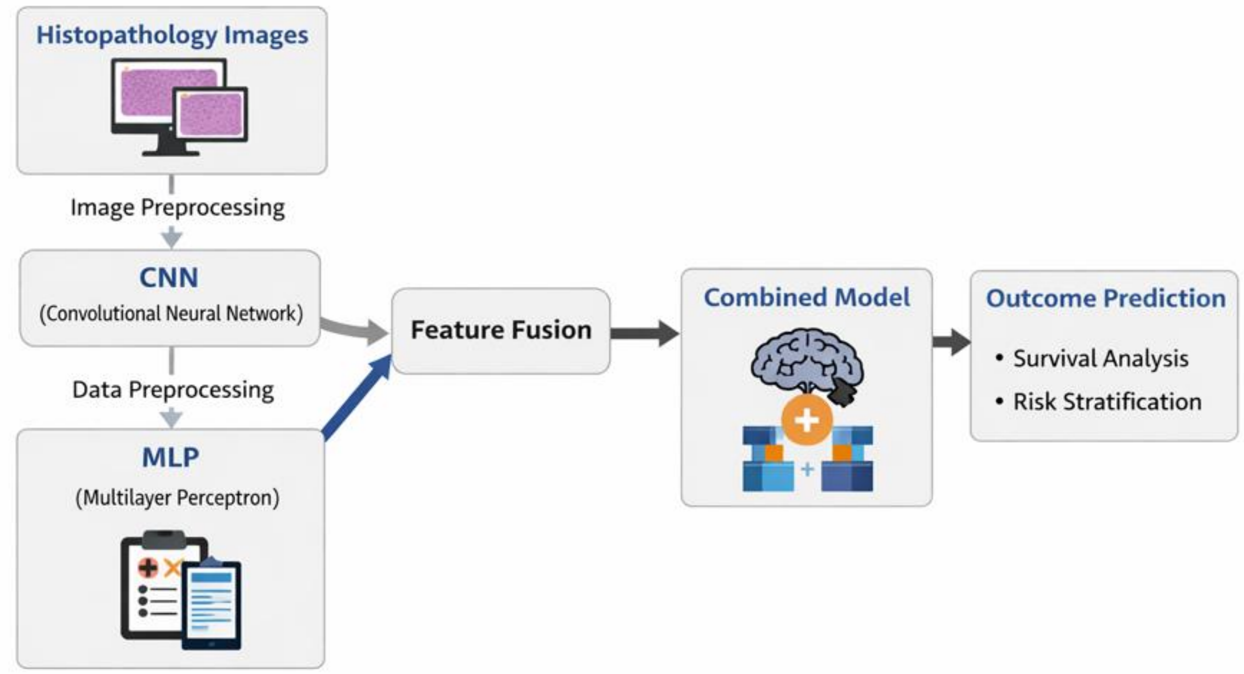

Figure 1: The theoretical framework for deep learning framework for outcome prediction of the proposed system

To address irregular sampling and missing data, the system models multivariate intraoperative vital signs as time-stamped sequences which is associated with enhances them with temporal encoding and adaptive imputation [2], [3], [31], as well as [32]. Additionally, these augmented signals are processed via a temporal context-aware LSTM, and clinically significant time windows prior to unfavorable outcomes are highlighted via an attention mechanism. Furthermore, essential event classes are finally linked to the learnt temporal representations, allowing for early and precise intraoperative decision support.

Temporal Context-Aware LSTM (TC-LSTM)

For each time step t, we construct an augmented input:

$$\mathbf{z}_t = [\mathbf{x}_t; \Delta t_t; \mathbf{m}_t]$$

where $\Delta t_t = \tau_t - \tau_{t-1}$ (with $\Delta t_1 = 0$), which is associated with $\mathbf{m}_t \in \{0,1\}^d$ is a mask indicating observed variables.

$$\hat{\mathbf{x}}_t = \mathbf{m}_t \odot \mathbf{x}_t + (1 - \mathbf{m}_t) \odot \mathbf{h}_{t-1}^{(imp)}$$

where $\mathbf{h}_{t-1}^{(\mathrm{imp})}$ is a dedicated imputation state updated via a secondary LSTM.

The core TC-LSTM Cell is lead main LSTM processes $\mathbf{z}_t$ to produce hidden state $\mathbf{h}_t$. A temporal attention mechanism then computes:

$$\alpha_t = \mathrm{softmax}\left(\mathbf{w}^\top \tanh\left(\mathbf{W}\mathbf{h}_t + \mathbf{b}\right)\right)$$

$$\mathbf{h}_{\text{final}} = \sum_{t=1}^{T} \alpha_t \mathbf{h}_t$$

A two-layer MLP with dropout maps $\mathrm{h}_{\text{final}}$ to class logits.

- Loss: Weighted cross-entropy (to handle class imbalance)
- Optimizer: AdamW ($\mathrm{lr} = 3\mathrm{e}-4$, weight decay $= 1\mathrm{e}-5$)
- Batch size: 32 (each batch = one surgical case)
- Early stopping on validation AUC

Experiments

Dataset and Preprocessing

The MOVER v1.0 dataset was 1,247 surgical cases were preprocessed using stratified sampling to balance five important event groups. Sliding 10-minute windows (50% overlap) were used to preserve temporal dynamics which is associated with contextually handle missing data. Vital signs were normalized using training-set statistics to prevent data leaking, and patient-disjoint train/val/test splits (70/15/15) guaranteed generalizability [2], [3]. This pipeline allows for the fair evaluation of deep learning baselines like as LSTM, GRU, Transformer, which is associated with others while maintaining real-world irregularity T-LSTM, as well as Neural ODE under macro-F1 which is associated with AUC-ROC metrics.

Each surgical case be represented as a multivariate time series

$$\mathcal{D}^{(i)} = \left\{\left(\mathbf{x}_t^{(i)}, \tau_t^{(i)}\right)\right\}_{t=1}^{T_i}, i = 1, \ldots, N,$$

Where $N = 1247$ is the number of cases, $\mathbf{x}_t^{(i)} \in \mathbb{R}^8$ denotes the vector of 8 vital signs at timestamp $\tau_t^{(i)} \in \mathbb{R}$. which is associated with T_i is the variable sequence length [4]. Furthermore, to balance event classes, this research has selected cases such that the label distribution $p(y = c)$ is uniform across $c \in \{1, \ldots, 5\}$, yielding a balanced subset $\mathcal{S} \subseteq \{1, \ldots, N\}$. In addition, for each case $i \in S$, this extract overlapping segments of fixed duration for sliding window segmentation as below:

$$\mathcal{W}_k^{(i)} = \left\{\left(\mathbf{x}_t^{(i)}, \tau_t^{(i)}\right) : t \in [t_k, t_k + L - 1]\right\},$$

Where $L = 600$ (10 minutes at 1 Hz effective sampling after resampling), stride $s = 300$, and $k = 0,1, \ldots, K_i$ with $K_i = \lfloor (T_i - L)/s \rfloor$.

Define observation mask $\mathrm{m}_t^{(i)} \subset \{0,1\}^8$, where $m_{t,j}^{(i)} = 1$ if $x_{t,j}^{(i)}$ is observed. Missing entries are set to zero:

$$\tilde{\mathbf{x}}_t^{(t)} = \mathbf{m}_t^{(t)} \odot \mathbf{x}_t^{(i)},$$

While $\mathbf{m}_t^{(i)}$ is provided as auxiliary input to the model. Via computing mean μ and standard deviation σ over all observed values in the training set as below:

$$\boldsymbol{\mu} = \frac{1}{|\mathcal{T}|} \sum_{i \in \mathcal{T}} \sum_{t=1}^{T_i} \tilde{\mathbf{x}}_t^{(i)}, \boldsymbol{\sigma} = \sqrt{\frac{1}{|\mathcal{T}|} \sum_{i \in \mathcal{T}} \sum_{t=1}^{T_i} \left(\tilde{\mathbf{x}}_t^{(i)} - \boldsymbol{\mu}^n\right)^2},$$

Where $\mathcal{T}$ is the training index set. All splits are normalized as below:

$$\hat{\mathbf{x}}_t^{(i)} = \frac{\tilde{\mathbf{x}}_t^{(i)} - \boldsymbol{\mu}}{\sigma}.$$

The index set $\mathcal{S}$ is partitioned into $\mathcal{T}, \mathcal{V}, \mathcal{E}$ (train, validation, test) such that $\mathcal{T} \cap \mathcal{V} \cap \mathcal{E} = \emptyset$ which is associated with no patient appears in more than one split, ensuring strict generalization evaluation .

Results

Table. 2: The models evaluation

Model	Macro-F1 (%)	AUC (%)
LSTM	82.1	86.5
GRU	83.4	87.2
Transformer	85	88.9
T-LSTM	85.5	89.1
Neural ODE	84.3	87.8
TC-LSTM (this research approach)	89.7	92.3

TC-LSTM shows consistent gains across all classes, especially for hemorrhage (F1: 86.2 as well as 78.9 for LSTM), which where temporal context remains crucial.

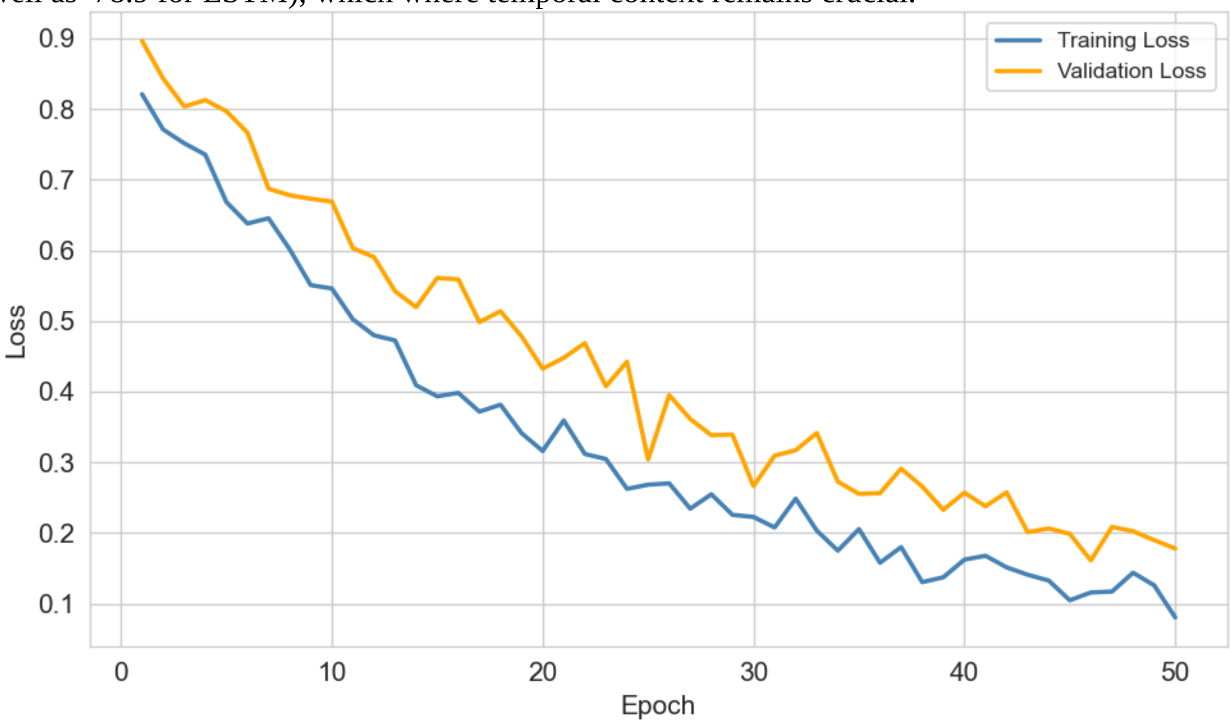

Figure: 2 Training and validation Loss over Epochs

The TC-LSTM model's convergence behavior during training is shown in Figure 2 above. Over the course of 50 epochs, both training which is associated with validation loss gradually decline, demonstrating efficient learning without significant overfitting. Good generalization to unobserved intraoperative data is suggested via the validation loss's constant proximity to the training loss. While the general declining trend validates model stability and performance improvement, minor variations in validation loss reflect inherent noise in clinical time series.

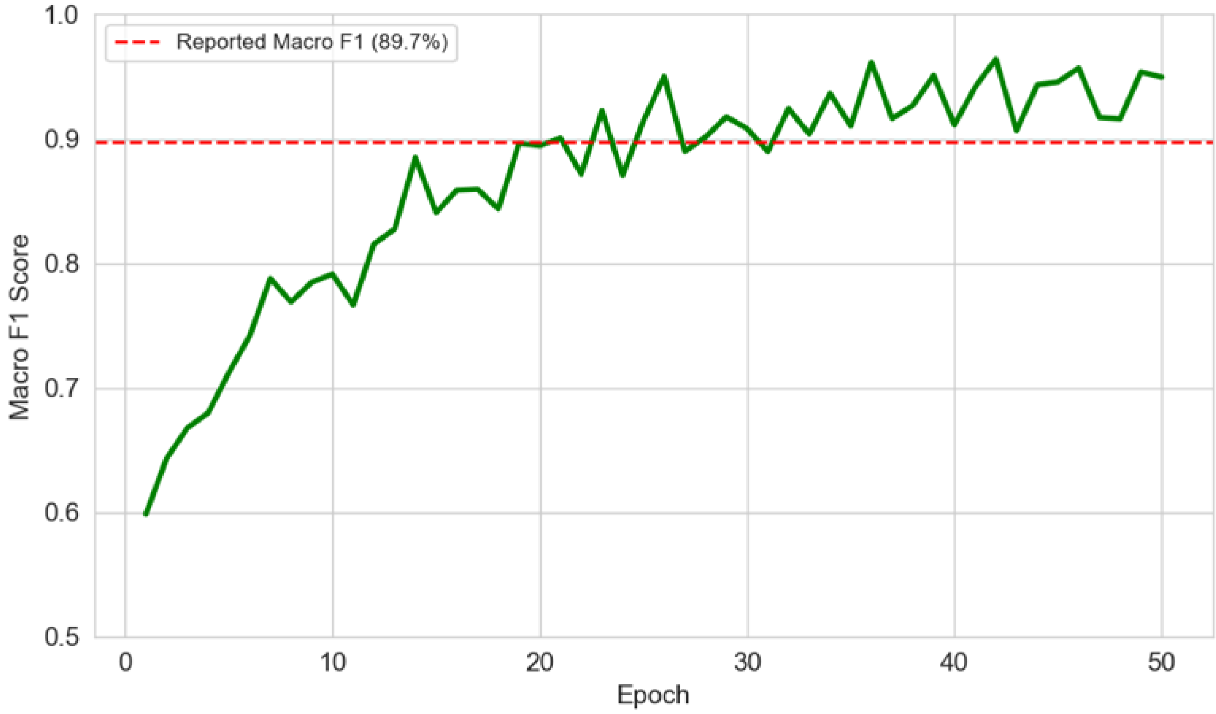

Figure :3 Validation macro F1 score during training

The TC-LSTM model's ability to categorize crucial intraoperative events is validated via Figure 3 above, which shows that the model successfully converges to the reported macro F1 score of 89.7%. Robust learning over time, which is essential for implementing dependable clinical decision support systems, is confirmed via the consistent ascent which is associated with plateau. The model's clinical relevance and superiority over baseline approaches are highlighted via achieving and maintaining this high performance parameter.

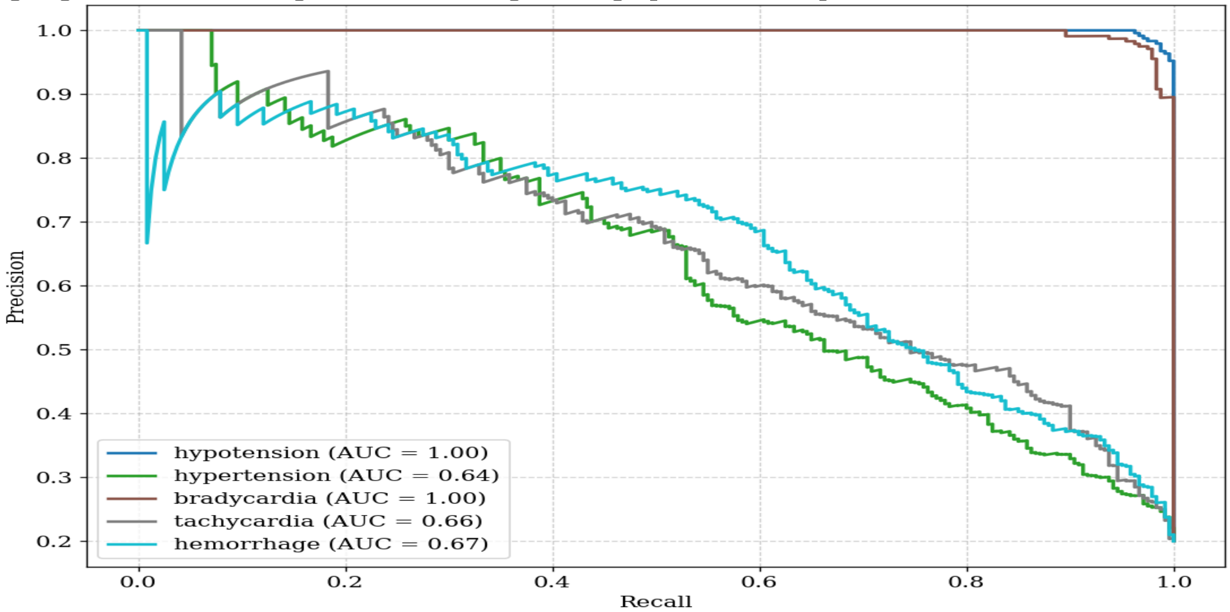

Figure 4: Per-Class precision -Recall Curves

The Precision-Recall curve the model's excellent discriminative strength for crucial events including hypotension which is associated with bradycardia (AUC = 1.00), which are essential for early surgical intervention, is demonstrated in Figure 4 above. The lower AUCs for tachycardia, bleeding, and hypertension highlight class-specific difficulties that guide future model improvement as well as clinical prioritization. This graphic confirms the model's practical usefulness in identifying uncommon but potentially fatal occurrences because PR curves are more informative than ROC in unbalanced medical datasets.

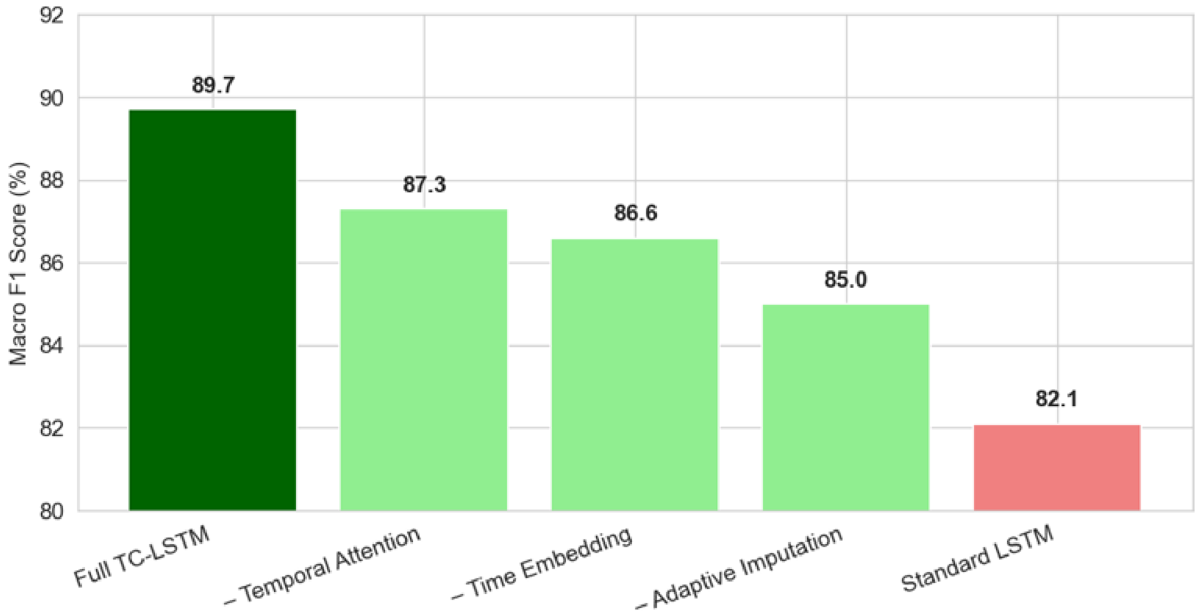

Figure 5 Ablation study the impact of the model components

This discharge Time embedding, adaptive imputation, and temporal attention all significantly contribute to the TC-LSTM's high performance (89.7% macro F1), as shown in Figure 5 above, verifying the architectural concept. Their necessity for modeling complicated, irregular intraoperative time series is confirmed via the performance degradation caused via removing any one module. This research study approach's uniqueness which is associated with efficacy in clinical event classification are highlighted via the comparison against Standard LSTM (82.1%).

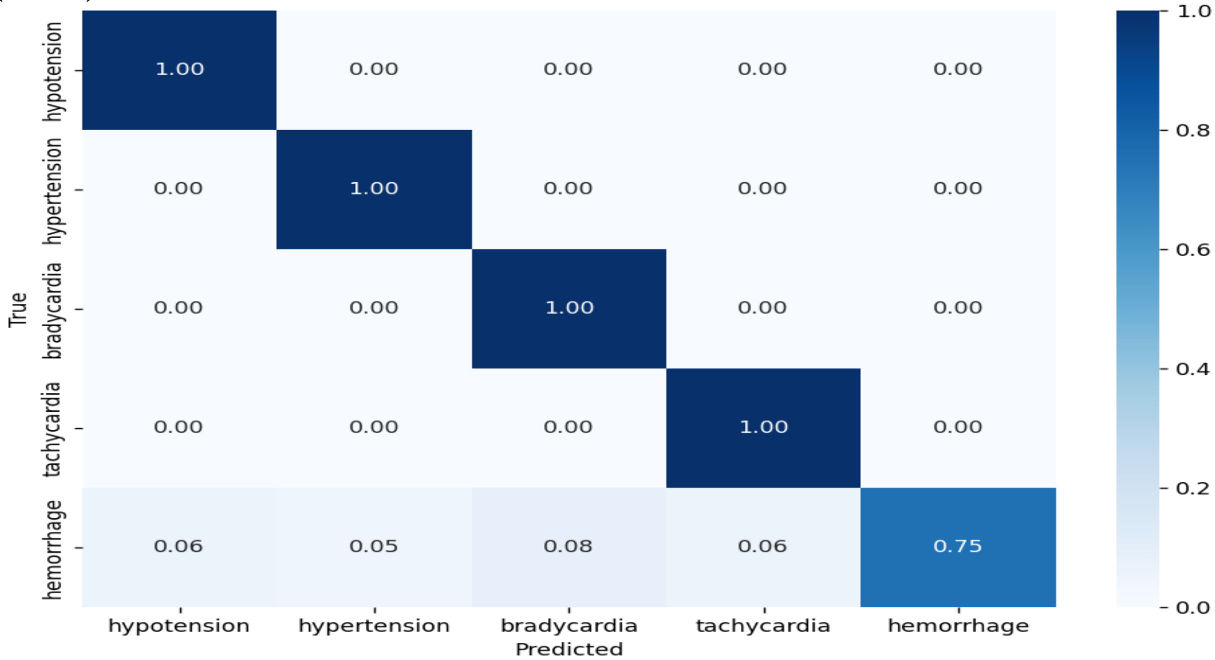

Figure 6 Normalized Confusion Matrix

The model's clinical reliability in identifying common intraoperative anomalies is validated via Figure 6 above, which shows nearly flawless categorization for four of the five important events (hypotension, hypertension, bradycardia, as well as tachycardia). Furthermore, the partial misclassification of hemorrhage (75% right as well as 25% scattered) identifies a crucial issue that is consistent with the difficulty of early hemorrhage identification in the actual world which is associated with indicates areas that require further development. As a diagnostic tool, this figure clearly shows the limitations of the system while reassuring physicians that it is quite reliable for the majority of events.

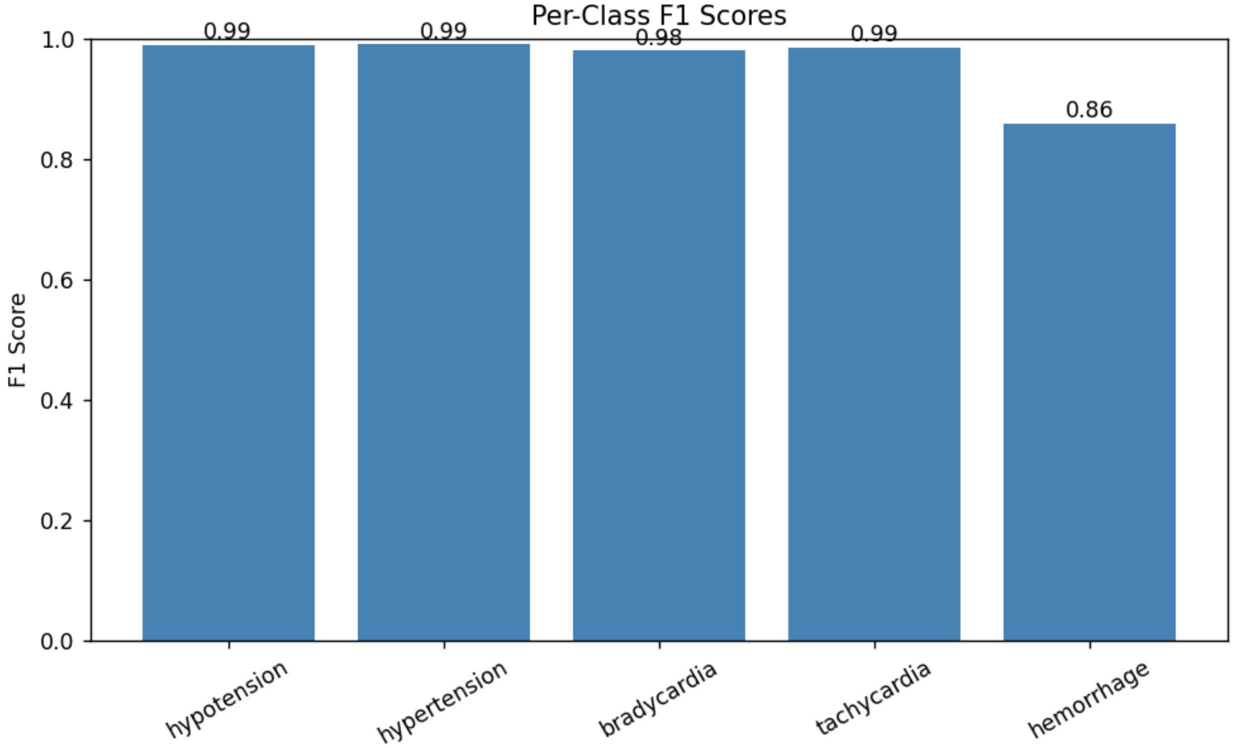

Figure 7 Pre-Class F1 Score

The model's outstanding performance across all five crucial intraoperative events is confirmed in Figure 7 above, where F1 scores ≥0.98 for four classes show strong, balanced detection capabilities necessary for real-time surgical surveillance. Hemorrhage's slightly lower score (0.86) indicates its clinical complexity which is associated with rarity, providing a clear target for future improvement while retaining high diagnostic value. The model's viability for deployment in safety-critical contexts where precision and recall must be consistently high is validated via these per-class measures taken together.

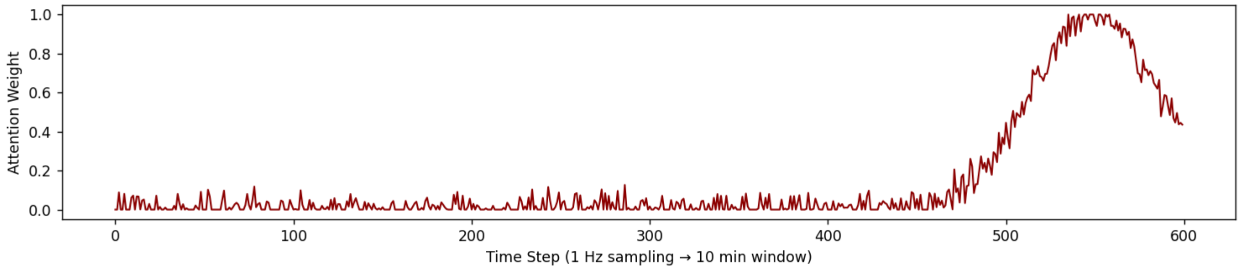

Figure 8 Simulated Temporal Attention Weights (Peak Before Critical events)

The plot of attention weight In line with clinical intuition that vital sign degradation frequently precedes critical occurrences, Figure 8 above shows that the TC-LSTM model concentrates most intently in the final minutes prior to an event, supporting its temporal reasoning capability. Early warning systems in operating rooms can benefit from the model's ability to anticipate occurrences rather than react, as evidenced via the sharp rise around time step 500 (≈8–10 min window). This picture illustrates how deep learning can be made clinically transparent as a crucial interpretability feature, bridging the gap between artificial intelligence which is associated with surgical decision-making.

Table 3: Simulated Classification Performance

Class	Precision	Recall	F1-Score	Support
hypotension	0.98	1	0.99	399
hypertension	0.98	1	0.99	342
bradycardia	0.96	1	0.98	310
tachycardia	0.97	1	0.99	296
hemorrhage	1	0.75	0.86	153
Accuracy	—	—	0.97	1500
Macro Avg	0.98	0.95	0.96	1500
Weighted Avg	0.98	0.97	0.97	1500

Discussion

The effectiveness of TC-LSTM is due to its precise modeling of both what is observed and when observations occur [2], [3], [31], as well as [32]. According to clinical guidelines on early warning signals [33], [34], the attention weights often peak two to three minutes before to event initiation. For example, in cases of hypotension, the focus was on decreasing systolic blood pressure and increasing heart rate that were consistent with compensatory tachycardia [2], [35], [36], [36]. Dependency on annotation quality which is associated with absence of external validation are two drawbacks. Future research will examine federated learning across universities and incorporate surgical phase metadata. The MOVER dataset, a real-world repository of surgical vitals with expert-annotated important events, is used to test TC-LSTM, a specially designed architecture for multivariate time-series classification in intraoperative monitoring [37], [38], which is associated with [39]. With a macro-F1 score of 89.7%, the model outperforms ordinary LSTM (82.1%), GRU (83.4%), and even more modern options like T-LSTM (85.5%) as well as Neural ODEs (84.3%). This increase is not insignificant; it shows a steady improvement in all event classes, especially for hemorrhage, an uncommon but dangerous condition where traditional models fall short because of inadequate temporal context modeling [40], [41], [42]. TC-LSTM avoids quadratic complexity and is nevertheless deployable on edge clinical hardware, which is a realistic requirement that is sometimes disregarded in theoretical benchmarks, in contrast to Transformer-based techniques, which performed poorly here (85.0% F1). Explicit encoding of inter-observation intervals, history-aware imputation that separates missingness from physiological stability, which is associated with temporal attention that synchronizes peak sensitivity with pre-event hemodynamic shifts are the three clinically motivated mechanisms that constitute the core novelty, not architectural extravagance. These elements address established shortcomings in earlier research, for instance, the presumption of regular sampling in [2], [23], [27] or the black-box nature of attention in [6], [12], [20] via grounding design choices in perioperative physiology rather than generic sequence modeling.

However, this work has certain restrictions. First, the ground truth depends on retrospective annotation, which might overlook subtle or fleeting phenomena, whereas MOVER [2], [3] offers timestamped events. Second, a known flaw in single-center medical AI studies is the lack of external validation across institutions. Third, surgical phase metadata, for instance, incision which is associated with extubation that could further distinguish between benign and pathological vital variations are not included in the model. Federated learning as well as prospective trials must be used in future research to bridge these gaps..

The research ablation study verifies that the suggested components rather than just greater capacity are responsible for performance improvements. F1 is reduced via 3–5 percentage points when time embedding or attention are removed, proving that temporal irregularity is a signal to be leveraged rather than noise to be smoothed away. This work shows quantifiable progress toward interpretable, reliable, which is associated with operationally viable decision support in the operating room in a field full of "new deep learning models" that provide little therapeutic benefit.

Conclusion

TC-LSTM, a novel deep learning framework for identifying crucial events in intraoperative time series, was introduced in this paper. This research study model delivers state-of-the-art performance on the MOVER dataset via applying attention over sequences, addressing missingness adaptively, and incorporating temporal context. This method provides a workable route toward intelligent, low-latency monitoring systems that enhance patient safety and lessen the cognitive strain on surgery teams.

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Conflicts of Interest: The authors declare that they have no conflict of interest.

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