IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received June 23, 2021, accepted July 11, 2021, date of publication July 16, 2021, date of current version July 28, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3097751

One-Dimensional CNN Approach for ECG Arrhythmia Analysis in Fog-Cloud Environments

OMAR CHEIKHROUHOU[1,2], REDOWAN MAHMUD[3], (Member, IEEE), RAMZI ZOUARI[1], MUHAMMAD IBRAHIM[4,5], ATEF ZAGUIA[6], AND TUAN NGUYEN GIA[7]

[1]CES Laboratory, National School of Engineers of Sfax, University of Sfax, Sfax 3038, Tunisia
[2]Higher Institute of Computer Science of Mahdia, University of Monastir, Monastir 5000, Tunisia
[3]School of Computing Technologies, STEM College, RMIT University, Melbourne, VIC 3000, Australia
[4]Department of Information Technology, The University of Haripur, Haripur 22620, Pakistan
[5]Department of Computer Engineering, Jeju National University, Jeju 63243, South Korea
[6]Department of Computer Science, College of Computers and Information Technology, Taif University, Taif 21944, Saudi Arabia
[7]Department of Computing, University of Turku, 20500 Turku, Finland

Corresponding author: Muhammad Ibrahim (ibrahimmayar@uoh.edu.pk)

This work was supported by Taif University Researchers Supporting Project through Taif University, Taif, Saudi Arabia, under Grant TURSP-2020/114.

ABSTRACT Cardiovascular diseases are considered the number one cause of death across the globe which can be primarily identified by the abnormal heart rhythms of the patients. By generating electrocardiogram (ECG) signals, wearable Internet of Things (IoT) devices can consistently track the patient's heart rhythms. Although Cloud-based approaches for ECG analysis can achieve some levels of accuracy, they still have some limitations, such as high latency. Conversely, the Fog computing infrastructure is more powerful than edge devices but less capable than Cloud computing for executing compositionally intensive data analytic software. The Fog infrastructure can consist of Fog-based gateways directly connected with the wearable devices to offer many advanced benefits, including low latency and high quality of services. To address these issues, a modular one-dimensional convolution neural network (1D-CNN) approach is proposed in this work. The inference module of the proposed approach is deployable over the Fog infrastructure for analysing the ECG signals and initiating the emergency countermeasures within a minimum delay, whereas its training module is executable on the computationally enriched Cloud data centers. The proposed approach achieves the F1-measure score $\approx$1 on the MIT-BIH Arrhythmia database when applying GridSearch algorithm with the cross-validation method. This approach has also been implemented on a single-board computer and Google Colab-based hybrid Fog-Cloud infrastructure and embodied to a remote patient monitoring system that shows 25% improvement in the overall response time.

INDEX TERMS Internet of Things, ECG analysis, 1D-CNN, fog computing, hybrid fog-cloud, heart disease.

I. INTRODUCTION

According to the World Health Organisation (WHO), cardiovascular diseases are the causes of an estimated 17.9 million deaths each year [1]. There are different forms of cardiovascular diseases, including coronary heart disease and heart failure. Although some of them cannot be completely cured, they can be controlled by adequately monitoring the heart status and taking preventive measures accordingly [2]. Several measures such as blood tests for troponin levels, chest X-ray, electrocardiogram (ECG), stress tests, and angiogram are available to determine whether the heart of a person is in stable condition or not [3]. Among them, ECG is preferable for continuous tracking as it is non-invasive, highly indicative, and requires less sophisticated machines [4].

Electrical impulses coordinate the contractions of different heart parts for blood circulation. During ECG, these impulses are read externally to determine their strength and the rhythm of the heartbeats [5]. Since the heart rhythms of any normal person follow a specific trend, any changes in the ECG signals indicate a cardiac condition. Several Internet of Things (IoT) devices, including smart vest, fitbit, and chest

The associate editor coordinating the review of this manuscript and approving it for publication was Alessandro Pozzebon.

strap, are utilised for perceiving the ECG signals at home and complement the realisation of remote cardiac patient monitoring system [6], [7]. However, to detect the cardiovascular diseases, the ECG signals collected from IoT-based systems should be analysed accurately.

A notable number of Edge computing or sensor device-centric approaches for ECG signal processing have been developed recently. Particularly, ECG signals are analysed at the wearable devices to detect abnormalities such as abnormal heartbeats or arrhythmia. In many cases, such approaches can achieve some levels of the accuracy and provide fast ECG analysis results in terms of a few seconds. However, these can be mainly used for normal daily usage but might not be suitable for sensitive healthcare applications as there are strict requirements for accuracy and low latency. In addition, Edge computing-based approaches still have limitations due to the resource constraints of wearable devices. For example, the ECG analysis at the wearable devices can reduce the life time of their batteries.

Recently, Artificial Intelligence (AI) based on Machine Learning (ML) and Deep Learning (DL) models have been widely adopted to perform disease analysis and classification of different healthcare diseases [8]–[12]. In such cases, the Cloud computing resources [13] are predominantly used for training and assessing these models [14]. However, the data centres of commercial Cloud service providers such as Google Cloud Platform and Amazon Web Services are located at a multi-hop distance from the IoT devices that significantly increases the communication delay while transferring the healthcare data [15]. Conversely, the reaction time or latency tolerance for any severe cardiac condition is very stringent that urges for real-time processing of the ECG signals and faster initiation of emergency services. Hence, the Cloud-based execution of ML models is considered to be less feasible for ECG signal analysis [16].

To overcome the high latency constraints of Cloud computing and meet the real-time processing requirements of critical healthcare data including IoT device-generated ECG signals, Fog computing solutions have been employed in many remote patient monitoring systems [17]. By acting as an intermediate layer between Cloud data centres and edge devices, the Fog paradigm brings the computing facilities in the vicinity of the data sources that reduce the data transfer delay and improve the overall response time in data processing [18]. In this paper, the proposed Fog computing platform consists of smart gateways which are interconnected and communicate together [19]. The Fog-based gateways receive data directly from the wearable devices via a wireless communication protocol such as Bluetooth-Low-Energy (BLE) or Wi-Fi. The convergence network of Fog-based gateways forms a Fog computing infrastructure that can offer many advantages such as distributed local data storage, distributed data processing, energy efficiency, and low latency [16], [20]. Nevertheless, Fog nodes such as single board computers, smart gateways, network switches and micro data centers are constrained in resource capacity that resists the execution of compute-intensive ML models for ECG analysis [21].

Focusing on the respective challenges of Cloud computing in processing ECG signals, we have proposed a modular 1D-CNN approach in this work. The inference module of the proposed approach exploits a trained ML model to predict cardiovascular diseases based on the ECG signals captured from the IoT wearable devices. This approach is feasible to deploy on the Fog computing infrastructure. It also helps to optimise the delay in initiating countermeasures such as calling an ambulance or medical assistance during emergency cardiac situations of remote patients. Similarly, the training module of the proposed DL approach (i.e., that creates the ML model based on historical evidence) is made executable on the Cloud data centres. This solution reduces the computational overhead from the Fog infrastructure and enables the periodic updates of the ML model for the inference module with new data. The major contributions of this work are listed below.

- A system architecture for remote cardiac patient monitoring that can ensure optimized delay in actuating emergency services.
- A modular 1D-CNN approach for analysing ECG signals captured from IoT wearable devices, that can simultaneously operate on hybrid Fog-Cloud infrastructure.
- A proof-of-concept prototype implemented on a single-board computer and Google Colab that detects arrhythmia cardiovascular disease with an accuracy of 99.46% on MIT-BIH Arrhythmia database.

The remainder of this paper is organised as follows. section II outlines the existing literature related to the remote cardiac patient monitoring systems. section III describes the remote patient monitoring system architecture. section IV discuses the proposed DL approach. The performance evaluation of the proposed system is presented and discussed in section V. Finally, section VI concludes the paper with the future directions.

II. RELATED WORKS

A considerable number of advanced IoT frameworks and systems are available in the literature that focuses on heart diseases and ECG signal analysis. Some of them aims at developing advanced methods (e.g., machine learning and deep learning) for ECG analysis while other approaches target to develop system architectures (i.e., fog and edge computing) for providing advanced services that help improve quality of ECG analysis. This section discusses the advanced method for ECG analysis on the Fog IoT system. In [16], the authors developed a Fog-based IoT system for remote and real-time monitoring. The system introduced a Fog computing multi-layer architecture that can offer advanced services such as distributed data storage, data processing, data compression, data analysis and push notification. Particularly, the system analysed the ECG data by applying the four-level discrete wavelet transformation with Daubechies 4 wavelet. Correspondingly, useful information from the acquired bio-signals (such as ECG, oxygen saturation, heart rate, and body temperature) and contextual data (such as room temperature, humidity, and air quality) can be extracted. Depending on the situation, the collected data could be analysed at the Fog or Cloud layer. The system could also provide some security solutions, including firewall, advanced encryption standard (AES), and lightweight security algorithms. When the system detects any abnormalities, it sends push notification messages to the medical caregivers accordingly. Although the system provided advanced services, including low-latency distributed ECG analysis, the accuracy of the analysis was limited (e.g., when comparing with the Cloud-based ECG analysis approaches).

In [22], the authors presented an intelligent Fog-based IoT system for real-time healthcare applications. The system had an advanced Fog-based architecture supporting distributed computation at the edge of the network. Particularly, the system had a collaborative machine learning approach distributed over different layers, including Edge, Fog and Cloud environment to enable real-time actionable insights that enhance decision making. A lightweight shallow feed-forward neural network was executed at the endpoint IoT device while the Convolution Neural Network having ECG images as inputs was run at the Fog layer. The results showed that the approach based on CNN could achieve accuracy and sensitivity of 98% and 96%, respectively. Although the latency of running the CNN-based approach at the Fog layer had not been shown in the paper, the system might not achieve very low latency as it uses ECG images as an input for the CNN model.

In [17], the authors presented a Fog-based IoT system for remote health monitoring. The system had an advanced Fog architecture in which smart gateways are interconnected and communicate with each other. Based on the architecture, various Fog services, including local data storage and management, data processing, data analysis, fault detection, interoperability and security, were provided. The system was able to collect and process three-dimensional (3-D) acceleration and 3-D angular velocity to detect fall. Particularly, when a sum vector magnitude of 3-D acceleration or a sum vector magnitude of 3-D angular velocity trespasses predefined threshold levels and satisfy verification requirements, a fall event is detected. The system was also able to extract ECG features and detect heart rate variability. Notably, an automated QT interval extraction algorithm was designed and run at smart Fog-based gateways to achieve real-time detection of heart abnormalities. Due to the lightweight ECG analysis algorithms, this system might not achieve highly accurate results compared to deep learning-based approaches.

In [25], the authors developed a low-cost Fog-based ECG monitoring system. The proposed system architecture had a Fog layer consisting of smart gateways that were built from the low-cost embedded board. The system had energy-efficient and low-cost wearable sensor devices that were able to collect and transmit 2-channel ECG in real-time to Fog-based gateways via nRF wireless communication protocol. At Fog-based gateways, several Fog services push notification, channel management, distributed data storage and lightweight security were provided. Particularly, ECG data were processed with an algorithm based on wavelet transform and threshold estimation to extract ECG features, including heart rate and RR intervals. End-users could access real-time raw or analysed ECG data via Cloud or Fog servers, depending on the situation. Although this approach helped achieve low-latency ECG analysis, the accuracy of the ECG analysis was not high.

In [27], the authors proposed a Fog-based IoT system for healthcare applications. The proposed system architecture used a smartphone, laptop or tablet as a gateway device that acts as a fog node to forward the collected data to broker/worker nodes. The broker node was responsible for receiving job requests from a gateway, managing resources and deciding the suitable worker node to which the job should be sent. The worker node was able to enable lightweight automatic heart patient data diagnosis using deep learning. The proposed system was tested and measured in a Fog computing environment in terms of network bandwidth, latency, jitter, execution time, and power consumption. Similar to other Fog-based approaches, the proposed lightweight deep learning approach achieved approximately 87-94% accuracy depending on the test cases.

Additionally, in [23], the authors proposed a health monitoring system with hierarchical Fog-based architecture. The proposed system ensures machine learning-based data analytics and autonomous adjustment with respect to the patient's conditions via a closed-loop management technique. The system was evaluated via a use case of arrhythmia detection and the results showed that the system can achieve a high level of accuracy with low latency. In [24], the authors also presented a Fog-based health motoring system for cardiovascular diseases. The collected ECG signals were sent via LoRa to Fog-based LoRa gateways where Fog-AI having deep learning module for the detection of Atrial fibrillation and other heart rhythms. The system was evaluated via a dataset of single-lead ECG and achieve an accuracy of 90% for atrial fibrillation. Although ECG analysis approaches in these systems could achieve quick response, the accuracy level was not as high as other machine learning and deep learning-based approaches (i.e., that often reached higher than 95% accuracy).

In [26], the authors proposed a Fog-based health monitoring system for diabetic people with cardiovascular diseases. The proposed system architecture consists of energy-efficient wearable sensor nodes able to collect different types of data, including motion-related data, ECG, body temperature and glucose. The collected data was sent to a network of Fog-based gateways where many advanced services (e.g., real-time push notification, human activities categorisation, nRF channel management and fall detection) were provided. These services were lightweight and able to provide fast results. Particularly, QT's length extraction algorithms for detecting hypoglycemia and hyperglycemia in real-time

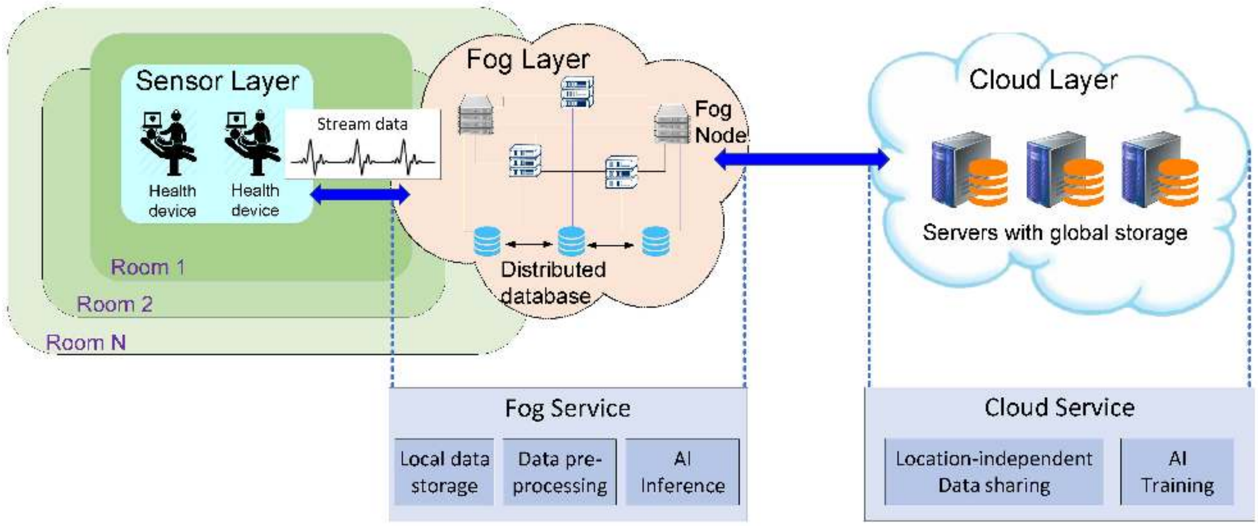


FIGURE 1. **The hybrid Fog-Cloud system architecture.**

were linear and based on several threshold values. The entire system was implemented and evaluated via several use cases of ECG monitoring and fault detection. The results showed that the system could achieve a high level of accuracy and help to improve the quality of healthcare services. However, the ECG analysis algorithms have not been evaluated with a large dataset collected from different patients or participants.

A summary of the related works is presented in Table 1. In comparison to the existing works, the proposed cardiac patient monitoring system balances a load of ECG signal processing effectively across hybrid Fog-Cloud environments. As a result, the proposed DL approach is capable of running even in single-board computers like Raspberry Pi with higher accuracy and faster response during critical scenarios. Our policy also facilitates the periodic update of the ML model so that it can operate by overcoming the concept drifting issues.

III. SYSTEM ARCHITECTURE

The proposed remote patient monitoring system encapsulates a three-layer architecture as shown in Figure 1.

- *Sensor Layer:* This layer is composed of wearable IoT devices that collects ECG signals of cardiac patients. These devices perform the sensing operation in a consistent manner and transmit the ECG signals to the Fog computing nodes instantly located at the Fog layer. Periodicity can also be set in the signal transmission as per the supervision of the medical professionals. Moreover, the sensor layer incorporates actuators, including alert systems and ambulance services that receive commands from the Fog layer and function as per the outcome of the ECG signal analysis operations. The sensor layer also notifies the Fog layer whether the response is applicable for the situation or not, using a feedback message.
- *Fog Layer:* This layer consists of a cluster of Fog nodes that performs the following operations.
  - *Local Data Storage:* To ensure the faster processing of patient's ECG signals, Fog nodes preserve the incoming data in a local storage. Additionally, when the processing of ECG signals cannot be conducted by the Fog nodes due to overhead, these data are forwarded to Cloud in a prioritized order for further processing. The priority of a data flow can be set dynamically based on the criticality of the patients and the respective location and time. During such operations, the local storage is considered as a cache to ensure a persistent data flow. Moreover, the local storage can be either encrypted or compressed based on the privacy preferences of the patients.
  - *Data Filtering:* Due to various reasons such as the electromagnetic interference from the nearby devices, the oscillations in electric power or the improper attachment of sensors to the patients' body, noises are usually aggregated to the ECG signals. Because of the internal mechanical complexities, the EEG signals perceived by the wearable IoT devices can also include complex shapes with small amplitude and different frequencies. Such noises can affect the faster processing of ECG signals and degrade the accuracy significantly. Therefore, the Fog nodes apply complex and robust data filtering techniques on the ECG signals to eliminate these noises and unnecessary or incomplete data.
  - *Data Analysis:* In this remote patient monitoring system architecture, the inference module of the proposed ML model is executed at the Fog layer. Based on the sensed ECG signal, the inference module classifies the signals and detects the abnormal cases of the patients. As a result, the system can offer real-time responses, thus enhancing the response time of the system. Furthermore, once an event of interest is detected by the inference module, the necessary command is forwarded to the sensor layer for the actuation of emergency services and the applicability of the operation is monitored. Later, the ECG signals, actuation command and the feedback from the sensor layer are sent to the Cloud layer so that the

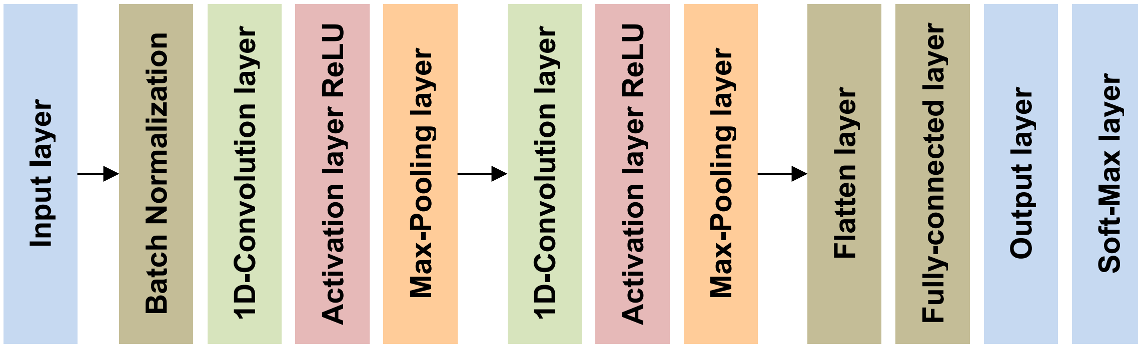


FIGURE 2. 1D Convolution Neural Network architecture.

TABLE 1. A summary of related work and their comparison.

Ref	Use case	IoT	AI	FC	Pros(+)/Cons(-)
[16]	General health, ECG feature extraction, heart rate	✓		✓	(+) Full system implementation; (-) not high level of security
[17]	Fall detection, general health, ECG feature extraction and heart rate variability	✓	✓	✓	(+) Full system implementation; (-) not focused security and data privacy
[23]	Fall detection, general health, ECG feature extraction and heart rate variability	✓	✓	✓	(+) Full system implementation; (-) not focused security and data privacy
[24]	ECG monitoring and classification	✓	✓	✓	(+) Full system implementation; long range and low power (-) not focused security and data privacy
[25]	ECG monitoring	✓		✓	(+) Full system implementation; low-cost; simple AES-256
[26]	ECG monitoring, fall detection and glucose monitoring	✓		✓	(+) Full system implementation; energy-efficient wearable sensor devices(-) simple security
[27]	Heart diseases	✓	✓	✓	(+) Full system implementation; measurement of accuracy, response time, network bandwidth and energy consumption ;(-) not focused security and data privacy
[22]	ECG-based arrhythmia detection	✓	✓	✓	(+) Hardware implementation of CNN and ANN; measurement of overheads, energy consumption, latency and performance; (-) not focused security and data privacy
This work	Fog-Cloud-based ECG signal analysis	✓	✓	✓	(+) Hybrid Fog-Cloud infrastructure; (+) Full prototype implementation; (+) Modular DL approach; (+) High Accuracy

training module can be updated in a consistent manner using these information. However, as most of the Fog nodes have limited physical resources (i.e., processing power and main memory) and could have energy limitations for performing data and compute-intensive operation, the inference module should be lightweight and capable of detecting cases accurately.

- *Cloud Layer:* The Cloud data centre operates as the backbone for the proposed patient monitoring system. It receives ECG signals, corresponding responses and service outcomes from the Fog layer and stores the information in a global database for location-independent sharing and access. The Cloud layer also supports the consistent training of the proposed ML model with new information. Once the training module completes execution, the old inference module at the Fog layer is replaced with the latest one. This approach resists the effect of concept drifting and enable the model to cope with the change in the distribution of the data over time [28]. Thus, the proposed system always retains an acceptable rate in case of prediction as time passes. Nevertheless, considering the high frequency and variations of ECG signals, the execution of the training module should be faster. This requirement makes the efficient allocation of the Cloud resources [29], [30] a must, which is also subject to extensive research.

IV. ECG DATA ANALYTIC MODULE

Recently, Deep Learning (DL) models have achieved very promising performances in the healthcare domain. They have the ability to extract high-level features from the healthcare input data using a stack of hidden layers. Among the variants of DL models, Convolution Neural Networks (CNN) are widely adopted in processing medical images [31], whereas Recurrent Neural Network (RNN) and Long short-term memory (LSTM) networks are used for analysing bio-signals including ECG, electroencephalogram (EEG), photoplethysmogram (PPG) [32].

A. 1D-CNN MODEL DESCRIPTION

In this work, we have proposed a 1D-CNN architecture for ECG Arrhythmia classification. It permits data extraction and classification. The extraction part includes batch normalization, convolution, activation and max-pooling layers, while the classification part is composed of flatten, fully-connected and SoftMax layers (Figure 2).

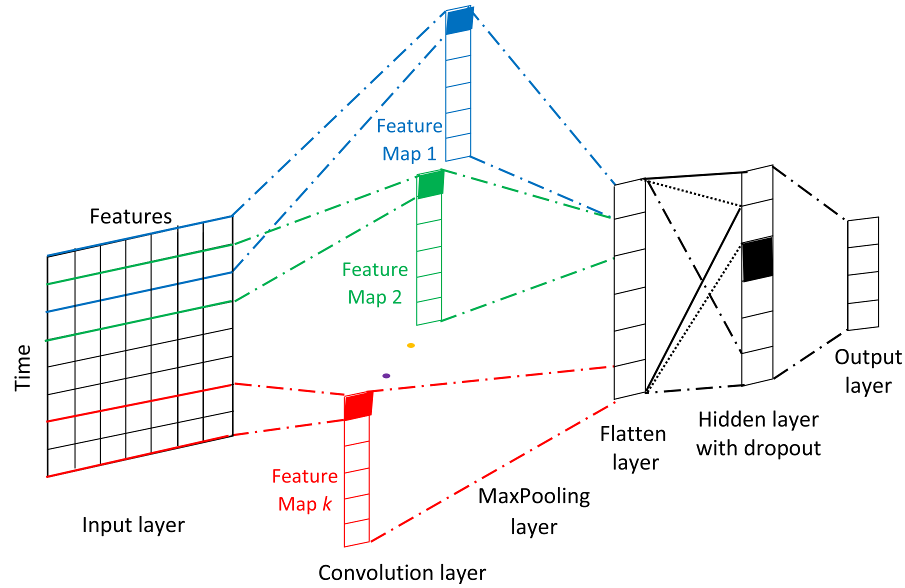


FIGURE 3. **1D CNN architecture.**

In the 1D-CNN input layer, the data is organised in 2D format. The vertical direction represents the time axis, while the horizontal direction corresponds to the features relative to each timestamp. The batch normalisation layer aims to standardise the input data by reducing internal co-variate shift [33]. In the one-dimensional convolution layer, each neuron is connected to a local window from the previous layer, called the receptive field, that shifts along the timestamp axis and share the synaptic weights(Figure 3). This model allows reducing the number of weights and facilitating the generalisation process. The neurons over the vertical direction represent the evolution of the input data over time that depends on the receptive field and delay values. The number of neurons along the horizontal direction can be defined manually that allow transforming the input features into another sequence of higher order. For each neuron, the rectified linear unit function (ReLU) is applied to return the weighted sum of the input data if it is positive and zero if not. Thereafter, we applied a one-dimensional max-pooling layer to preserve for each activation map the neuron with the higher value. The classification part is similar to a multi-layer perceptron. The flatten layer consists of converting the data of the extraction part to a 1D-vector format. We implemented one hidden layer with the dropout function, and the neurons of the output layer corresponds to the classes of heartbeats disease.

B. 1D-CNN MODEL CONFIGURATION

The proposed 1D-CNN input layer is composed of 319 nodes representing the ECG heartbeat segments length. The extraction part includes two blocks of convolutions, activation and max-pooling layers. In the training stage, the Dropout function is applied to avoid the over-fitting [34]. It is a regularisation method that consists of temporarily dropping out random units from the neural network. In the simplest case, each unit is retained with a fixed probability p independent of the other units. The classification part contains one hidden layer of 512 nodes fully connected to the units of the Flatten layer. The output layer nodes of the proposed model represent 6 different heartbeats groups as specified by the Association for the Advancement of Medical Instrumentation (AAMI) standard. Table 2 provides a summary of the proposed 1D-CNN model.

TABLE 2. **1D-CNN network configuration.**

Network part	Description	
Input layer	319 neurons	
Extraction part Block$_{1,2}$	Conv1D	Kernels=64 receptive field=2 stride=1
	Activation	ReLU
	Dropout	probability=0.4
	Max-pooling	pool size=2
Classification part	FC layer	512 neurons
	Dropout	probability=0.2
	Output layer	6 neurons

V. PERFORMANCE EVALUATION

In this section, we have evaluated the performance of the proposed DL model and demonstrated the efficiency of Fog computing in processing ECG signals and dealing with critical cardiac scenarios. The findings of the performance evaluation are discussed below.

A. EFFICIENCY OF THE ECG SIGNAL ANALYSIS MODEL

First, we present the efficiency of the proposed 1D-CNN model in classifying ECG signals. To evaluate the

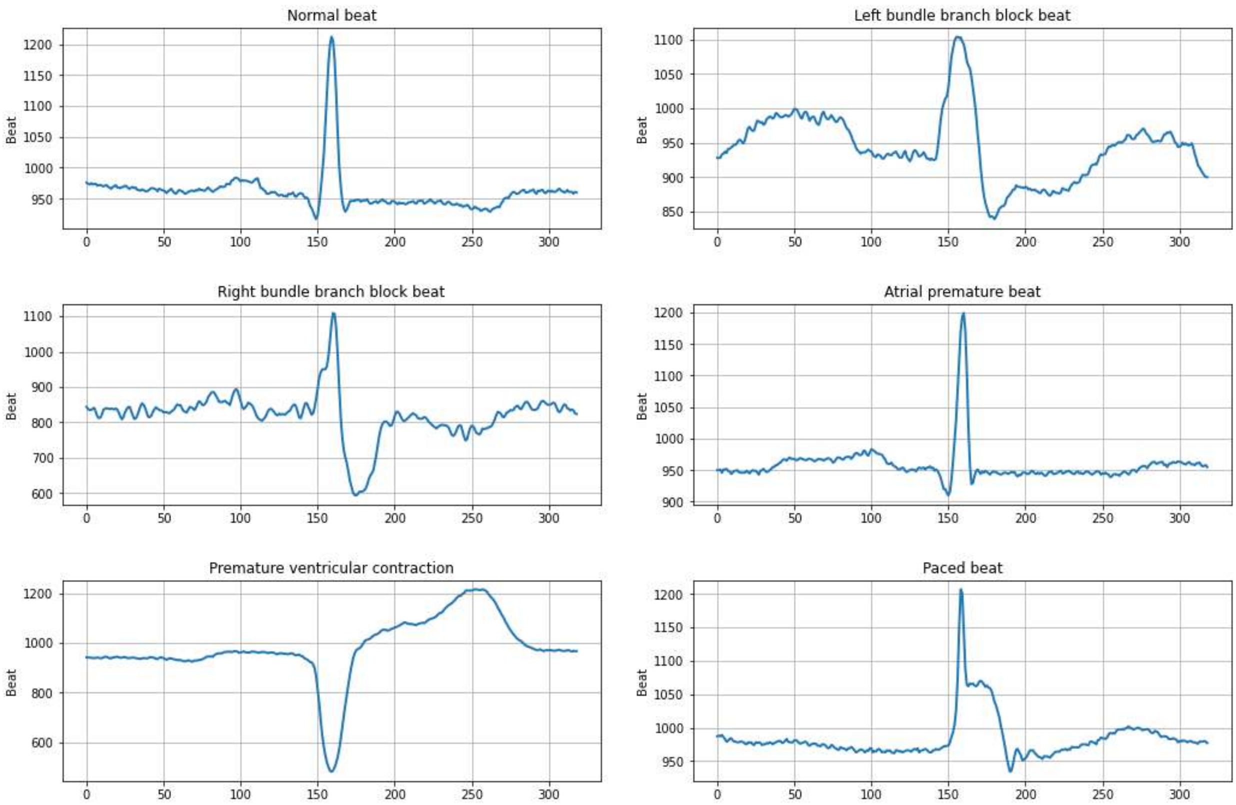


FIGURE 4. MIT-BIH Arrhythmia heartbeats.

performance of the proposed 1D-CNN model, accuracy, loss, recall, precision, and F1-score are used as the performance metrics.

1) DATASET OVERVIEW

The performance evaluation experiments are conducted on MIT-BIH database [35]. It is a publicly available database, which provides standard benchmark investigation material for the detection of heart arrhythmia. This database includes **48 ECG record files** of 47 individuals. Each record file with two-lead ECG signals lasts approximately thirty minutes long and samples at 360 Hz. The ECG records and their annotations are saved in CSV and TXT files, respectively, and are then classified into 6 groups according to the AAMI standard. For each record file, the ECG signal is segmented into heartbeats according to the PQRST (Preview, Question, Read, Study, Test) sequence. The P-wave represents the atrial depolarization process, the QRS complex denotes the ventricular depolarisation process and a T-wave representing the ventricular repolarization. An illustration of the heartbeats is depicted in Figure 4. Furthermore, based on the aforementioned specifications, we obtain a total of **42021 ECG heartbeat segments of length 319ms**. The details of the ECG heartbeat segments is presented in Table 3.

For the experiments, we have divided MIT-BIH database into train, validation and test subsets. The training dataset have been used for training the 1D-CNN model, while the validation dataset is useful to give an estimate of the model skill while tuning model's hyper-parameters. The testing dataset is used to evaluate the skill of the final tuned model on the unseen data. Moreover, we have applied the cross-validation method to avoid the over-fitting problem and improve the model generalisation. This method involves randomly dividing the dataset into k folds with different training, and validation samples [36]. Thus, each sample has the opportunity to be used in the hold out set 1 time and used to train the model $(k-1)$ times. The result of k-fold cross-validation runs are often summarised with the mean of the model skill scores [37].

TABLE 3. ECG heartbeat segments distribution.

Beat group	Samples
Normal	9997
Left bundle	8071
Right bundle	7255
Atrial	7129
Premature ventricular	7023
Paced	2546
Total	42021

2) EXPERIMENTS RESULTS

In the training stage, we run the proposed 1D-CNN model with different values of batch size, learning rate, and optimiser using GridSearchCV algorithm. Table 4 presents the

TABLE 4. Hyper-parameters tuning.

Hyper-parameter	Range	Best value
Batch size	[16, 32, 64, 128]	64
Learning rate	[0.01, 0.001, 0.0001]	0.001
Optimizer	[Adam, Adagrad, Nadam]	Adam

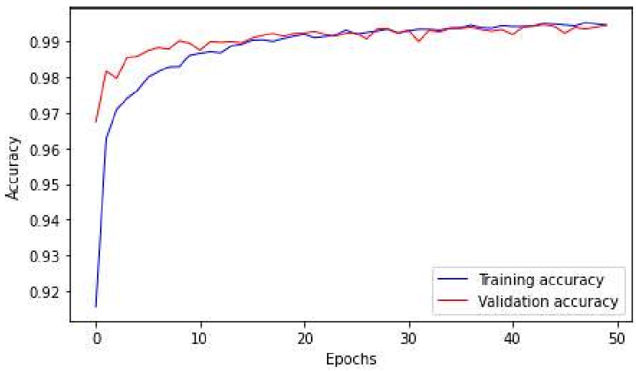


FIGURE 5. Training and validation accuracy per epoch.

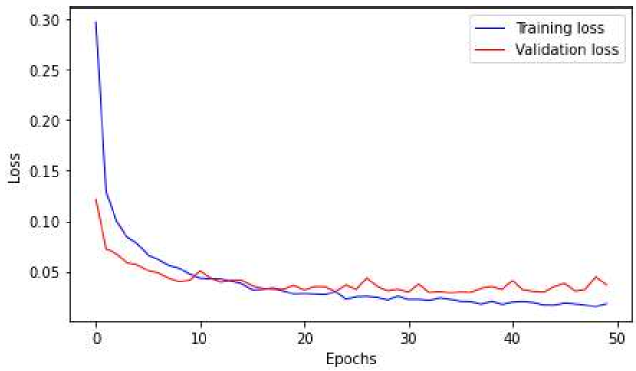


FIGURE 6. Training and validation Losses per epoch.

specification of these hyper-parameters. Moreover, we have applied the cross-validation method with a number of folds k equal to 10. Interestingly, we have obtained an accuracy of 99.46% with a number of 44 epochs. The best values of the hyper-parameters are 64, 10^{-3}, and Adam for batch-size, learning rate, and optimiser, respectively.

Figure 5 and Figure 6 show the evolution of accuracy and value losses in training and validation subsets during the inference. Table 5 demonstrates the performance measures in terms of precision, recall and F1-score in different classes. These measures are defined as per the True Positive (TP), False Positive (FP) and False Negative (FN) values using Equation 1.

$$\begin{cases} Precision = \dfrac{TP}{TP + FP} \\ Recall = \dfrac{TP}{TP + FN} \\ F1score = \dfrac{2TP}{(2TP + FP + FN)} \end{cases} \tag{1}$$

Figure 7 represents the Average Receiver Operating Characteristic (ROC) curve. It shows the trade-off between TP and FP rates. We have noticed that ROC curve is close to the left-hand border and therefore the proposed model is very accurate. The average Area Under the Curve rate is greater than 0.99 which is very close to 1.

TABLE 5. 1D-CNN performance measures.

	Precision	Recall	F1-score	Support
Normal	0.9919	0.9969	0.9944	979
Left bundle	0.9925	0.9962	0.9943	793
Right bundle	0.9909	0.9974	0.9941	763
Artial	0.9878	0.9681	0.9779	251
Premature ventricular	0.9973	0.9841	0.9907	754
Paced	0.9970	1.0000	0.9985	663
Accuracy			99.46	4203

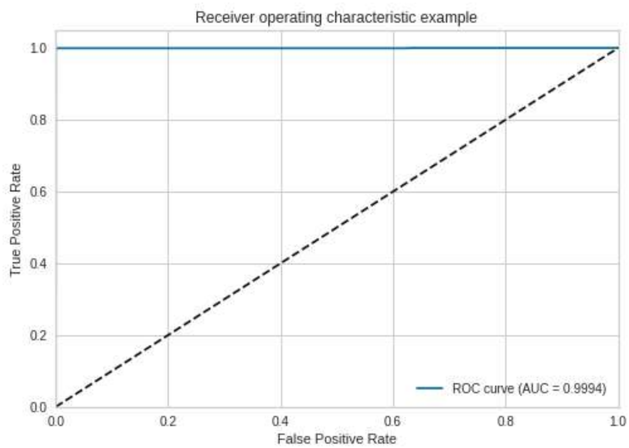


FIGURE 7. Average ROC curve of ECG Arrhythmia classes.

Moreover, we have compared our proposed 1D-CNN model with some existing models evaluated over the same dataset. The results of this comparison are shown in Table 6. In comparison with other models applied on ECG Arrhythmia classification and evaluated on MIT-BIH database, the proposed model has shown promising results with a limited number of epochs. Furthermore, our model has reached these performances with only two 1D-convolution layers contrary to the existing systems where a stack of convolution and LSTM hidden layers were implemented (Table 6). Another strength of the proposed model is concerning the speed of the training stage. This can be explained by the small number of trainable parameters, due to the shared weights between receptive fields of the same convolution layer. In fact, the training stage was completed in less than ten minutes.

B. EFFICIENCY OF THE HYBRID FOG-CLOUD INFRASTRUCTURE

To demonstrate the distributed deployment of the proposed DL model in hybrid Fog-Cloud infrastructure, we have modelled a Fog environment with Raspberry Pi 4 (4G RAM and 1.5 GHz ARM Cortex-A72 Quad-core CPU) devices and exploited the Cloud environment offered by Google Colab using model Tesla K80 with 13GB RAM and a storage of 68GB. The Fog environment has been developed using the *Con-Pi* framework that provides various application

TABLE 6. **Performance comparison of DL models evaluated with MIT-BIH dataset.**

Ref	Descriptors	Model	Accuracy (%)
[38]	Fourier Transform	2D-CNN	99.11
[39]	Morphological and temporal features	Random Forest	97.98
		Gradient Boost Tree	96.75
[40]		Echo state Network	98.9
[41]	ECG beats	Parallel Network	97.7
[42]		Deep Residual Network	93.4
[43]		RNN-LSTM	99.26
[44]		Deep LSTM	99.73
This work		**1D-CNN**	**99.46**

programming interfaces to i). run the inference and training module of DL models in from of microservices, ii). make a cluster of the single board computers, iii). initiate operations through actuators and iv). integrate Cloud resources. The performance of our proposed approach is compared with two existing approaches, namely IoT-Cloud [45] and IoT-Fog [24]. The IoT-Cloud solution uses AWS to run the DL model for processing IoT-device generated ECG signals in Cloud, whereas the IoT-Fog prototype exploits a cluster of 3 Raspberry Pi devices having Intel Neural Compute Stick 2 (NCS 2) to conduct the same operation on the Fog. However, during experiments, we have mainly focused on implementing the operational infrastructure of these approaches. Figure 8 depicts the percentage of CPU utilization in IoT-Cloud, IoT-Fog and proposed hybrid Fog-Cloud solution for both training and inference module of our DL model. Since the Fog resources are not computationally enriched, the execution of the DL model using IoT-Fog, more specifically, the deployment of the compute-intensive training module on resource-constrained devices, incur significant overhead. Our proposed cardiac patient monitoring system overcomes this issue by executing the training module at the Cloud and inference module on the Fog infrastructure. On the other hand, for IoT-Cloud solution, the overall CPU utilisation of our DL model is less compared to the proposed hybrid approach because of using computationally enriched resources to run the inference module. However, the purpose of the training module is periodic, whereas the inference module functions on a consistent basis. As our proposed solution extensively exploits the local resources for continuous operations, thus resulting in less financial cost than running the monolithic DL model on the expensive Cloud resources [46].

Moreover, Figure 9 illustrates the relative latency for executing the training and inference module of our DL model in IoT-Cloud, IoT-Fog and proposed hybrid Fog-Cloud solution. When the inference module of the proposed DL model is executed on the Cloud, the transfer of ECG signals and actuation commands between the IoT devices and the remote data centres adds additional delay to the overall response

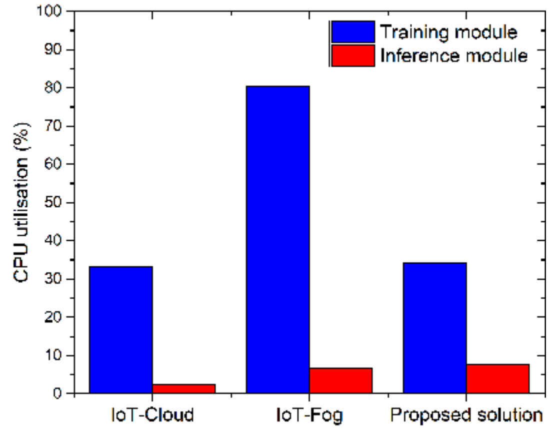


FIGURE 8. **Performance in balancing CPU usage.**

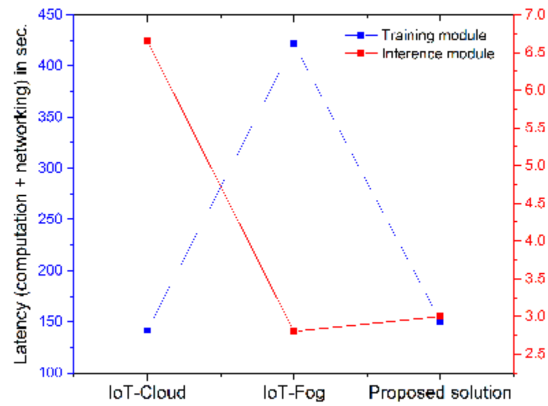


FIGURE 9. **Performance in optimising latency.**

time of the system. The distribution of training and inference modules in hybrid Fog-Cloud infrastructure according to their resource requirements and sensitivity resolves this issue for the proposed solution with 25% improvement in the response time and helps in keeping the relative run-time latency for both modules at the lower bound.

VI. CONCLUSION AND FUTURE WORK

In this work, we have developed a distributed DL model that simultaneously harnesses the Fog and Cloud infrastructures to run the inference and training operations. For the DL model, we have used a 1D-CNN architecture and extensively evaluated our model on the MIT-BIH Arrhythmia database. A proof-of-concept remote cardiac patient monitoring system is also implemented on top of the proposed DL model. Through experiments, it has been proved that the proposed solution can offer low-latency responses in identifying emergency situations for cardiac patients by processing the IoT device-generated ECG signals with higher accuracy (around 99.46%).

As future work, we are planning to add more advanced DL models to the remote patient monitoring system so that other events, including blood volume. Moreover, the proposed model will also be extended and employed for other latency-sensitive health applications.

REFERENCES

[1] *Cardiovascular Diseases (CVDs)*. Accessed: Mar. 9, 2021. [Online]. Available: https://www.who.int/en/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

[2] M. Sanz, A. M. del Castillo, S. Jepsen, J. R. Gonzalez-Juanatey, F. D'Aiuto, P. Bouchard, I. Chapple, T. Dietrich, I. Gotsman, F. Graziani, and D. Herrera, ''Periodontitis and cardiovascular diseases: Consensus report,'' *J. Clin. Periodontol.*, vol. 47, no. 3, pp. 268–288, 2020.

[3] J. H. Park, D. Dehaini, J. Zhou, M. Holay, R. H. Fang, and L. Zhang, ''Biomimetic nanoparticle technology for cardiovascular disease detection and treatment,'' *Nanosc. Horizons*, vol. 5, no. 1, pp. 25–42, 2020.

[4] T. Frikha, N. Abdennour, F. Chaabane, O. Ghorbel, R. Ayedi, O. R. Shahin, and O. Cheikhrouhou, ''Source localization of EEG brainwaves activities via mother wavelets families for SWT decomposition,'' *J. Healthcare Eng.*, vol. 2021, pp. 1–11, Apr. 2021.

[5] D. Doyen, P. Moceri, D. Ducreux, and J. Dellamonica, ''Myocarditis in a patient with COVID-19: A cause of raised troponin and ECG changes,'' *Lancet*, vol. 395, no. 10235, p. 1516, May 2020.

[6] M. Ijaz, G. Li, L. Lin, O. Cheikhrouhou, H. Hamam, and A. Noor, ''Integration and applications of fog computing and cloud computing based on the Internet of Things for provision of healthcare services at home,'' *Electronics*, vol. 10, no. 9, p. 1077, May 2021.

[7] G. Xu, ''IoT-assisted ECG monitoring framework with secure data transmission for health care applications,'' *IEEE Access*, vol. 8, pp. 74586–74594, 2020.

[8] M. Masud, G. Muhammad, H. Alhumyani, S. S. Alshamrani, O. Cheikhrouhou, S. Ibrahim, and M. S. Hossain, ''Deep learning-based intelligent face recognition in IoT-cloud environment,'' *Comput. Commun.*, vol. 152, pp. 215–222, Feb. 2020.

[9] M. Masud, G. Muhammad, M. S. Hossain, H. Alhumyani, S. S. Alshamrani, O. Cheikhrouhou, and S. Ibrahim, ''Light deep model for pulmonary nodule detection from CT scan images for mobile devices,'' *Wireless Commun. Mobile Comput.*, vol. 2020, pp. 1–8, Jul. 2020.

[10] M. Masud, H. Alhumyani, S. S. Alshamrani, O. Cheikhrouhou, S. Ibrahim, G. Muhammad, M. S. Hossain, and M. Shorfuzzaman, ''Leveraging deep learning techniques for malaria parasite detection using mobile application,'' *Wireless Commun. Mobile Comput.*, vol. 2020, pp. 1–15, Jul. 2020.

[11] R. Mahmud, F. L. Koch, and R. Buyya, ''Cloud-fog interoperability in IoT-enabled healthcare solutions,'' in *Proc. 19th Int. Conf. Distrib. Comput. Netw.*, New York, NY, USA, Jan. 2018, p. 32.

[12] G. Muhammad, M. S. Hossain, and N. Kumar, ''EEG-based pathology detection for home health monitoring,'' *IEEE J. Sel. Areas Commun.*, vol. 39, no. 2, pp. 603–610, Aug. 2020.

[13] M. Ibrahim, M. A. Iqbal, M. Aleem, and M. A. Islam, ''SIM-cumulus: An academic cloud for the provisioning of network-simulation-as-a-service (NSaaS),'' *IEEE Access*, vol. 6, pp. 27313–27323, 2018.

[14] G. S. Aujla, A. Jindal, R. Chaudhary, N. Kumar, S. Vashist, N. Sharma, and M. S. Obaidat, ''DLRS: Deep learning-based recommender system for smart healthcare ecosystem,'' in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2019, pp. 1–6.

[15] W. Yanez, R. Mahmud, R. Bahsoon, Y. Zhang, and R. Buyya, ''Data allocation mechanism for Internet-of-Things systems with blockchain,'' *IEEE Internet Things J.*, vol. 7, no. 4, pp. 3509–3522, Apr. 2020.

[16] A. M. Rahmani, T. N. Gia, B. Negash, A. Anzanpour, I. Azimi, M. Jiang, and P. Liljeberg, ''Exploiting smart e-health gateways at the edge of healthcare Internet-of-Things: A fog computing approach,'' *Future Gener. Comput. Syst.*, vol. 78, pp. 641–658, Jan. 2018.

[17] T. N. Gia and M. Jiang, ''Exploiting fog computing in health monitoring,'' *Fog and Edge Computing: Principles and Paradigms*. Hoboken, NJ, USA: Wiley, 2019, pp. 291–318.

[18] R. Mahmud, K. Ramamohanarao, and R. Buyya, ''Application management in fog computing environments: A taxonomy, review and future directions,'' *ACM Comput. Surv.*, vol. 53, no. 4, pp. 1–43, Sep. 2020.

[19] T. N. Gia, M. Jiang, A.-M. Rahmani, T. Westerlund, P. Liljeberg, and H. Tenhunen, ''Fog computing in healthcare Internet of Things: A case study on ECG feature extraction,'' in *Proc. IEEE Int. Conf. Comput. Inf. Technol.; Ubiquitous Comput. Commun.; Dependable, Autonomic Secure Comput.; Pervas. Intell. Comput.*, Oct. 2015, pp. 356–363.

[20] T. N. Gia, M. Jiang, A.-M. Rahmani, T. Westerlund, K. Mankodiya, P. Liljeberg, and H. Tenhunen, ''Fog computing in body sensor networks: An energy efficient approach,'' in *Proc. IEEE Int. Body Sensor Netw. Conf. (BSN)*, Jan. 2015, pp. 1–7.

[21] W. Li and M. Liewig, ''A survey of ai accelerators for edge environment,'' in *Proc. World Conf. Inf. Syst. Technol.* Cham, Switzerland: Springer, 2020, pp. 35–44.

[22] B. Farahani, M. Barzegari, F. S. Aliee, and K. A. Shaik, ''Towards collaborative intelligent IoT eHealth: From device to fog, and cloud,'' *Microprocessors Microsyst.*, vol. 72, Feb. 2020, Art. no. 102938.

[23] I. Azimi, A. Anzanpour, A. M. Rahmani, T. Pahikkala, M. Levorato, P. Liljeberg, and N. Dutt, ''HiCH: Hierarchical fog-assisted computing architecture for healthcare IoT,'' *ACM Trans. Embedded Comput. Syst.*, vol. 16, no. 5s, pp. 1–20, Oct. 2017.

[24] J. A. Rincon, S. Guerra-Ojeda, C. Carrascosa, and V. Julian, ''An IoT and fog computing-based monitoring system for cardiovascular patients with automatic ECG classification using deep neural networks,'' *Sensors*, vol. 20, no. 24, p. 7353, Dec. 2020.

[25] T. N. Gia, M. Jiang, V. K. Sarker, A. M. Rahmani, T. Westerlund, P. Liljeberg, and H. Tenhunen, ''Low-cost fog-assisted health-care IoT system with energy-efficient sensor nodes,'' in *Proc. 13th Int. Wireless Commun. Mobile Comput. Conf. (IWCMC)*, Jun. 2017, pp. 1765–1770.

[26] T. N. Gia, I. B. Dhaou, M. Ali, A. M. Rahmani, T. Westerlund, P. Liljeberg, and H. Tenhunen, ''Energy efficient fog-assisted IoT system for monitoring diabetic patients with cardiovascular disease,'' *Future Gener. Comput. Syst.*, vol. 93, pp. 198–211, Apr. 2019.

[27] S. Tuli, N. Basumatary, S. S. Gill, M. Kahani, R. C. Arya, G. S. Wander, and R. Buyya, ''HealthFog: An ensemble deep learning based smart healthcare system for automatic diagnosis of heart diseases in integrated IoT and fog computing environments,'' *Future Gener. Comput. Syst.*, vol. 104, pp. 187–200, Mar. 2020.

[28] A. A. Toor, M. Usman, F. Younas, A. C. M. Fong, S. A. Khan, and S. Fong, ''Mining massive E-health data streams for IoMT enabled healthcare systems,'' *Sensors*, vol. 20, no. 7, p. 2131, 2020.

[29] M. Ibrahim, S. Nabi, A. Baz, H. Alhakami, M. S. Raza, A. Hussain, K. Salah, and K. Djemame, ''An in-depth empirical investigation of state-of-the-art scheduling approaches for cloud computing,'' *IEEE Access*, vol. 8, pp. 128282–128294, 2020.

[30] M. Ibrahim, M. Imran, F. Jamil, Y.-J. Lee, and D.-H. Kim, ''EAMA: Efficient adaptive migration algorithm for cloud data centers (CDCs),'' *Symmetry*, vol. 13, no. 4, p. 690, Apr. 2021.

[31] A. S. Lundervold and A. Lundervold, ''An overview of deep learning in medical imaging focusing on MRI,'' *Zeitschrift Medizinische Physik*, vol. 29, no. 2, pp. 102–127, 2019.

[32] Z. Ebrahimi, M. Loni, M. Daneshtalab, and A. Gharehbaghi, ''A review on deep learning methods for ECG arrhythmia classification,'' *Expert Syst. Appl., X*, vol. 7, Sep. 2020, Art. no. 100033.

[33] S. Ioffe and C. Szegedy, ''Batch normalization: Accelerating deep network training by reducing internal covariate shift,'' 2015, *arXiv:1502.03167*. [Online]. Available: https://arxiv.org/abs/1502.03167

[34] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, ''Dropout: A simple way to prevent neural networks from overfitting,'' *J. Mach. Learn. Res.*, vol. 15, no. 1, pp. 1929–1958, 2014.

[35] G. B. Moody and R. G. Mark, ''The impact of the MIT-BIH arrhythmia database,'' *IEEE Eng. Med. Biol. Mag.*, vol. 20, no. 3, pp. 45–50, May/Jun. 2001.

[36] K. T. Chui, R. W. Liu, M. Zhao, and P. O. D. Pablos, ''Predicting students' performance with school and family tutoring using generative adversarial network-based deep support vector machine,'' *IEEE Access*, vol. 8, pp. 86745–86752, 2020.

[37] D. Gholamiangonabadi, N. Kiselov, and K. Grolinger, ''Deep neural networks for human activity recognition with wearable sensors: Leave-one-subject-out cross-validation for model selection,'' *IEEE Access*, vol. 8, pp. 133982–133994, 2020.

[38] A. Ullah, S. M. Anwar, M. Bilal, and R. M. Mehmood, ''Classification of arrhythmia by using deep learning with 2-D ECG spectral image representation,'' *Remote Sens.*, vol. 12, no. 10, p. 1685, Apr. 2020.

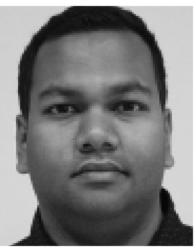
[39] F. I. Alarsan and M. Younes, ''Analysis and classification of heart diseases using heartbeat features and machine learning algorithms,'' *J. Big Data*, vol. 6, no. 1, pp. 1–15, Dec. 2019.

[40] M. Alfaras, M. C. Soriano, and S. Ortín, ''A fast machine learning model for ECG-based heartbeat classification and arrhythmia detection,'' *Frontiers Phys.*, vol. 7, p. 103, Jul. 2019.

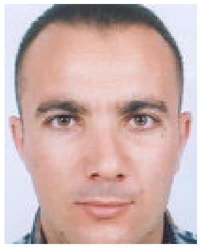
[41] G. Van Steenkiste, G. van Loon, and G. Crevecoeur, ''Transfer learning in ECG classification from human to horse using a novel parallel neural network architecture,'' *Sci. Rep.*, vol. 10, no. 1, pp. 1–12, Dec. 2020.

[42] M. Kachuee, S. Fazeli, and M. Sarrafzadeh, "ECG heartbeat classification: A deep transferable representation," in *Proc. IEEE Int. Conf. Healthcare Informat. (ICHI)*, Jun. 2018, pp. 443–444.
[43] J. Gao, H. Zhang, P. Lu, and Z. Wang, "An effective LSTM recurrent network to detect arrhythmia on imbalanced ECG dataset," *J. Healthcare Eng.*, vol. 2019, pp. 1–10, Oct. 2019.
[44] B.-H. Kim and J.-Y. Pyun, "ECG identification for personal authentication using LSTM-based deep recurrent neural networks," *Sensors*, vol. 20, no. 11, p. 3069, May 2020.
[45] N. C. Taher, I. Mallat, N. Agoulmine, and N. El-Mawass, "An IoT-cloud based solution for real-time and batch processing of big data: Application in healthcare," in *Proc. 3rd Int. Conf. Bio-eng. Smart Technol. (BioSMART)*, Apr. 2019, pp. 1–8.
[46] R. Mahmud, S. N. Srirama, K. Ramamohanarao, and R. Buyya, "Profit-aware application placement for integrated fog–cloud computing environments," *J. Parallel Distrib. Comput.*, vol. 135, pp. 177–190, Jan. 2020.
[47] R. Mahmud and A. N. Toosi, "Con-Pi: A distributed container-based edge and fog computing framework for raspberry pis," *CoRR*, vol. abs/2101.03533, Jan. 2021. [Online]. Available: https://arxiv.org/abs/2101.03533 and https://dblp.org/rec/journals/corr/abs-2101-03533.bib

OMAR CHEIKHROUHOU received the B.S., M.S., and Ph.D. degrees in computer science from the National School of Engineers of Sfax, in March 2012. His Ph.D. deals with security in wireless sensor networks and more precisely in secure group communication in wireless sensor networks. He is currently an Assistant Professor with the College of Computer and Information Technology, Taif, Saudi Arabia. He is also a member of CES Lab (Computer and Embedded System), National School of Engineers of Sfax, University of Sfax. He has several publications in several high-quality international journals and conferences. His research interests include the areas related to wireless sensor networks, cybersecurity, edge computing, blockchain, and multi-robot system coordination. He has received some awards, including the "Governor Prize" from the Governor of Sfax, in 2005.



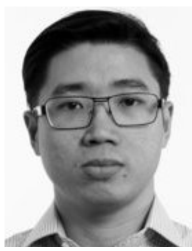
REDOWAN MAHMUD (Member, IEEE) received the B.Sc. degree from the Department of Computer Science and Engineering, University of Dhaka, Bangladesh, and the Ph.D. degree from the School of Computing and Information Systems, The University of Melbourne, Australia, in 2020. During his Ph.D., he actively participated in developing iFogSim simulator and FogBus open-source software that have been used by many universities and research organizations. He is currently working as a Research Fellow (Academic Level B) with the School of Computing Technologies, RMIT University. Prior to joining RMIT University, he served as a Postdoctoral Research Associate for the Cloud Computing and Distributed Systems (CLOUDS) Laboratory, The University of Melbourne. He also worked as a Research Assistant with the Faculty of Information Technology, Monash University, Australia. His research interests include fog and edge computing, the Internet of Things, software-defined networking, and mobile cloud computing.



RAMZI ZOUARI received the master's degree in new technologies of dedicated informatics systems, in 2012, and the Ph.D. degree in engineering of information systems from the University of Sfax, Tunisia. His research interests include handwriting trajectory modeling and applications of intelligent methods to pattern recognition.

MUHAMMAD IBRAHIM received the Ph.D. degree in computer science from the Capital University of Science and Technology, Islamabad, in 2019. He is currently doing his postdoctoral training with Jeju National University, South Korea. He is also working as an Assistant Professor with The University of Haripur. His research interests include large-scale network simulation and modeling in cloud computing, VM migration, and task scheduling in cloud computing.

ATEF ZAGUIA received the bachelor's degree in computer engineering from the University of Ottawa, and the M.S. and Ph.D. degrees in computer science from the École de Téchnologie Supérieure (E.T.S.), University of Quebec, Montreal, Canada. For one year, he held a postdoctoral position at E.T.S., University of Quebec. He was working on developing application for newborn cry-based diagnosis system with the integration of interaction context, supported by the Bill and Melinda Gates Foundation. He is currently an Associate Professor with the College of Computers and Information Technology, Taif University, Saudi Arabia. He has published papers in national and international conferences and journals. His research interests include multimodal systems, pervasive and ubiquitous computing, and context-aware systems. He was a Program Committee Member of the Tenth International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies (UBICOMM 2016), Venice, Italy.



TUAN NGUYEN GIA received the Ph.D. degree in technology. He is currently a Senior Researcher and the Vice Leader of the Turku Intelligent Embedded and Robotic Systems Research Group (tiers.utu.fi), University of Turku, Finland. He has published more than 50 international peer-reviewed articles. He is also working on reconfigurable computing with FPGA and CGRA, and energy efficiency of wearable devices and remote monitoring systems. His primary research interests include the Internet of Things, edge-AI, edge computing, and fog computing, including architectures and applications in autonomous systems, drones, and e-health. He is also an Editor and a Topic Editor of *Vehicles* and *Sensors* journals.