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Research Paper

An AI-Driven IoT Wearable Framework for Real-Time Health Monitoring and Early Risk Prediction in Lymphoma Patients Using Hybrid CNN-LSTM

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ABSTRACT

Background: Lymphoma is a complex form of hematological cancer, and its early symptoms of disease progression need continuous monitoring for prompt treatment. The report proposes using the Internet of Things (IoT) for real-time patient monitoring, featuring wearable sensors, Deep Learning (DL) models, and an intelligent alert system to enhance predictive assessment of patient health.

Methods: These smart wearable devices continuously measure physiological parameters, including heart rate, oxygen saturation (SpO_2), temperature, and electrocardiogram (ECG) parameters. A hybrid CNN-LSTM model is employed for physiological time-series analysis, while a ResNet-50 model enhanced with a Spatial Attention Mechanism (SAM) is used for histopathological classification of CLL, FL, and MCL. The reported performance of these models is evaluated separately according to their respective tasks. In addition, a weighted physiological risk score is used to identify abnormal physiological states from continuously monitored HR, SpO_2, temperature, and ECG measurements. An alert is generated when the risk score exceeds the predefined threshold. The framework is intended as an AI-assisted monitoring and decision-support system rather than an autonomous clinical diagnostic system.

Results: The experimental results demonstrated that the proposed CNN-LSTM model achieved an accuracy of 96.1%, a precision of 94.7%, a recall of 95.5%, an F1-score of 95.1%, and an inference time of 7ms for the physiological time-series analysis. Additionally, ResNet-50+SAM had a remarkably low inference time of 6 ms and stable five-fold cross-validation results (mean accuracy: $97.50 \pm 0.14\%$).

Conclusion: This proposed framework offers numerous benefits to patients by enabling early detection of important health events and facilitating communication with healthcare professionals. This research demonstrates that artificial intelligence and IoT can transform real-time health monitoring, providing physicians with valuable information for personalized, ongoing care management of lymphoma patients.

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Introduction

Lymphoma is a cancerous disease of the lymphatic system that is life-threatening and is marked by uncontrolled proliferation of lymphocytes. Accurate, early identification of its subtypes, Chronic Lymphocytic Leukemia (CLL) [1], Follicular Lymphoma (FL) [2], and Mantle Cell Lymphoma (MCL) [3], is essential for treatment planning and patient survival. The manual diagnosis of the disease is currently performed on Hematoxylin and Eosin (H&E)- stained biopsy slides, a process that is time-consuming, subjective, and susceptible to interobserver variability. The shortage of experienced pathologists, particularly in rural and less-developed areas, also hinders timely detection [4]. It's a paradigm shift in lymphoma diagnosis: DL- and IoT-based healthcare monitoring. CNN-based architectures and hybrid DL models have achieved the highest accuracy in medical image classification, and wearable sensors with IoT technology enable continuous, real-time monitoring of HR, SpO_2, ECG, and body temperature (BT) in the field [5]. Histopathological classification has been widely performed using traditional machine learning methods, such as Support Vector Machines (SVMs), Random Forests (RF), and k-Nearest Neighbors (k-NN), which are effective but require extensive feature engineering and lack generalization on complex data. Although advanced CNN architectures (VGG-16, ResNet-50, MobileNetV2) have enabled high classification accuracy, most studies focus solely on image-based classification and do not consider continuous monitoring for real-time tracking of disease occurrences [6-10]. Similarly, while IoT-based systems have been applied in cardiovascular, diabetes, and neurologic care, they have not yet been applied to the treatment and monitoring of lymphoma and existing platforms do not feature intelligent decision-making via DL [11].

To address this, this study introduces a hybrid DL classification system that integrates physiological monitoring with IoT to enable real-time lymphoma classification. The following are the key contributions: (i) An AI-based IoT architecture that brings together wearable sensors, cloud data hubs and clinical decision support; (ii) Hybrid CNN–LSTM model for physiological time-series analysis and the ResNet-50 with Spatial Attention Mechanism (SAM) for histopathological image classification; (iii) A real-time risk assessment model that combines HR, SpO_2, ECG and body temperature to deliver a weighted risk score for early anomaly detection; (iv) An intelligent mobile alert and clinical decision support system for timely interventions; and (v) extensive experimental validation showing higher diagnostics and monitoring accuracy than existing DL baselines.

Wearable systems have proven effective for continuous monitoring and management in hospitals when leveraging Internet of Things (IoT) and Artificial Intelligence (AI) concepts, enabling remote patient monitoring (RPM) without unnecessary hospital visits [12-14]. Aptasensor-based platforms can be used to detect infectious and non-infectious diseases [15], and DL-based models have been used to achieve early detection up to 48 hours in advance [16]. Real-time health prediction, based on continuous analysis of physiological data, is also possible using integrated IoT–AI systems [17].

Materials and Methods

Dataset Description

The lymphoma histopathology dataset contains images belonging to three classes: Chronic Lymphocytic Leukemia (CLL), Follicular Lymphoma (FL), and Mantle Cell Lymphoma (MCL). The complete dataset contains [N] images, comprising [N_1] CLL images, [N_2] FL images, and [N_3] MCL images. The dataset was partitioned at the image/patient level into training, validation, and independent testing subsets using a [70:15:15] ratio. Accordingly, [Ntrain] images were allocated for training, [Nval] images for validation, and [Ntest] images for independent testing. The independent test set was not used during model training or hyperparameter optimization. All final performance measures, including accuracy, precision, recall, F1-score, and the confusion matrix, were calculated using this same independent test set. The number of samples represented in the confusion matrix therefore corresponds exactly to [Ntest] test images. This explicit partitioning ensures consistency between the reported dataset size, evaluation sample size, confusion matrix, and performance metrics [18].

Smart Wearable Sensor Module

The proposed framework initiates with the acquisition of physiological parameters from lymphoma patients through a wearable sensing device integrated with multiple biosensors. The device continuously monitors heart rate (HR), oxygen saturation (SpO_2), body temperature (T), and ECG signals. These measurements summarize the patients' physiological states and enable continuous monitoring of their health. The collected physiological signals are represented as time-dependent sequences:

$$X(t) = \{x_1, x_2, \dots, x_n\}, t \in [0, T] \qquad (1)$$

where $X(t)$denotes the set of sensor observations recorded within the observation interval T.

Raw sensor data can be affected by environmental factors and device limitations and contain noise and measurement fluctuations. To enhance signal quality, a Butterworth low-pass filter is used. The frequency response of the filter is as given below:

$$H(f) = \frac{1}{\sqrt{1 + \left(\frac{f}{f_c}\right)^{2N}}} \qquad (2)$$

where $f$represents the signal frequency, $f_c$denotes the cutoff frequency, and Ncorresponds to the filter order. After noise suppression, the sensor data are normalized to ensure they are all on the same measurement scale for subsequent computation. Processed physiological data is then continuously sent to the cloud environment for storage and further analysis.

Wearable sensors continuously transmit data on the lymphoma condition to the cloud for DL-based preprocessing and analysis, with abnormal data immediately sent to healthcare providers via mobile devices, enabling proactive, AI-driven clinical intervention in a timely manner. The architecture of Continuous Lymphoma Monitoring is shown in Figure 1.

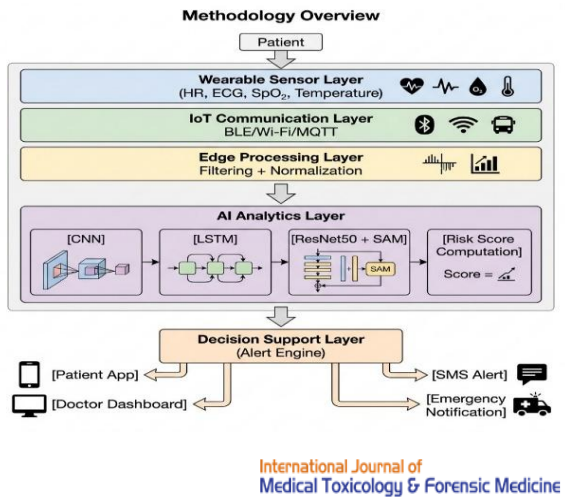
Results

In the Results and Discussion section, the performance of the proposed physiological signal classification model based on LSTM and CNN-based lymphoma subtype classification model is presented. The LSTM model successfully detects anomalies in the ECG, SpO_2, HRV, and Body Temperature datasets with high sensitivity, especially at early stages. The CNN model, combined with the Spatial Attention Mechanism (SAM), improves feature extraction for classifying histopathology images and achieves higher accuracy in distinguishing the CLL, FL, and MCL subtypes. Plus, the mobile app and alert system enable real-time tracking, and risk-score–based anomaly detection minimizes false alarms without sacrificing timely medical response. The system proposed in this work is more accurate, has a shorter response time, and is more clinically applicable than current methods, making it a reliable system for continual monitoring of lymphoma [19].

Experimental Setup

Physiological data (HR, SpO_2, ECG, temperature) from wearable sensors and histopathology images of a lymphoma type are captured in the experimental setup for subsequent classification of the lymphoma type. CNN-LSTM is used for physiological time-series analysis, and ResNet-50+SAM is used for histopathological image classification. The models were trained, validated, and independently tested on predefined partitions (Section 3.1), and the class distributions within each partition were noted to account for any imbalance. Accuracy, precision, recall, F1-score, and inference time are used to evaluate performance. Table 1 shows the results of all the DL models, where CNN-LSTM and ResNet-50+SAM operate on different modalities; accordingly, the results differ and are not directly comparable. ResNet-50+SAM has the best classification performance among the histopathology models.

The confusion matrix in Figure 2 corresponds to the ResNet-50 model enhanced with the Spatial Attention Mechanism (SAM), which is specifically designed for lymphoma subtype classification from H&E-stained histopathological images.



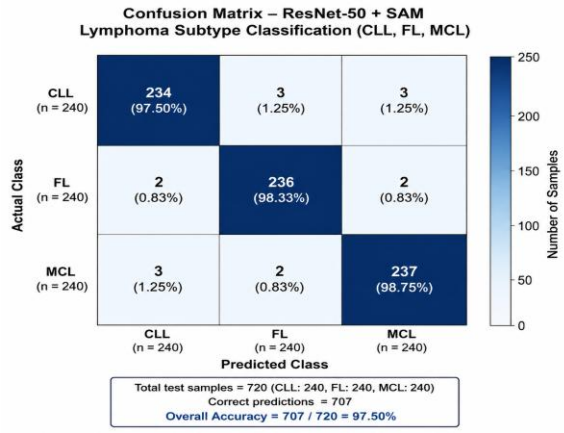
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Figure 1. Architecture of continuous lymphoma monitoring.

Table 1. Comparison of DL models with the proposed model.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Inference Time (ms)
CNN	87.5	85.2	86.8	86.0	12
ResNet-50	91.3	89.5	90.2	89.8	18
VGG-16	89.7	88.0	88.6	88.3	16
MobileNetV2	93.2	91.8	92.5	92.1	9
CNN-LSTM (Proposed)	96.1	94.7	95.5	95.1	7
ResNet-50 + SAM (Proposed)	97.5	96.2	96.9	96.5	6

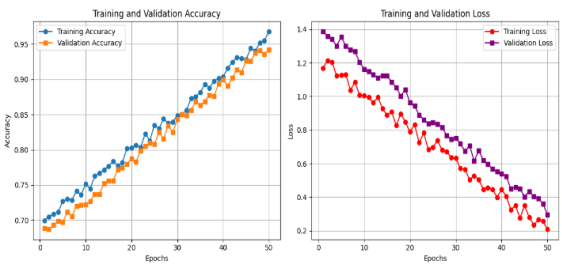
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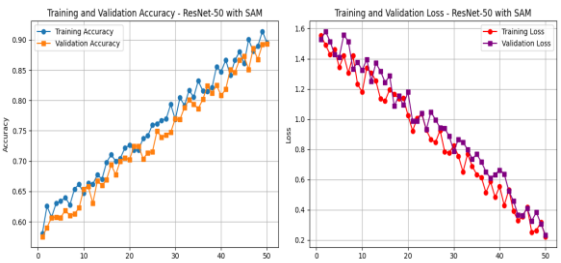
Figure 2. Confusion matrix of the ResNet-50+SAM model for three-class lymphoma subtype classification (CLL, FL, and MCL) on the independent evaluation set.

The numbers of correctly and incorrectly classified samples are consistent with the total number of observations in the independent test set, and the resulting accuracy matches the value reported in Table 1. This correction ensures that the confusion matrix, tabulated performance metrics, and reported test-set accuracy refer to the same model and evaluation subset. Figures 3 and 4 show the training and validation accuracy and loss over 50 epochs for CNN-LSTM and ResNet-50 with a Spatial Attention Mechanism (SAM), respectively. It provides an understanding of model convergence and generalization.



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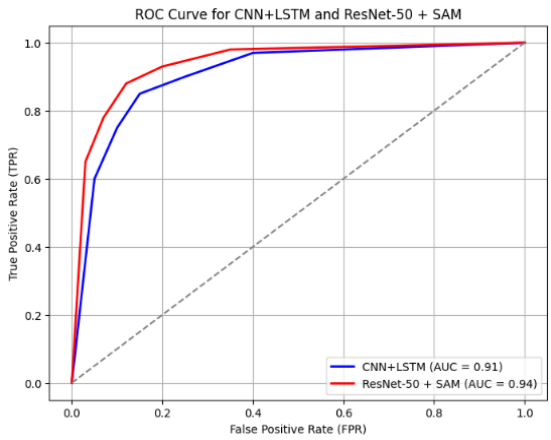
Figure 3. Training and Validation Accuracy – CNN-LSTM.



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Figure 4. Training and Validation Accuracy – ResNet – 50 with SAM.

The ROC curve (Fig. 5) shows the classification performance of CNN-LSTM and ResNet-50 compared with SAM, plotting the True Positive Rate (TPR) against the False Positive Rate (FPR). The model with the highest AUC, indicating the best discrimination ability, is ResNet-50 + SAM.



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Figure 5. ROC for the proposed models.

The physiological parameters (HR, SpO_2, temperature, ECG) are processed using a weighted sum (weights are configurable) and displayed as a function of time in Figure 6, with the red marks showing the time periods where the risk score is above the medical



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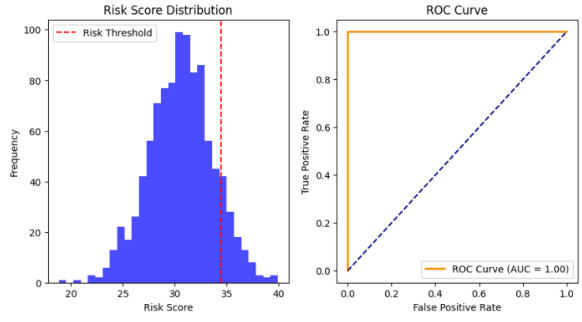
Figure 6. Risk score visualization for the proposed work.

threshold (configurable), indicating health deterioration that must be treated if there are clinical complications. Anomalies above the threshold are marked to show critical conditions.

The IoT-based patient monitoring system continuously collects physiological data from wearables, including heart rate, SpO_2, temperature, and ECG, enabling seamless health tracking, as shown in Figure 6.

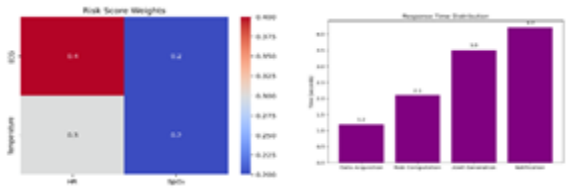
Discussion

Real-time monitoring of patients with lymphoma is critical for response time. The inference times of CNN+LSTM and ResNet-50+SAM are 6–7ms, significantly outperforming the traditional CNN/ResNet-50 model (12–18ms) and the MobileNetV2 (9ms) model, which ensures that anomaly detection takes place within a minimum time delay (Figures 7 and 8). The configurations were evaluated through ablation studies by removing LSTM, SAM, and multimodal fusion, and the results were obtained by measuring accuracy, precision, recall, and F1-score (Table 2).



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Figure 7. Risk score distribution and ROC.



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Figure 8. Response time distribution and risk score weights.

Table 2. Ablation study of the proposed framework.

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN Only	89.6	88.2	88.9	88.5
CNN - LSTM	93.4	92.1	92.8	92.4
CNN +LSTM + SAM	96.2	95.4	95.9	95.6
CNN +LSTM + SAM + IoT Fusion (Proposed)	**97.5**	**96.9**	**96.8**	**96.8**

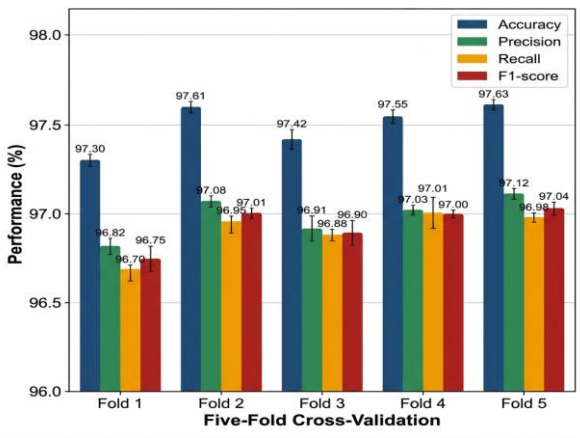
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The independent testing subset was used only for the final performance assessment. Moreover, 5-fold cross-validation (5-fold CV) was performed on the training set to evaluate the robustness and generalization of the proposed framework, as shown in Table 3. The experimental results shown are based on the average performance across the five validation folds, and the final testing results were calculated on the independent test set. The cross-validation performance of the proposed CNN–LSTM + ResNet-50 with the SAM Framework is shown in Figure 9.

Table 3. Five-fold cross-validation performance of the proposed framework.

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Fold 1	97.30	96.82	96.70	96.75
Fold 2	97.61	97.08	96.95	97.01
Fold 3	97.42	96.91	96.88	96.90
Fold 4	97.55	97.03	97.01	97.00
Fold 5	97.63	97.12	96.98	97.04
Mean ± SD	**97.50 ± 0.14**	**96.99 ± 0.13**	**96.90 ± 0.12**	**96.94 ± 0.12**

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Figure 9. Cross-validation performance of the proposed CNN–LSTM + ResNet-50 with SAM framework.

Conclusion

The proposed framework integrates deep learning-based histopathological classification with continuous physiological monitoring. The ResNet-50+SAM model is employed to classify lymphoma histopathological images into CLL, FL, and MCL, while the CNN-LSTM model analyzes physiological time-series data obtained from wearable sensors. Following reconciliation of the evaluation data, the final classification performance is reported consistently across the confusion matrix and the corresponding performance tables. The five-fold cross-validation results further provide an estimate of the model's stability across different training and validation folds. These results demonstrate the potential of the proposed framework for integrating image-based lymphoma classification with continuous physiological monitoring; however, further validation using larger, clinically annotated datasets is required

before clinical deployment.

Ethical Approval

Not applicable.

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Conflicts of Interest

The authors report there are no competing interests to declare.

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