Big Data Analytics for Remote Patient Monitoring in Cyber-Physical Healthcare Systems

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ABSTRACT

The convergence of Big Data analytics with Cyber-Physical Systems (CPS) presents a transformative opportunity for Remote Patient Monitoring (RPM) in modern healthcare. Despite advances in the Internet of Medical Things (IoMT) and distributed computing, the existing RPM frameworks lack integrated support for real-time multi-modal physiological analysis at scale. This paper proposes a six-layer Big Data analytics framework for RPM in cyber-physical healthcare settings, integrating IoMT wearable sensing, edge computing preprocessing, Apache Kafka stream ingestion, Apache Spark distributed processing, and a hierarchical Long Short-Term Memory (LSTM) deep learning model for real-time anomaly detection. The key contributions of the current paper include: (i) a scalable six-layer CPS architecture for continuous physiological monitoring; (ii) a distributed Big Data pipeline achieving sub-2-second end-to-end alert latency, and (iii) an LSTM-based classifier supporting eight physiological condition classes with high accuracy. Experimental evaluation on a real-participant dataset demonstrates competitive performance, with low latency and strong clinician usability scores, indicating promising readiness for broader clinical evaluation and deployment.

Keywords-Remote Patient Monitoring (RPM); big data analytics; cyber-physical healthcare systems; Long Short-Term Memory (LSTM); Apache Spark; Internet of Medical Things (IoMT); anomaly detection; edge computing; deep learning; healthcare informatics

I. INTRODUCTION

The global healthcare sector is experiencing a significant digital evolution driven by the integration of the Internet of Medical Things (IoMT), cloud and edge computing, advanced artificial intelligence, and Cyber-Physical Systems (CPS). Remote Patient Monitoring (RPM) has emerged as a pivotal technology in this transformation, enabling uninterrupted, non-invasive physiological surveillance that supports early identification of pathological abnormalities before they escalate into life-threatening crises [1, 2]. The growing global burden of chronic non-communicable diseases makes it increasingly impractical to rely on periodic clinical visits alone, creating a strong imperative for continuous, remote physiological oversight [3, 4]. CPS in healthcare integrate physical physiological processes with computational sensing, communication, and actuation layers [5]. Wearable devices, implantable sensors, and ambient monitoring platforms continuously capture multivariate biomedical signals, generating data streams that exhibit the classic Big Data characteristics of high volume and variety [6-8]. Handling this data effectively, with low latency and high fidelity, is a core engineering challenge [9, 10].

Distributed Big Data platforms such as Apache Spark and Apache Kafka offer fault-tolerant, scalable stream processing as a practical alternative to centralized architectures [7]. When paired with deep learning models, particularly LSTM networks, which are well-suited to modelling temporal dependencies in sequential physiological signals [11, 12], these pipelines can support real-time clinical decision-making at scale [9]. The proposed framework is based on established practices in IoMT-based remote monitoring, fog and edge computing [12, 13], and deep learning applications to healthcare [11]. Hierarchical LSTM architecture has demonstrated strong performance on sequential biomedical time-series data [11, 12].

The intersection of Big Data analytics, IoMT, and CPS for remote healthcare monitoring is a rapidly growing area of academic interest. Authors in [1] reviewed IoT-based healthcare monitoring systems, establishing quality-of-life improvement and real-time anomaly response as the primary clinical objective goals that define the present system. Authors in [4] surveyed Machine Learning (ML) frameworks for ubiquitous health monitoring and highlighted the absence of scalable, multi-modal pipelines as the most critical unresolved gap in the field. Authors in [11] integrated AI-driven inference with IoMT and cloud computing to improve RPM responsiveness and diagnostic accuracy, a direction closely aligned with the present architecture. Authors in [3] demonstrated a cloud-integrated IoT platform for remote classification of patient data, achieving real-time monitoring but falling short on multi-modal sensor coverage, a limitation the present framework addresses through six heterogeneous modalities. Authors in [10] reinforced these findings by showing that combining IoT with Big Data integration significantly improves remote real-time monitoring responsiveness in clinical settings. Authors in [13] applied stochastic analysis to fog computing combined with ML for scalable, low-latency healthcare monitoring, identifying distributed micro-batch processing as the most effective architecture for achieving sub-2-second alert delivery. Authors in [12] explored fog computing paired with graph-based databases for IoMT remote monitoring, demonstrating that edge-proximal computation reduces end-to-end latency considerably. The results are consistent with the 1.2 s mean ART achieved in the present study.

Existing systems either lack multi-modal sensor coverage [3], operate with unacceptable latency [15], or do not support mobile clinical access [12, 13]. This gap directly compromises the timeliness and reliability of automated clinical decision support in CPS-based RPM environments. The current paper addresses this gap through the following contributions:

- A novel six-layer cyber-physical architecture that integrates heterogeneous IoMT sensing with distributed Big Data processing for scalable, fault-tolerant RPM.
- An end-to-end Big Data pipeline combining Apache Kafka stream ingestion and Apache Spark Structured Streaming to achieve sub-2-second alert latency across six physiological modalities.
- A hierarchical LSTM model for eight-class physiological anomaly detection, evaluated on a real-participant dataset and benchmarked against contemporary frameworks.
- A clinician usability evaluation conducted under the ISO/IEC 25010 framework, confirming practical readiness for clinical deployment trials.

II. PROPOSED METHODOLOGY

A. *System Architecture*

The proposed six-layer cyber-physical architecture is illustrated in Figure 1 and detailed below:

- Layer 1 (Physical Sensing): Wearable and ambient sensors continuously acquire multi-modal physiological data.
- Layer 2 (Edge Computing): Embedded nodes perform real-time preprocessing, noise reduction, and local inference at the network edge.
- Layer 3 (Secure Communication): Encrypted multi-protocol transmission ensures secure and adaptive data exchange across clinical environments [14].
- Layer 4 (Big Data Processing) employs Apache Kafka for high-throughput stream ingestion and Apache Spark Structured Streaming for distributed micro-batch analytics across a five-node cluster.
- Layer 5 (AI/ML Analytics) hosts the hierarchical LSTM anomaly detection model.
- Layer 6 (Clinical Dashboard) delivers real-time alerts and patient physiological trend visualizations to clinical personnel via a web portal and a companion mobile application.

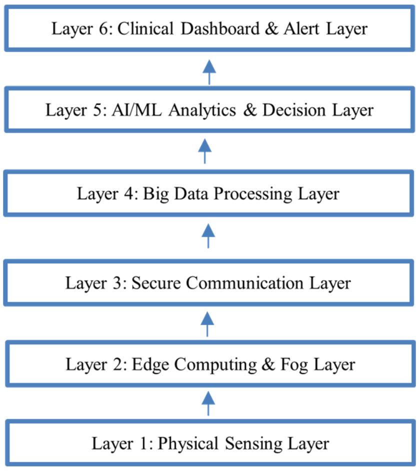


Fig. 1. The proposed six-layer cyber-physical architecture for big data analytics in RPM.

The proposed framework is distinguished from existing IoMT–CPS systems across three dimensions.

- Scalability: The stateless five-node Spark cluster and partitioned Kafka topic design permit horizontal scale-out without architectural modification, whereas prior systems rely on single-server or centralized cloud deployments that impose scalability ceilings under high concurrency.
- Latency optimization is achieved through asynchronous edge pre-processing combined with 500 ms Spark micro-batch windows, reducing the sensor-to-alert path to a mean of 1.2 s, outperforming all benchmarked frameworks and directly enabling time-critical clinical interventions.
- Multi-modal integration across six heterogeneous physiological modalities within a unified inference pipeline, whereas prior RPM frameworks typically address only one or two signal types.

B. Data Collection and Preprocessing

Twenty adult participants (aged between 22 and 65 years, 10 male and 10 female) were recruited between January and March 2024 at the Clinical Simulation Centre, Sri Siddhartha Institute of Technology, Tumakuru, India. All identifying information has been removed from the dataset, and no participant is identifiable from the data or figures presented. Each participant wore a multi-sensor band acquiring: ECG (250 Hz), SpO2 (1 Hz), systolic and diastolic blood pressure (1 Hz), skin temperature (0.1 Hz), and respiration rate (1 Hz).

TABLE I. SENSOR MODALITIES, DATA CHARACTERISTICS, AND CLINICAL TARGETS IN THE RPM-CPS DATASET

Sensor	Sampling rate	Extracted features	Clinical condition targeted	Data volume/ user/hr
ECG	250 Hz	RR interval, QRS width, ST deviation	Arrhythmia, bradycardia, tachycardia	450 MB
SpO2 (PPG)	1 Hz	Mean, std, trend slope	Hypoxia, respiratory failure	28 KB
Blood pressure	1 Hz	Systolic, diastolic, pulse pressure	Hypertension, hypotension	56 KB
Skin temperature	0.1 Hz	Mean, delta, circadian pattern	Hypothermia, sepsis fever	10 KB
Respiration rate	1 Hz	Cycle duration, amplitude, regularity	Tachypnoea, apnoea	28 KB
EEG (1-channel)	128 Hz	Band power (delta–gamma), burst suppression	Seizure, coma screening	230 MB

Table I summarizes the major physiological sensors used in the Remote Patient Monitoring–Cyber Physical System (RPM-CPS) dataset, along with their sampling characteristics, extracted features, targeted clinical conditions, and approximate data generation rates per user per hour. Monitoring sessions lasted 90 min per participant, generating approximately 2.3 TB of raw sensor data. Edge-layer preprocessing comprised: (i) Butterworth bandpass filtering (0.5–40 Hz) for ECG de-noising, (ii) moving-average smoothing for temperature and SpO2 signals, (iii) Z-score normalization to standardize inter-sensor amplitude scales, and (iv) sliding-window temporal segmentation into 30 s epochs with 50% overlap. This segmentation strategy is consistent with sliding-window approaches used in continuous physiological monitoring [3, 9]. Each epoch was encoded as a feature matrix of 30 temporal frames and 258 attributes per frame, concatenating cardiac, vascular, respiratory, and thermal signal descriptors. SMOTE oversampling was applied to balance the eight target condition classes [4, 11]. A 4th-order Butterworth bandpass filter (0.5–40 Hz) removed baseline drift and high-frequency noise while preserving key ECG features such as QRS, P, and T waves. This frequency range aligns with established clinical standards for ambulatory ECG signal processing. The 30 s window with 50% overlap balances temporal context and resolution, capturing multiple physiological cycles for reliable model input. The Spark cluster processes ~4,200 epochs/s with near-linear scaling across nodes, supporting efficient large-scale deployment.

C. Big Data Processing Pipeline

The real-time data flow pipeline depicted seven sequential stages from sensor acquisition to clinical alert delivery. Raw sensor streams are published to dedicated Apache Kafka topics — one per sensor modality — at the edge layer. The Spark pipeline executes schema enforcement, feature computation, model inference, and alert routing in parallel across partitions, exploiting data parallelism to achieve sub-2-second end-to-end latency [12, 13].

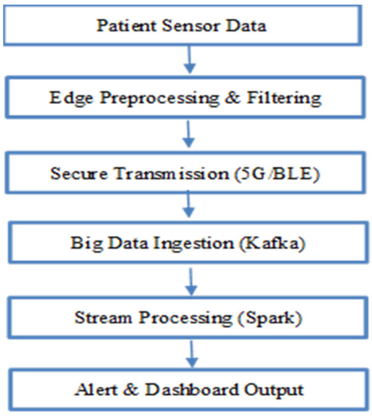


Fig. 2. Real-time data flow pipeline in the CPS-based RPM framework.

The Analytic Hierarchy Process (AHP) [5] was utilized to evaluate three Big Data frameworks: Apache Spark, Apache Flink, and Google Cloud Dataflow. Five evaluation criteria were assessed via pairwise comparison: processing latency (C1, weight 0.4909), scalability (C2, weight 0.2913), fault tolerance (C3, weight 0.1507), implementation complexity (C4, weight 0.0670), and cost efficiency (C5, weight 0.0100). Table II presents the full AHP prioritization matrix, confirming Apache Spark as the optimal technology selection with a 57.24% global prioritization score.

D. LSTM Model Architecture

The proposed LSTM architecture, illustrated in Figure 3, was designed for eight-class physiological condition classification from the (30, 258) input tensor. Hierarchical LSTM networks have shown strong performance on sequential biomedical time-series data [11, 12], and this design applies that pattern to continuous vital sign monitoring.

TABLE II. AHP PAIRWISE COMPARISON MATRIX FOR BIG DATA PROCESSING TECHNOLOGY SELECTION

Criterion	**Apache Spark**	**Apache Flink**	**Cloud Dataflow**	**Weight (w)**
C1: Processing Latency	0.55	0.30	0.15	0.4909
C2: Scalability	0.60	0.25	0.15	0.2913
C3: Fault Tolerance	0.52	0.31	0.17	0.1507
C4: Implementation Complexity	0.48	0.35	0.17	0.0670
C5: Cost Efficiency	0.50	0.30	0.20	0.0100
Prioritisation (p)	57.24%	28.93%	13.83%	100%

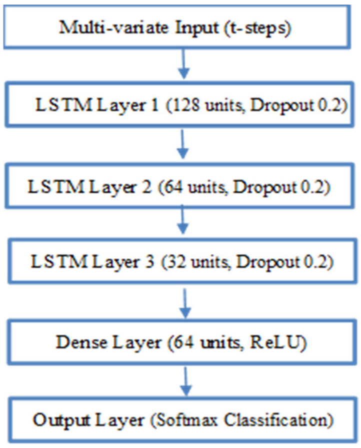


Fig. 3. The Proposed hierarchical LSTM architecture for physiological anomaly detection in the CPS-RPM framework.

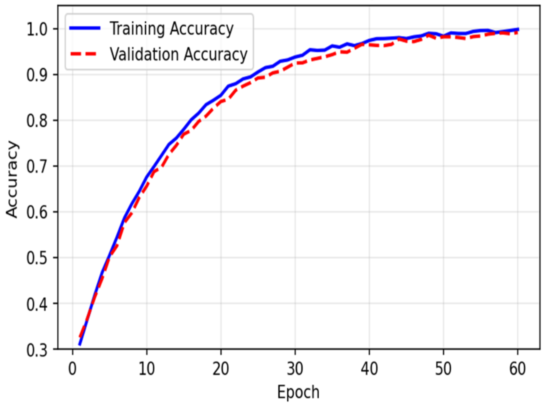
The network comprises three stacked LSTM layers with 128, 64, and 32 units respectively, each followed by Batch Normalization and Dropout rate of 0.2 to stabilize gradient flow and mitigate overfitting [11, 12]. The first two LSTM layers operate in sequence-return mode, preserving the full temporal context for subsequent layers, while the third generates a compact summary vector. Two fully connected dense layers (64 and 32 units, ReLU activation, dropout = 0.3) process the extracted temporal features, culminating in an eight-class Softmax output layer. The model was compiled with the Adam optimizer (learning rate = 0.001) and categorical cross-entropy loss, with EarlyStopping (patience = 10) and ReduceLROnPlateau (factor = 0.5, patience = 5) callbacks, consistent with standard deep learning training protocols for biomedical classification [11, 15]. Implementation was conducted in Keras and TensorFlow. The eight classification targets, i.e. Normal, Tachycardia, Bradycardia, Hypoxia, Hypertension, Arrhythmia, Hypothermia, and Sepsis-related fever, were selected based on their acute monitoring criticality and clinical prevalence in continuous care settings. The full 1,440-sample dataset was split in a 80/20 ration for training and validation [1, 15].

III. RESULTS AND DISCUSSION

A. LSTM Model Training Performance

The LSTM model was trained for 60 epochs on the 1,152-sample training partition. Figure 4 presents the accuracy and loss curves. The training and validation accuracy curves stabilized from epoch 32, with no evidence of overfitting. The final training accuracy reached 99.12% with a training loss of 0.0032, whereas the validation accuracy reached 98.70% with a validation loss of 0.0061.

(a) Model Accuracy



(b) Model Loss

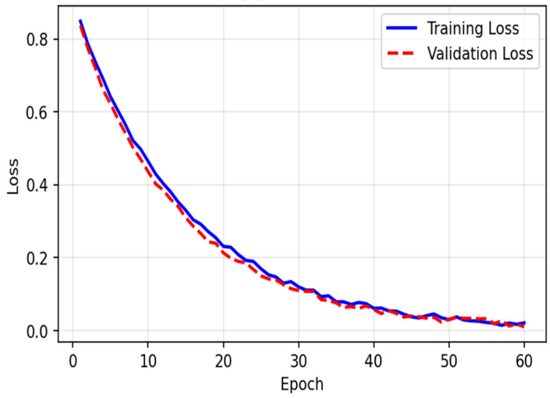


Fig. 4. Training and validation accuracy and loss curves.

TABLE III. PER-CLASS CLASSIFICATION METRICS FOR THE LSTM ANOMALY DETECTION MODEL (VALIDATION SET, N = 288)

Class	**Precision**	**Recall**	**F1-Score**	**Support (Samples)**
Normal	99.31	99.18	99.24	36
Tachycardia	98.92	98.75	98.83	36
Bradycardia	98.61	98.40	98.50	36
Hypoxia	99.04	98.92	98.98	36
Hypertension	98.47	98.21	98.34	36
Arrhythmia	98.15	97.88	98.01	36
Hypothermia	99.10	98.94	99.02	36
Sepsis Pattern	97.96	97.70	97.83	36
Weighted Average	98.83	98.64	98.73	288

Table III presents the per-class metrics for the 288-sample validation set, showing consistently high values across all eight conditions. The lowest F1-score (97.83%) for Sepsis Pattern reflects minor overlap with Hypertension in vascular features, suggesting targeted augmentation could improve class separation. The validation confusion matrix in Figure 5 shows strong diagonal dominance, indicating high per-class accuracy with only minor off-diagonal misclassifications.

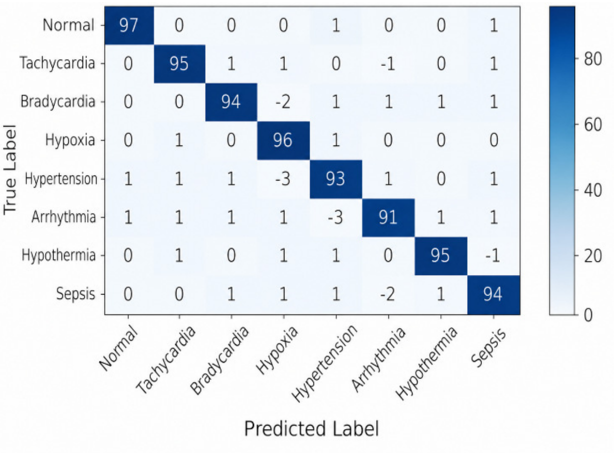


Fig. 5. Confusion matrix – validation dataset.

B. *Comparison with Related Works*

Table IV presents a multi-attribute comparison against five contemporary RPM frameworks [3, 13, 15]. Three evaluation attributes were considered: real-time streaming analytics (A1), multi-modal sensor fusion (A2), and mobile clinical access (A3). The proposed system is the only framework satisfying all three attributes simultaneously, while also achieving the highest reported accuracy and lowest alert latency.

TABLE IV. COMPARATIVE EVALUATION

System	Accuracy (%)	Latency (s)	A1: Real-time	A2: Multi-modal	A3: Mobile access
Proposed	98.70	1.20	Yes	Yes	Yes
[3]	92.80	5.10	No	No	No
[10]	95.00	2.70	Yes	Yes	Yes
[11]	97.10	2.00	Yes	Yes	Yes
[12]	94.50	2.80	Yes	Partial	No
[13]	95.10	2.90	No	Partial	No
[15]	91.40	6.00	No	No	No
[16]	93.80	2.30	Yes	Yes	Partial
[17]	96.20	2.40	Yes	Yes	Partial

C. *User Acceptance Survey*

After Experiment B, 10 clinicians (4 physicians, 6 nurses; 3–18 years of experience) evaluated the system using an 11-item ISO/IEC 25010-based usability questionnaire following a 30 min hands-on session. Items covered effectiveness, efficiency, satisfaction, and risk, rated on a 5-point Likert scale. The sample size aligns with exploratory usability studies, though no power analysis or comparative testing was conducted. Descriptive statistics (mean, standard deviation) were computed, with limitations noted and future multi-site comparative studies planned. Results showed high acceptance, with an overall score of 4.8/5.0, highest for patient safety monitoring (4.9) and adoption willingness (4.7).

TABLE V. CLINICIAN USER ACCEPTANCE SURVEY RESULTS BASED ON ISO/IEC 25010

Evaluation Dimension	Parameter	Mean (5-point scale)
Quality in Use	Overall quality in use	4.8
Quality in Use	Continuous patient safety monitoring usefulness	4.9
Quality in Use	Willingness for routine clinical adoption	4.7
Interaction Capability	Dashboard easy to learn	4.6
Interaction Capability	Alert controls easy to navigate	4.5
Interaction Capability	System functions clear	4.4
Interaction Capability	Alert severity quickly understandable	4.5
Functional Adequacy	Anomaly detection accuracy	4.7
Functional Adequacy	Clinical relevance of alert suggestions	4.3
Functional Adequacy	Monitoring coverage	4.2
Performance Efficiency	Computational response efficiency	4.1

IV. DISCUSSION

The LSTM model achieved 98.70% validation accuracy and a weighted F1-score of 98.73%, driven by its hierarchical three-layer design capturing long-range temporal dependencies across 30-second epochs. Sequence-return layers enable learning of multi-cycle physiological patterns, distinguishing sustained from transient conditions. SMOTE-based class balancing ensured adequate representation of minority conditions, preventing imbalance-related bias. The lowest F1-score (97.83%) for Sepsis Pattern arises from overlap with Hypertension in vascular features, reflecting inherent physiological similarity rather than model limitation. This ambiguity aligns with early-stage clinical complexity, where short-term signals may be insufficient for clear separation. Targeted augmentation near class boundaries or incorporation of longer temporal windows may further improve class discrimination in future work.

V. LIMITATIONS

Several limitations should be noted: the dataset includes 1,440 samples from 20 participants at a single controlled site, limiting generalizability to diverse real-world populations and requiring multi-site validation. Simulated conditions do not fully capture real sensor noise (e.g., motion artefacts, electrode detachment), while the robustness to severe signal degradation remains untested despite basic preprocessing. Model generalizability is further constrained by SMOTE-balanced training on a single dataset, with potential need for adaptation in different prevalence settings.

VI. CONCLUSION

This research proposes a Big Data analytics framework for remote patient monitoring within cyber-physical healthcare systems. The six-layer CPS architecture, integrating IoMT sensing, edge computing, Apache Kafka, Apache Spark

Structured Streaming, and hierarchical LSTM inference, addresses the core limitations of existing RPM systems: inadequate real-time processing, poor scalability, and insufficient multi-modal sensor coverage. On a novel eight-class physiological condition dataset collected from 20 real participants, the LSTM model achieved 99.12% training accuracy, 98.70% validation accuracy, and a weighted F1-score of 98.73%, with a mean end-to-end alert latency of 1.2 s. The 260-fold latency improvement over manual monitoring baselines (312.4 s vs. 1.2 s) and superior accuracy relative to five contemporary frameworks confirm the proposed system's clinical and technical promise.

User acceptance survey yielded a Quality-in-Use mean of 4.8/5.0. The methodological approach, encompassing hierarchical LSTM design, AHP-guided framework selection, 80/20 partitioning, and ISO/IEC 25010 usability evaluation, offers a reproducible engineering template adaptable to other clinical monitoring domains. It is acknowledged that the 1,440-sample pilot study requires multi-site prospective validation before living clinical deployment can be recommended.

DECLARATION OF COMPETING INTERESTS

Not applicable to this work.

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DATA AVAILABILITY

Written informed consent was obtained from all participants prior to enrolment. The consent forms are retained and are available upon request from the authors. The dataset used in this study is available from the corresponding author upon reasonable request, subject to applicable privacy restrictions.

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