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A Context-Responsive LSTM based IoT Enabled E-Healthcare Monitoring System for Arrhythmia Detection

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Abstract— Detecting Arrhythmia, a life-threatening cardiac condition, in real-time is crucial for timely intervention and improved healthcare outcomes. Traditional manual methods for Arrhythmia detection using Electrocardiogram (ECG) signals are error-prone and resource-intensive. To address these limitations, this paper presents an automated system based on the Context Responsive Long Short-Term Memory (CR-LSTM) model for real-time Arrhythmia classification. The system leverages IoT technology to continuously monitor vital signs and effectively combines contextual information with temporal sensor data to accurately discern different types of Arrhythmias. The CR-LSTM model achieves an impressive accuracy of 99.72% in multiclass classification of Arrhythmias, making it a promising solution for dynamic healthcare settings and proactive personalized care.

Keywords- IoT, healthcare monitoring, context responsiveness, LSTM, Arrythmia.

I. INTRODUCTION

Arrhythmias, a prevalent kind of heart disease, have seen a considerable growth globally in the last two decades, impacting around 4 billion individuals, which is comparable to 0.5% of the total population [1]. If they are not addressed, they might result in serious complications such as a cardiac arrest or a stroke. Recent studies have showed a troubling spike in mortality that are connected to atrial fibrillation, particularly among younger persons. This is cause for concern. These results underscore the urgent need for better techniques to identify and treat atrial fibrillation in order to prevent the negative outcomes that are linked with it. The growing incidence rate and severe effects of arrhythmias, most notably atrial fibrillation, highlight the critical need for automated methods in their diagnosis and treatment. The conventional method, which involves manually analyzing ECG patterns, is both time-consuming and prone to producing inaccurate results. For the purpose of providing a real-time and accurate categorization of arrhythmias, which enables quick treatments and reduces adverse effects, complex algorithms and artificial intelligence are used. This helps overcome the constraints previously mentioned. In addition, the incorporation of wearable sensors and Internet of Things

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networks contributes to the improvement of healthcare systems by making it possible to carry out continuous monitoring of vital signs and by making it easier to provide remote patient care.

The exponential rise of the world's population and the increase in the prevalence of chronic diseases call for healthcare systems that are both effective and economical [2]. Real-time health monitoring systems, which make use of the Internet of Things (IoT), play an essential part in the process of continually monitoring vital signs. These solutions integrate medical equipment, sensors, and data analytics platforms in order to do this task. The Internet of Things enables healthcare practitioners to gather, transmit, and analyze patient data in real time, which enables them to make more informed choices and to intervene more promptly, ultimately leading to improved patient outcomes [3]. These Internet of Things-based technologies provide healthcare alternatives that are both comfortable and accessible, therefore decreasing the need for frequent hospital visits and maximizing the use of available resources. The adoption of solutions that are based on the Internet of Things (IoT) improves healthcare and efficiently handles the issues provided by the rise of the population and chronic illnesses.

Because it can evaluate complex and varied data in an effective manner, deep learning is an essential component of Internet of Things-based smart healthcare systems [4]. These models are able to learn representations directly and work in real time, which enables them to provide exact diagnostics, individualized therapies, and preemptive interventions with high-dimensional data. In addition to this, they are able to manage enormous datasets in an effective manner, adapt easily to changing requirements in the healthcare industry, and consistently enhance their overall performance. Integrating deep learning into IoT-based smart healthcare systems not only greatly improves decision-making processes but also reveals vital information. The significance of context responsiveness in IoT-based healthcare monitoring systems lies in their ability to provide valuable capabilities. By incorporating patient characteristics, real-time data, and long-term trends, these systems offer personalized healthcare, timely interventions, and optimized resource allocation. Moreover, they enhance decision support, user experience, and proactive disease management. Continuous monitoring and analysis of context data enable informed decisions, addressing individual patient needs, and promptly detecting health abnormalities, leading to improved outcomes and satisfaction. Overall, context-responsive IoT-based healthcare monitoring systems play a crucial role in elevating the efficiency, accuracy, and quality of healthcare services in a personalized and proactive manner.

This research introduces the Context Responsive Long Short-Term Memory (CR-LSTM) model, which leverages context responsiveness in IoT-based healthcare monitoring systems. Integrating patient characteristics, real-time data, and long-term trends, the CR-LSTM model enables personalized healthcare, timely interventions, optimized resource allocation, enhanced decision support, improved user experience, and proactive disease management. This study emphasizes the crucial role of context awareness in enhancing the effectiveness and precision of healthcare monitoring, ultimately resulting in improved patient outcomes and satisfaction. The noteworthy contributions of this study are as below.

1. A novel arrhythmia detection architecture which relies on context responsiveness and data dependencies.
2. An extendable model which can be customized for classification problems in diverse pathologies

The paper follows a well-structured organization. Section II presents a comprehensive review of relevant research works. In Section III, the authors discuss the dataset utilized in their research and outline the architecture of the proposed CR-LSTM. Moving on to Section IV, the paper presents the empirical results of the model evaluation and provides their interpretations. Finally, Section V concludes the paper.

II. RELATED WORKS

Remote health monitoring, driven by wearable devices and IoT technology, has gained popularity for its ability to enhance patient care and lower healthcare expenses. This process involves real-time data collection through IoT devices and sensors, which is analyzed and provided as feedback to healthcare providers. Deep learning models, particularly Convolutional Neural Networks (CNNs), have been extensively developed and explored for classifying health issues based on physiological data [9]. Haq et al. [10] conducted a notable study using a customized CNN on Magnetic Resonance (MR) images for brain tumor classification. Through transfer learning and an augmented dataset, they achieved a remarkable highest classification accuracy of 99.90%, outperforming basic CNN classifiers. In a collaborative endeavor, researchers aimed to enhance Multiple Sclerosis (MS) prediction accuracy by integrating human expertise and machine intelligence [11]. They developed a hybrid approach that leveraged both aspects, achieving more precise MS prediction. Another research project focused on rapid heart disorder detection using an Internet of Things (IoT)-based wearable gadget [12]. The researchers utilized a Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) networks to create an ensemble network, Convnet-LSTM, which exhibited exceptional performance in automatically recognizing atrial fibrillation cardiac rhythms. Subsequently, Hammad et al. extended the Convnet-LSTM model to facilitate the automated detection of arrhythmia from Electrocardiogram (ECG) signals acquired using sensors [13]. The model was trained with 2D

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representations of these signals on established datasets and demonstrated a remarkable detection accuracy of 98%.

An innovative deep learning architecture integrating attention mechanisms has been proposed to enhance classification performance [14]. In their research, Yao et al. [15] introduced a time-incremental CNN model that incorporates attention mechanisms to accurately classify various types of arrhythmias using ECG recordings with different durations. The model independently extracts features from each lead of the 12-lead ECG and integrates multiple convolution kernels, allowing it to capture diverse information from the ECG signal with varying receptive fields. The results demonstrated a classification accuracy of 81.2%, showcasing the potential of attention-based classifiers in providing valuable insights for improved healthcare monitoring and diagnosis. This study highlights the significance of attention mechanisms in advancing the field of healthcare classification. In the heart disease classification study [16], a bidirectional LSTM (biLSTM) was implemented to harness the advantages of bidirectional information flow, incorporating both forward and backward data analysis. By focusing on ECG signals, this biLSTM model achieved an impressive accuracy of 98.6%, effectively detecting and categorizing various heart disease conditions. Through this approach, the model gained a comprehensive understanding of the underlying patterns and abnormalities by accounting for temporal dependencies in the data. The utilization of biLSTM facilitated a thorough examination of the data, leading to enhanced insights into heart disease detection and classification. An automated method for classifying cardiac arrhythmias was introduced by Kim et al. [17]. The approach combines a residual network with a biLSTM, enabling the model to effectively extract essential features from ECG signals and accurately categorize them into different types of arrhythmias. The empirical findings demonstrate the remarkable efficacy of this innovative approach, achieving an impressive 99.2% accuracy in categorizing irregular heart rhythms. In a recent research conducted by Islam et al. [18], they proposed an Internet of Things (IoT) based solution aimed at enabling remote surveillance and timely detection of cardiac issues within domestic healthcare settings. The system integrates multiple sensors to measure crucial parameters such as blood oxygen saturation, pulse rate, ECG readings, and body temperature. Patient data is transmitted to a server using the Message Queuing Telemetry Transport (MQTT) protocol, where disease classification is performed using an attention-based CNN. The system is capable of identifying various heart conditions and determining fever/non-fever status, providing a comprehensive report on the patient's vital signs.

This review identifies research gaps in deep learning for healthcare monitoring, including limited labeled data, interpretability challenges, adaptability to dynamic healthcare environments, handling class imbalance and rare events, and addressing real-time processing requirements. LSTM and attention-based models are promising solutions, offering advantages in processing sequential data, capturing long-term dependencies, enhancing feature extraction, improving interpretability, and accommodating variable-length inputs. These models show potential in effectively tackling data scarcity, and other challenges in healthcare monitoring.

III. PROPOSED CR-LSTM

A. The healthcare monitoring framework and the CR-LSTM model for Arrhythmia detection from sensor data are presented in this section. The proposed framework aims to monitor the health of subjects by analyzing the sensor data captured from them. The CR-LSTM model is employed to detect Arrhythmia from this data.

A. Dataset

The MIT-BIH Arrhythmia dataset [19] is used to evaluate the performance of CR-LSTM. This dataset consists of 48 numbers of ECG recordings each comprising 30 minute segments , which were collected from a total of 47 individuals. The distribution of the dataset is provided in Table 1, where it is categorized into five different classes.

Table 1. Data Distribution

Arrhythmia Type	**No. of Training Samples**	**No. of Testing Samples**
Normal Beat (NB)	72472	18118
Supraventricular Premature Beat (SPB)	2224	556
Premature Ventricular Contraction (PVC)	5792	1448
Fusion of Ventricular (FV)	648	162
Unclassifiable Beat (UB)	6432	1608
Total	87568	21892

B. CR-LSTM Prediction Model

The CR-LSTM architecture Comprising the following components is illustrated with Figure 1.

1. IoT Devices:
   a. Oxygen Level Monitor: A portable and non-invasive pulse oximeter sensor is used to measure oxygen levels (O2) in the blood. This device is equipped with

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a microcontroller and wireless communication capabilities.

b. ECG Sensor: A compact and wearable ECG sensor is utilized to capture the electrical activity of the heart. The sensor incorporates an integrated chip for signal processing and data storage.

c. Heart Rate Monitor: A wireless heart rate monitor is worn on the user's chest or wrist. It uses optical sensors to track heart rate variations during daily activities.

d. Body Temperature Sensor: A small and discreet body temperature sensor is placed on the body's surface to monitor temperature changes accurately.

2. Network Configuration: The architecture employs a wireless mesh network topology to enable seamless communication between the IoT devices and the central node. The mesh network ensures robust and reliable data transmission, even in scenarios with signal fluctuations or device mobility.
3. Central Node (Gateway): The central node serves as the gateway for data aggregation and transmission. A Raspberry Pi-based gateway device is utilized, acting as the central hub that communicates with all the IoT devices in proximity.
4. Communication Protocol: The architecture employs the MQTT protocol for efficient data transmission, which is well-suited for IoT applications due to its low overhead and ability to handle intermittent connections.
5. Data Encryption and Security: To ensure the privacy and security of transmitted health data, end-to-end encryption is implemented using advanced encryption algorithms.
6. Power Management: IoT devices are optimized for power efficiency, utilizing low-power components and sleep modes when not actively transmitting data.
7. Cloud Server: The data acquired from the IoT devices is transmitted to a remote cloud server for storage and analysis. The cloud server is equipped with powerful data processing capabilities, enabling real-time data analysis and generating actionable insights.

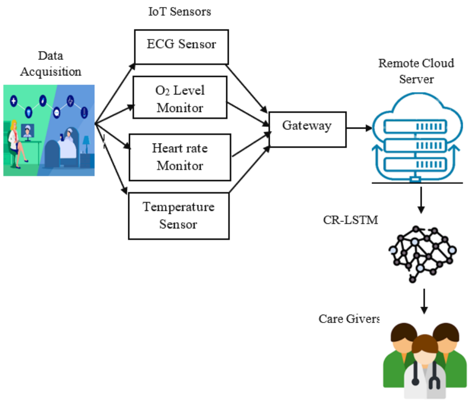

Fig.1. Context Responsive Healthcare Monitoring System

The heart disease detection system proposed in the research utilizes the CR-LSTM model as a multiclass classifier. This model effectively identifies heart disorders from wearable sensor inputs, including ECG data, body temperature, and historical information. It generates a comprehensive report that provides valuable analysis of the patient's vital signs, determining whether they fall within acceptable ranges. In critical situations, the system promptly establishes a connection with the nearest doctor for rapid diagnosis and treatment. By leveraging IoT and deep learning, this framework significantly enhances remote health monitoring, thereby improving the overall quality of care. The classifier utilizes the context responsiveness mechanism, which effectively incorporates both local and global attention in sequential modeling. Its application lies in the field of heart disease detection, where it operates on the premise that cardiac disorders are characterized by specific physiological parameters. By analyzing sensor data, the classifier can discern these diseases from normal body conditions by capturing both local and global context. Fig. 2 displays the schematic of the CR-LSTM with its components, which work in tandem to enhance the performance of the classifier in detecting heart diseases by considering the broader context and relevant details from the sensor data.

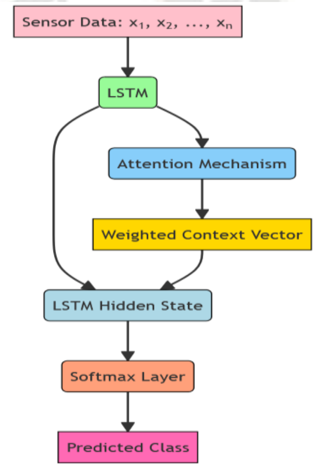

Fig.2. CR- LSTM Architecture

1. **Input Layer (Sensor Data):** The model takes in sequential sensor data, represented as $x_1, x_2, ..., x_n$, as input.
2. **LSTM Layer:** The LSTM (Long Short-Term Memory) layer processes the input sequential data. LSTMs are a type of recurrent neural network that can effectively capture temporal patterns and dependencies in sequential data.
3. **Attention Mechanism:** The LSTM hidden states are then passed through an attention mechanism. The attention mechanism calculates the importance or weight of each hidden state, emphasizing more relevant information for the task at hand.

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4. **Weighted Context Vector:** Based on the attention weights, the attention mechanism generates a weighted context vector. This vector represents a combination of the LSTM hidden states, where more important states are given higher weights.
5. **LSTM Hidden State (Intermediate Output):** The LSTM hidden state is an intermediate output representing the processed sequential information. It contains valuable information about the sequential patterns present in the sensor data.
6. **Softmax Layer:** The LSTM hidden state, combined with the weighted context vector, is then fed into a Softmax layer. The Softmax layer calculates the probabilities for each class in the multi-class classification problem.
7. **Output (Predicted Class):** The predicted class is the final output of the model. It corresponds to the class with the highest probability calculated by the Softmax layer and represents the model's prediction for the input sensor data.

C. *Context Responsive Attention Mechanism*

The context responsiveness mechanism is a crucial component of the architecture. It employs an attention mechanism to enhance the LSTM model's ability to capture relevant information from the sequential sensor data $(x_1, x_2, \ldots, x_n)$ as below.

LSTM Hidden State (h_t): The LSTM hidden state is computed based on the input data and the previous hidden state (h_{t-1}). It captures sequential patterns and information from the current time step (t) in the sensor data. It is represented as in (1).

$$h_t = LSTM(x_t, h_{t-1}) \quad (1)$$

Attention Mechanism: The attention mechanism calculates the attention weight α_t for each LSTM hidden state h_t by considering the relevance of the hidden state to the overall context. It employs a scoring function to quantify the importance of each hidden state. The attention weights are then obtained using a softmax function as in (2).

$$\alpha_t = softmax(score(h_t)) \quad (2)$$

Weighted Context Vector (C): The weighted context vector (C) is obtained by taking the weighted sum of the LSTM hidden states h_t using the attention weights α_t. This step emphasizes more relevant hidden states and suppresses less important ones, creating a context-aware representation of the input data. Mathematically, the weighted context vector can be computed as in (3).

$$C = \sum_{t=1}^{n} (\alpha_t \cdot h_t) \quad (3)$$

IV EXPERIMENTAL RESULTS AND DISCUSSIONS

The section presents the experimental setup for training and testing the CR-LSTM model, along with the performance metrics used to evaluate its effectiveness.

A. *Experimental Setup*

The CR-LSTM model is deployed on a powerful computing infrastructure with an Intel Core i9 processor, 64GB of RAM, and an NVIDIA Quadro RTX 6000 GPU, ensuring efficient data processing and accelerated model training for fast and accurate healthcare data analysis. It utilizes TensorFlow 2.8 as the deep learning framework with Python 3.9 and essential libraries like NumPy, Pandas, and Matplotlib, providing a comprehensive ecosystem for data manipulation, visualization, and analysis. This setup enables CR-LSTM to facilitate real-time analysis, predictive modeling, and improved healthcare outcomes. Grid searching is utilized to determine the optimal hyperparameters of the CR-LSTM model. It undergoes evaluation with various parameter combinations until reaching a desired level of training accuracy. The hyperparameters for the optimal configuration of the CR-LSTM model are presented in Table 2. The stopping criterion for training the CR-LSTM model is based on the validation loss. Training was halted when the validation loss did not decrease for five consecutive epochs, ensuring prevention of overfitting.

Table 2. Model Hyperparameters

Parameter	Value
Maximum No. of Epochs	100
No. of Hidden Nodes	100
Learning Rate	0.001
Batch Size	64
Optimization	ADAM
Weight Decay	0.05
Dropout	5

B. *Performance Evaluation*

The proposed CR-LSTM is evaluated on the test dataset, with accuracy (Acc), precision (Pre), sensitivity of recall (Sn) and F1 score metrics. These metrics are derived from the True Positive (TP), False Positive (FP), True Negative (TN) And False Negative (FN) values. Acc is the proportion of correctly classified samples over the total number of samples in the dataset, as in (5).

$$\text{Acc} = \frac{TP+TN}{TP+FP+TN+FN} \quad (5)$$

Pre is the ratio of correctly classified positive instances to all positive predictions of the model, as defined in equation (6). A high precision score indicates a low FP rate, signifying that the model makes minimal false positive detections.

$$\text{Pre} = \frac{TP}{TP+FP} \quad (6)$$

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Sn quantifies the proportion of actual positive samples predicted by the model correctly, as in (7). It assesses the model's capability to accurately detect all positive cases in the dataset.

$$\text{Sn} = \frac{TP}{FN+TP} \tag{7}$$

F1 score evaluates the harmonic mean of precision and recall, as in (8). It offers a balanced evaluation of model performance by incorporating both precision and recall. F1 spans a scale from 0 to 1, where a value of 1 signifies flawless precision and recall, while 0 signifies inadequate performance.

$$\text{F1} = 2 \times \frac{\text{Pre}\times Sn}{\text{Pre}+\text{Sn}} \tag{8}$$

The performance of the CR-LSTM is evaluated for each target class and the objective metrics are presented in Table 3. As shown in the table, CR-LSTM is capable of distinguishing the NB and UB cases with a good degree of accuracy. The precision values ranging from 0.9457 to 0.9995 also suggest that the model has a low FP rate, making fewer incorrect positive predictions. The sensitivity values are also consistently high, ranging from 0.9020 to 0.9997, testifying the ability of the model to detect the actual positive cases under each category.

The CR-LSTM model's classification performance is well-balanced, as evident from the F1 scores based on precision and sensitivity. The confusion matrix in Figure 4 provides a comprehensive assessment, revealing good performance for NB and PVC classes but lower metrics for FV, attributed to limited samples. To improve the performance of the model, FV data can be augmented and model optimization could be considered.

Table 3. CR-LSTM Performance Metrics

Target Class	Acc	Pre	Sn	F1
FV	0.9691	0.9457	0.9691	0.9573
NB	**0.9997**	**0.9995**	**0.9997**	**0.9996**
PVC	0.9931	**0.9979**	**0.9931**	**0.9955**
SPB	0.9820	0.9855	0.9820	0.9837
UB	**0.9950**	0.9937	**0.9950**	0.9944

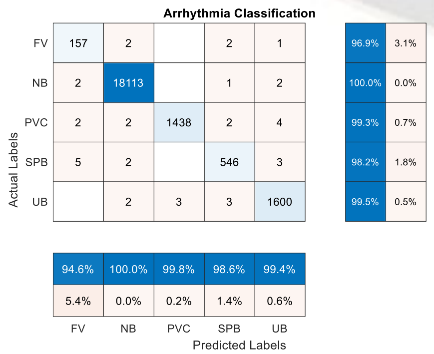

Fig.3. Confusion Chart for Arrhythmia Classification

Table 4 demonstrates CR-LSTM's superior performance compared to LSTM and attention-based CNN models in real-time healthcare monitoring. This underscores the importance of integrating contextual awareness for accurate anomaly detection and outcome prediction. CR-LSTM's remarkable effectiveness reaffirms its potential to improve patient care and monitoring in healthcare systems. Optimizing device and software configurations can further enhance its applicability in this context.

Table 4. Comparison with State-of-the-art

Model	Acc	Pre	Sn	F1
ConvLSTM Hummad et al. [13] (2022)	0.9374	0.9166	0.9189	0.9177
BiLSTM Nancy et al. [16] 2022	0.9473	0.9263	0.9286	0.9275
ResNet+biLSTM Kim et al. [17] (2022)	0.9274	0.9068	0.9091	0.9080
CNN+Attention Islam et al. [18] (2023)	**0.9503**	**0.9361**	**0.9384**	**0.9372**
CR-LSTM (Proposed)	**0.9983**	**0.9845**	**0.9878**	**0.9861**

The learning ability of the CR-LSTM is visualized using the Receiver Operating Characteristics (ROC) curve, which plots the True Positive (TP) rate against the False Positive (FP) rate. This enables a thorough evaluation of the trade-off between sensitivity and specificity. Figure 4 illustrates an ROC curve with an impressive Area Under the Curve (AUC) value of 0.9690, showcasing the exceptional discriminative capabilities and strong predictive performance of the CR-LSTM model. The CR-LSTM's outstanding results are attributed to its well-configured device and software settings, which have been suitably optimized for the task.

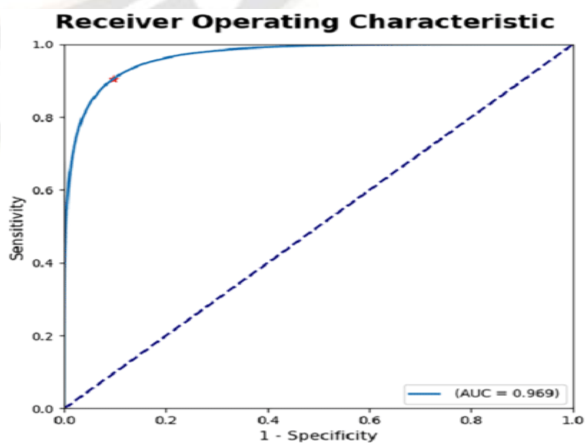

Fig.4. ROC Curve for CR-LSTM

V. CONCLUSION

In this research paper, a novel model called CR-LSTM is introduced for real-time arrhythmia classification using data from wearable sensors. The CR-LSTM capitalizes on the strengths of context awareness and long-term dependency offered by LSTM to effectively classify five different types of arrhythmias. The model achieves an impressive overall accuracy of 99.83%, surpassing the performance of existing models in this domain. The results of CR-LSTM hold great promise for applications in remote health monitoring and swift detection of arrhythmias. Moreover, the potential for employing transfer learning techniques allows for the extension of this model to various other healthcare domains, enabling proactive disease management and personalized interventions

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