



A smart ontology-based IoT framework for remote patient monitoring

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ABSTRACT

The Internet of Things (IoT) is the most promising technology in health technology systems. IoT-based systems ensure continuous monitoring in indoor and outdoor settings. Remote monitoring has revolutionized healthcare by connecting remote and hard-to-reach regions. Specifically, during this COVID-19 pandemic, it is imperative to have a remote monitoring system to assess patients remotely and curb its spread prematurely. This paper proposes a framework that provides the updated information of the Corona Patients in the vicinity and thus provides identifiable data for remote monitoring of locality cohorts. The proposed model is IoT-based remote access and an alarm-enabled bio wearable sensor system for early detection of COVID-19 based on ontology method using sensory 1D Biomedical Signals such as ECG, PPG, temperature, and accelerometer. The proposed ontology-based remote monitoring system analyzes the challenges of encompassing security and privacy issues. The proposed model is also simulated using cooza simulator. During the simulation, it is observed that the proposed model achieves an accuracy of 96.33 %, which establishes the efficacy of the proposed model. The effectiveness of the proposed model is also strengthened by efficient power consumption.

1. Introduction

Biomedical Signals play an essential role in IoT-based Healthcare monitoring systems. The integration of these different signals allows us to a better healthcare monitoring system and detect other health-related issues. Healthcare IoT is predominantly a resonant concept in medicine to connect a person, device, or virtually any place as it evolves to change the very concept of care. Healthcare with IoT and remote patient monitoring has transformed healthcare during the past few decades due to the field's technological revolution [1,2]. The application of IoT in the medical domain, referred to as the Internet of Medical Things (IoMT) paved the way for telemedicine, telecare, and remote health services. It encompasses the collection of various medical devices, systems, or applications that can connect to a computer network and further comprising of the collection of health data, its analysis, and transmission through the Internet in consort with connected medical devices and

medical applications. The future of IoMT has potential as a result of cloud computing that allows connected devices to store the data on the cloud in order to provide uninterrupted availability, thus opening new opportunities in the field of healthcare. Further, IoMT is the first generation of wireless healthcare IT systems and thus is an essential milestone in developing smart healthcare systems and medical devices. The various IoMT applications in hospitals and clinics include intelligent apps to connect patients and doctors in remote locations.

There are several technological solutions for remote patient monitoring (RPM) that offer various services and devices. Resultantly, RPM gains traction in the front line of healthcare with the introduction of IoMT technologies. When a doctor monitors patient remotely using IoT-based medical devices, there is enhanced scope for specialized and tailored treatments. This is achieved as a result of enhanced access to remote patient data in the future. In this direction, bio wearable trackers are the principal component as they can collect, analyze, generate, and

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transmit data directly to a healthcare provider's network. As a result, a patient's health data can be transferred to any location at par with a mobile phone operator's reach, such as a doctor's office, hospital, or even a hospital emergency room. These wearable trackers can measure vital physiological parameters such as stress levels, heart rate, sleep, blood pressure, cholesterol, glucose levels, blood sugar levels, etc., that help to monitor patient health [3] continuously.

This research paper aims to employ the efficacy of remote monitoring to curb the spread of the latest epidemic that has hit the entire world in an unprecedented manner. The novel Corona infection COVID-19 has spread rapidly across the globe since its inception in December 2019 from the Wuhan District of China. By considering its spread scope and pace, it was declared a pandemic by WHO (World Health Organization) [4]. Since then, the entire research community is engaged in finding viable solutions to contain the disease's spread. Governments of the nations also implemented all obligatory steps to ensure that citizens are well prepared to face the challenge posed by this pandemic [5,6]. The most crucial factor in preventing the spread of this virus locally is to educate the citizens with the right information to adopt all precautionary measures as advised by medical practitioners. Further, existing slow mechanisms of COVID-19 tests and the unavailability of vaccines currently in the market make it imperative to develop robust disease detection techniques and timely monitoring of the individuals.

In this paper, the authors attempt to propose a facilitated solution through bio-wearable sensors to identify the COVID-19 patient. Also, the same information can be used to warn the people in the vicinity to get cautious and adopt preventive measures with utmost care. The technology has already been applied to correlate physiological metrics to daily activities. The same is proposed to be escalated further towards the early prediction of the COVID-19 incidences that are a necessity during this pandemic period. The proposed system tracks the individuals and records their behavior. It may also receive online diagnoses to manage its health. Thus, it becomes possible to monitor health, make an online diagnosis, and even efficiently manage health from a mobile phone's comfort without leaving home with the adoption of remote medical monitoring. This is a great achievement as it ensures controlling the spread of the virus by a huge margin.

Further, analyzing the evaluated metrics with the predictive platforms can take this application to the next level by generating alert messages for these bio-wearable devices' users. These alert messages are generated whenever there is a significant deviation in the vital health metrics associated with COVID-19. Further, Pseudo-anonymous data restricted to a particular region may be provided to the public health officials and researchers that enable them to track and mitigate the spread of the coronavirus. The proposed framework aims to provide the updated information regarding susceptible Corona patients in any locality. It also provides identifiable data in terms of remote monitoring of locality cohorts (colleagues, family members, visitors, etc.) associated with an individual exhibiting COVID-19 symptom or diagnosed with the same. In this paper, three main technologies are employed for IoT-based patient monitoring applications, viz. RFID, microcontrollers, and sensors.

This paper presents a framework that consists of an IoT infrastructure that provides relevant information. It semantically represents the knowledge obtained through IoT devices and sensors. Further, it presents an ontological contextual model and associated middleware for remote monitoring of chronic patients in the network.

1.1. Contribution

The proposed work's novel contribution is to provide the architecture for IoT-operated remote accessible and alarm enabled bio wearable sensor system for early COVID-19 detection using sensory 1D biomedical signals such as ECG, PPG, temperature, and accelerometer. Following are the objectives for developing an IoT operated remote accessible and alarm enabled bio wearable sensor system for early COVID-19 detection:

- To measure COVID-19 related biological or physical parameters of humans by developing IoT enabled Bio Wearable Sensor (BWS) system.
- To design a standalone monitoring device with local memory and IoT remote server accessibility to store COVID-19 measured data in the form of sensory 1D biomedical signals such as ECG, PPG, temperature, and accelerometer.
- To design an analytical system for recorded COVID-19 parameters to predict COVID-19 infection.

1.2. Organization

This paper is structured as follows. Section 2 presents the related works. Required preliminaries are presented in Section 3. The proposed framework and methodology are elaborated in Sections 4 and 5, respectively. Results are discussed in Section 6, and finally, Section 7 concludes the paper and outlines directions for future work.

2. Related work

IoT and health technologies may revolutionize the healthcare industry over the next decade and thus significantly impact the healthcare system. The current section presents the recent work related to digital health systems that use technologies such as IoT, cloud computing, and big data and are designed to connect patients and providers across different healthcare systems seamlessly.

Easy admittance to patients' medical care information through synchronous announcing and checking by means of associated gadgets will grow medical care suppliers' capacity to offer proof-based therapies and redo therapies for patients. Nowadays, most medical devices, diagnostic imaging tools [42], and sensors constitute a core component of IoT. In essence, the IoT provides efficient scheduling of limited resources by ensuring the best use of the resources while serving maximum patients. The clinical workforce can utilize this assortment of exact wellbeing information to make educated choices that minimize the clinical blunders [7]. Thus, there will be a decline in superfluous visits to the medical clinic, bringing down the expense of care [40,43-46]. Different issues must be addressed to transform medical services through IoT advancement, as discussed in [8,9]. However, the medical services scene is changing rapidly with the evolution of IoT and is getting prepared to provide customized medical assistance at any place [34].

Many researchers are recently working to curb the spread of the recent COVID-19 pandemic [10-13,33,36,38,39]. Several researchers, during their research, have implied IoT for its diagnosis and treatment. For example, a COVID-19 intelligent diagnostic and treatment assistant program (nCapp) is proposed to detect COVID-19 [14]. An IoT-based ecosystem/locality with different smart systems and architectures is proposed for monitoring, controlling, preventing, and mitigating COVID-19 [15]. This is supported by another study that also believes in smart cities' concept to reduce the impact and outbreak of COVID-19 [16]. A smart delivery unit is proposed to deliver essential goods to people in a non-contact manner. For the same, it employed more tech-connected communities to mitigate and fight back with COVID. A Blended Learning (BL) model is also proposed to create a smart and intelligent learning environment for interaction with different users to collect the required database [17]. This database can be used to minimize contact with the infected person by transferring crucial information in a short period of time.

IoT's prime contribution towards fighting the current pandemic is through effective control of data, superior treatment, and improved diagnosis [18,34,35]. IoT can also help produce intelligent ventilation systems, masks, medical equipment that can self-monitor the patients and thus can minimize the contact of the patient with medical staff [19]. Further, contact tracing among the people through mobile-based data is possible using IoT. Additionally, intelligent point-of-care testing kits can be developed to assist the diagnostic units. It processes the real-time

captured data and other vital information of the affected persons. To capture data, it also collects, monitors, and manages the entire data for future processing by inter-connected networks [20]. Such smart systems ensure that each infected person is scanned and every symptom is continuously captured. Thus, it plays a crucial role in assisting medical professionals in providing supervised assistance and thus ensures an optimized quarantine period. The prime advantage in IoT based systems is that it digitally captures the data without requiring any physical contact [22]. Thus, IoT can provide a more automated and transparent diagnostic process in situations like COVID-19.

As discussed IoT-based healthcare systems are capable of analyzing patient data easily however it has some associated limitations. For instance, IoT devices have very little memory, which hinders them from meeting the needs of an IoT-based health network [21]. Further, the heterogeneous devices used in an IoT-based health care system poses another challenge as it requires scrutiny by using IoT-controlled, non-invasive checks. In addition, MCOM uses an ontological context model to process and determine a patient’s health status and stores it in health monitoring [22]. Such MCOM framework for remote monitoring of healthcare is based on international standards and implements ontological context models [23].

It can safely be concluded that IoT offers remote monitoring of patients in the most precise manner. Using IoT, real-time patient data, decision-making systems, and medical data can be integrated into a system to assist patients. Further, it can also monitor precise health parameters from a remote location. It thus may aid doctors in assessing the medical condition of the patients based on vital health parameters such as blood pressure, heart rate, and blood sugar levels [41]. Thus, IoT systems help physicians evaluate patients’ physical and mental health status, enabling them to provide patient care in a more efficient, efficient, and effective manner. ECG which is used to measure the electrical activities, and its most essential indicator in health indicator. However, most wearable devices used to measure ECG suffers from memory and energy consumption. CULT [46] overcome this issue by using the compressing approach.

As far as the deployment of IoT in Covid-19 is concerned [25], various authors have given some promising frameworks to control the virus’s spread. For instance, authors in [21,24] proposed a smart helmet-based thermal imaging system. It scans the crowd by recording the temperature in order to detect any infected person. The proposed model also has a facial recognition system. In this model, if it detects a high temperature for any person, it captures the person’s image through the optical camera. It alerts the local authorities by providing them with an image and location. Further, the authors [26] also proposed a cost-effective solution that performs a diagnostic check to determine if COVID-19 infects an individual or not. The proposed model is based on artificial intelligence and can navigate through crowded areas to diagnose an individual. It employs machine learning on the real-time data fetched through various sensors used to measure related physiological factors. Thus, it is evident that IoT has proven to be a promising approach during this crisis that the whole world is witnessing.

3. Preliminaries

COVID-19 is associated with several physiological symptoms that can be monitored using wearable sensors, as mentioned in Table 1 [27].

Table 1
Sensor modalities (1D Biomedical Signals such as ECG, PPG, temperature, and accelerometer) for monitoring physiological metrics relevant to COVID-19.

Sensors	Rest/Sleep	Skin Temperature (ST)	Body Temperature (BT)	Heart Rate (HR)	HR Variability (HRV)	Resting HR	Respiration Rate (RR)	SPO ₂
ECG			✓	✓	✓	✓	✓	✓
PPG			✓	✓	✓	✓	✓	✓
Accelerometer	✓							
Temperature		✓	✓					

Presently, several metrics such as temperature, blood pressure, heart rate, etc., which can serve as possible indicators for COVID-19, are already in the market by big companies such as Apple Watch, Fitbit, etc., using their own restrictions and limitations [28]. A detailed comparison of the existing bio-wearable bands is presented in Table 2.

The justification of the proposed system with respect to the existing systems is detailed as under:

- 1 Most of the BWS available in the market report monitor physiological metrics related to cardiac and accelerometer-related metrics. These devices measure parameters such as stress, recovery, activity, and sleep. It has been observed that the changes in electrocardiogram (ECG) pattern may reveal information indicative of an infection. Nevertheless, there is not a single device available in the market which measures all related metrics.
- 2 The body temperature and arterial oxygen saturation (SpO2) are vital parameters owing to the high pervasiveness of fever and respiration-related symptoms in COVID-19. Despite the same, these parameters are not regularly monitored by the available commercial wearable devices [29–32,36].
- 3 Although many wearable devices support monitoring of COVID-19, few devices enable IoT-enabled support and analytics related to that.
- 4 An alarming system can prove to be beneficial to contain the spread of the disease. It can prove helpful to the ordinary person, health practitioners, and even to the entire nation.

4. Proposed framework of Bio Wearable Sensor (BWS) system

The proposed framework is explained as follows. Initially, the anticipated model is simulated. The blueprint of the model is designed using software tools in which the components are connected to each other to determine the flow of data through the simulated model. The proposed circuit uses ATmega325, which enables successful simulation of the results. Further, a blueprint of the designed circuit is printed for the further process of PCB designing.

After the design of the PCB, the fabrication process is carried out. Followed by these steps, the embedded code is designed for the model in the programming phase to carry out all the proposed model processes. As the model requires the data to be processed regularly, the proposed model is connected with the IoT server through a suitable networking process, as illustrated in Fig. 1. The purpose of incorporating IoT servers is to carry out data synchronization and its communication with the control unit and remote access. The 1D Biomedical signals received through wifi module that is processed using AI-based image processing techniques. Afterward, the diagnosis of the model is performed for pre-recorded data that check its working.

The next phase is deployment; the model is deployed in the real-time environment. This is an important phase of system designing as it validates the deployed model in a real-time environment. It includes the human beings wearing a designed band that records biological and physical parameters, as demonstrated in Fig. 2. Further, the recorded values are evaluated according to the expected outcome for the system. If the output is observed as expected, then the system will be considered as effective unless it encounters any issue. If any issue is found, debugging of the system is carried out. Eventually, the proposed model analysis is performed to validate its efficacy in presenting current health

Table 2
A Detailed Survey of Commercially Available Bio-Wearable Devices.

Device	Wearing Type	BT	ST	RR	HR	HRV	Early Detection for COVID-19	IoT Eabled	Mobile App	Price
Apple Watch	Wrist band	X	X	✓	✓	✓	X	X	X	400\$
Biobeat	Wrist band	✓	✓	✓	✓	✓	✓	X	X	NA
FitBit Charge	Wrist band	X	X	X	✓	X	X	X	X	150\$
Fitbit Ionic	Wrist band	X	X	X	✓	X	X	X	X	250\$
Fitbit Versa	Wrist band	X	X	X	✓	X	X	X	X	200\$
Garmin Fenix	Wrist band	X	X	X	✓	X	X	X	X	500\$
Forerunner 945	Wrist band	X	X	✓	✓	X	X	X	X	550\$
Venu	Wrist band	X	X	✓	✓	X	X	X	X	300\$
VivoActive	Wrist band	X	X	✓	✓	X	X	X	X	270\$
Bio-strap	Wrist band	X	X	✓	✓	X	X	X	X	175–320\$

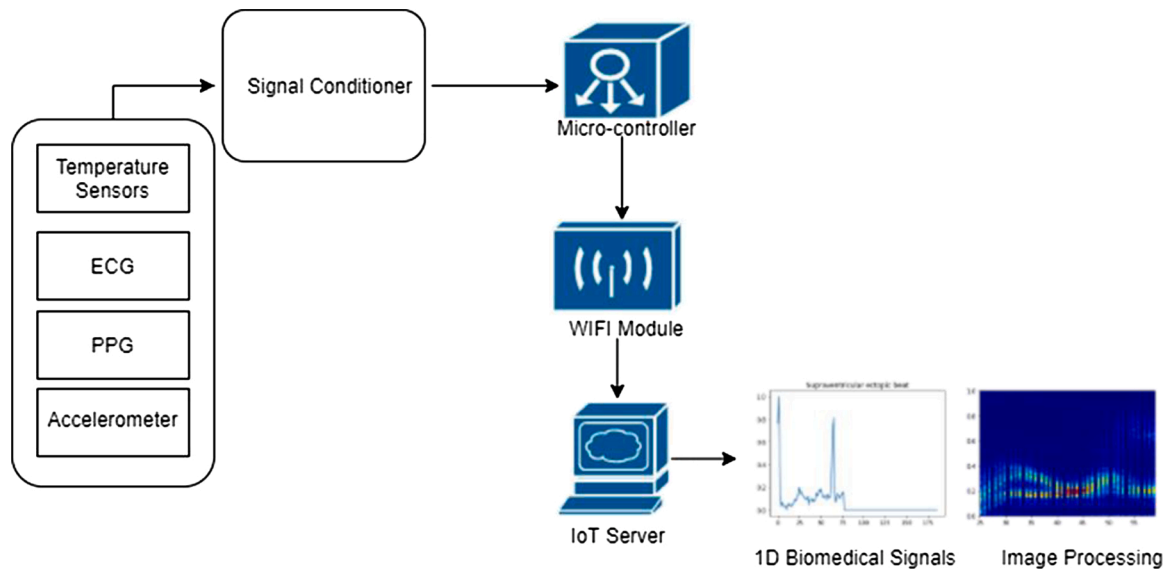


Fig. 1. Architecture Diagram of Proposed Bio Wearable Sensor System for Covid-19 Early Detection using sensory 1D Biomedical Signals such as ECG, PPG, temperature, and accelerometer.

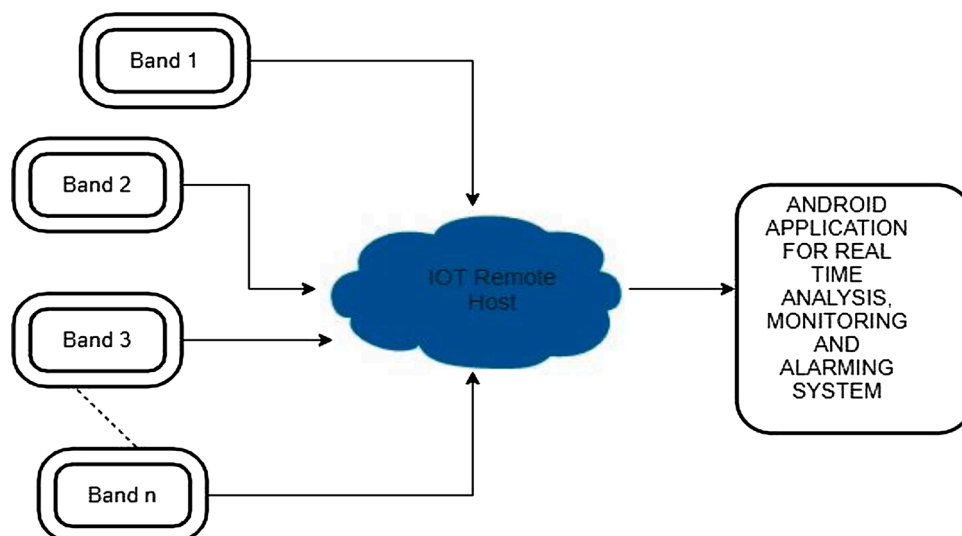


Fig. 2. Communication Model of Proposed BWS System with IoT Server and Remote Analysis and User Alerting System.

status and alarming the user and registered co-workers when the symptoms and actions are considered COVID-19 related.

The model, once finalized, will incorporate ontology-based IoT as it makes decision-making easier for medical practitioners in emergencies. The ontology built by the doctor for treating a particular disease could

help in better decisions, thereby lowering the mortality rates. Similarly, the hospital location and the practitioner details will be publicly available through the ontology database.

5. Proposed diagnostic model

The data is acquired from the four modalities, namely ECG, PPG, Temperature, and accelerometer. The modalities from two states: healthy and prone, are utilized in the cloud using the WAN interface. The WAN can have any system for transferring data such as Wi-Fi, Ethernet, or cellular connection. The cloud consists of a cloud supervisor that provides the data related to a particular group stored in the data storage center. The cloud manager controls the data flow to and from different servers and adequately handles the communication (sending and receiving), data storage, and other data-related queries. Afterward, the data is sent to the cognitive engine for the final processing of the data. The cognitive engine is basically the intelligence of an IoT-based framework that analyzes the given data. It contains an entire feature extraction and classification unit that generates the output for assisting the doctors in making their decision about the current status of the COVID-19 patient.

The schematic block diagram representing the detailed view of the proposed diagnostic model is shown in Fig. 3. It consists of input data from four modalities, i.e., ECG, PPG, Temperature, and accelerometer. The extracted features from the different modalities are input to the fusion analysis model, i.e., Kernel Multiview Canonical Correlation Analysis (KMCCA), to evaluate associations across all the modalities. Afterward, the data classification into their respective groups is performed using Machine Learning (ML) based classifiers [42].

5.1. Channel wise Average Fusion (CAF)

The motive behind using Channel-wise Average Fusion (CAF) is to exploit the complementary information computed among ECG signals' different channels. Let us suppose that the features computed from various channels are given as input to CAF that finds the average of the features and provide a single fused feature set ($X \in R^{m \times n}$). This significantly reduces the computational complexity and enhances the classification performance of the diagnostic system.

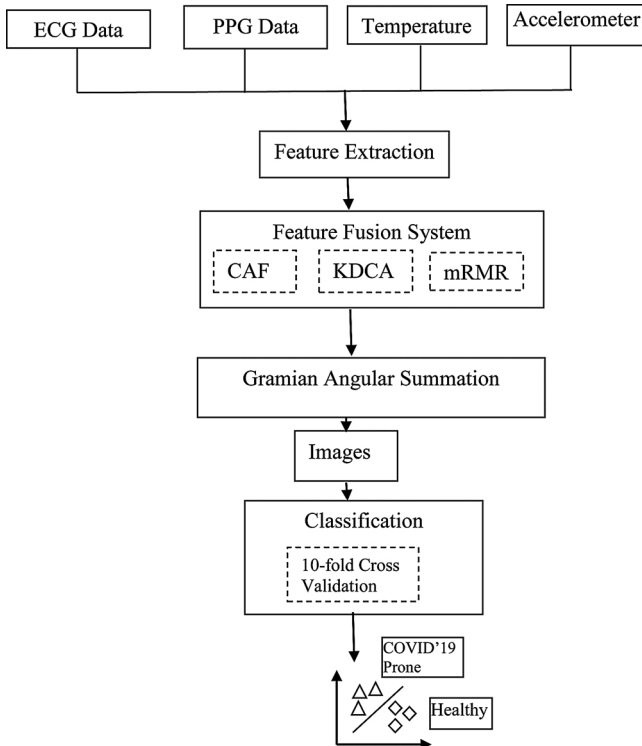


Fig. 3. Schematic Block Diagram of the proposed Diagnostic Model.

5.2. Kernel-Based Discriminant Correlation Analysis (KDCA)

The kernel method [37] outperforms the conventional linear as well as nonlinear neural network performances. From machine learning techniques to dimensionality reduction approaches, the Kernel-based trick has demonstrated its efficiency through the following:

- (i) it applies a non-linear mapping to a higher-dimensional space where the non-linear input data turns to linear or alike-linear;
- (ii) it reduces the computational complexity as the parameter evaluation is shifted to a Kernel space.

The kernelization trick inserts the features in lower-dimensional space into higher-dimensional space, which separates the original inseparable data into linear separable. Let matrices $A \in R^{a \times n}$, $B \in R^{b \times n}$, $C \in R^{c \times n}$, represents the three different feature sets corresponding to ECG (output from CAF), eye-tracking and behavioral performance data, respectively. For MDCA, the features sets will be sorted by their rank, such that ($rank(A) > rank(B) > rank(C)$). Based on this feature set, A and B are fused using DCA producing output AB with vector length $\min(c-1, rank(A), rank(B))$. Thereafter, the output AB is fused with feature set C. Each of the feature set consists of n columns (representing separate groups G involved in the study; $n = \sum_{q=1}^G n_q$) with a-dimensional, b-dimensional, and c-dimensional feature vectors.

5.2.1. Kernel trick

The introduction of the kernel into the DCA algorithm provides a solution by projecting the feature vectors (X, Y and Z) into a high-dimensional Hilbert space. Let us consider that a non-linear function δ maps X to Γ

$$\delta : x^{pq} \rightarrow \delta(x^{pq}) \quad (1)$$

$$X \rightarrow \Gamma$$

where Γ represented a higher-dimensional feature matrix containing elements as

$\Gamma = [\delta(x^{11}, \dots, x^{pq}, \dots, x^{nq, G})]$ or simply, we can say $\Gamma = [\delta^{11}, \dots, \delta^{pq}, \dots, \delta^{nq, G}]$. The element $x^{pq} = X$ reflects the feature vector corresponding to p^{th} sample of q^{th} group. The parameter $\bar{\delta}^q$ is mean of q^{th} group and $\bar{\delta}$ is whole feature-set mean.

$$\bar{\delta}^q = \sum_{p=1}^{n^q} \frac{\delta^{pq}}{n^q} \quad (2)$$

$$\bar{\delta} = \frac{1}{n} \sum_{q=1}^G \sum_{p=1}^{n^q} \delta^{pq} \quad (3)$$

The between-group scatter matrix can be given as:

$$SB_{X(axa)} = \sum_{p=1}^G n^q \nabla^q (\nabla^q)^T = \Phi_{X(axG)} \Phi_{X(axG)}^T \quad (4)$$

where $\nabla^q = (\bar{\delta}^q - \bar{\delta})$ and $\Phi = [\sqrt{n^1} \nabla^1, \dots, \sqrt{n^G} \nabla^G]$

5.2.2. DCA of kernelized features

The next steps will be similar to the DCA algorithm, which is to diagonalize the inter-group scatter matrix. Basically, in DCA, first, an inter-group scatter matrix is utilized for discriminant analysis of features, and then the correlation between the feature sets is directed by diagonalizing the inter-group covariance matrix. As the number of features is higher in the present study than the number of the groups, thus the co-variance matrix ($\Phi_X^T \Phi_X$) $_{G \times G}$ is computed instead of ($\Phi_X \Phi_X^T$) $_{axa}$. If the groups are well-separated, then $\Phi_X^T \Phi_X$ would be a diagonal matrix, and to achieve this, the transformation applied will be:

$$U^T(\Phi_X^T \Phi_X)U = \Lambda_X \quad (5)$$

with U as the orthogonal eigenvector matrix and Λ_X as the diagonal matrix with eigenvalues in decreasing order. The matrix $\Phi_X^T \Phi_X$ has the diagonal elements equal to 1 and non-diagonal elements are 0, which provides minimum correlation between centroids of different groups, which ensures that groups are separated. Let V_{Gxr} is another matrix containing r eigenvectors corresponding to large-valued eigenvectors from U , such that:

$$V^T(\Phi_X^T \Phi_X)V = \Lambda_{rxr} \quad (6)$$

The eigenvector of SB is obtained by transforming $V \rightarrow \Phi V$.

$$(\Phi V)^T SB (\Phi V) = \Lambda_{rxr} \quad (7)$$

where $\Lambda_X = \text{diag}(\gamma_1, \gamma_2, \dots, \gamma_r)$ and $V_X = [v_1, v_2, \dots, v_r]$. The diagonalization is basically solving for eigenvalues and eigenvectors of SB such that:

$$SB v = \gamma v \quad (8)$$

The dimensionality of the higher-dimensional feature vector space (say F) is arbitrarily large and could be even infinite, but by following the kernel method, the inner product in F can be replaced by the kernel function in the input feature space (say R). It can be given as:

$$\delta^{ij}, \delta^{rh} = k(x^{ij}, x^{rh}) \quad (9)$$

5.2.3. Correlation

Next, the correlation between X and Y is maximized by diagonalizing the inter-class covariance matrix of the transformed feature set using singular value decomposition:

$$S_{XY(rxr)}' = H \sum J^T \quad (10)$$

that employ

$$H^T S_{XY(rxr)}' J = \sum \quad (11)$$

Where, \sum is a diagonal matrix. Similar to scatter matrix, we have to apply transformations for covariance matrix, i.e., $W_{CX} = H \sum^{-1/2}$ and $W_{CY} = B J$ such that

$$(H \sum^{-1/2})^T S_{XY}' J \sum^{-1/2} = I \quad (12)$$

this will turn the feature sets as:

$$X^* = W_{CX} X' = W_{CX} A_X^T K_X \quad (13)$$

$Y^* = W_{CY} Y' = W_{CY} A_{Y(bxn)}^T K_Y$ where W_X and W_Y represents transformation matrices. By using these matrices, it can be shown that:

$$SB_X^* = \sum^{-1} \quad (14)$$

Finally, the feature-level fusion is acquired by computing either the summation or concatenation of the transformed feature vectors. The present paper has considered the summation method.

$$Z = [X^* + Y^*] \quad (15)$$

Consequently, the output of fusion of two feature sets is fused with the third feature set. In this manner, the KMDCA normalizes the sets, fuses them using both linear and non-linear features, and performs dimensional reduction on the fused datasets, thus overcoming the hindrances of fusing the different types of features.

The fused feature set (S_G) is fed to the minimal-Redundancy Maximal-Relevance (mRMR) approach in order to minimize the redundant features and keep only relevant features. The acquired optimized feature set (O_G).

$$O_G = \text{argmax}_{F \subset S_G} \frac{D(F, G)}{R(G)} \quad (16)$$

In the mRMR method, the relevance (D) and redundancy (R) of the features are evaluated in terms of mutual information. Basically, the correlation between the features is computed, and from mutually-correlated feature sets, only one of the features is considered for further processing, and another one is discarded.

5.3. Transformation of 1D biomedical signals to images

The features extracted from 1D biomedical signals obtained are converted into images. The rationale behind this is to establish a method capable of translating Biomedical signals into significant images. The primary concern regarding this is to be certain that the signals encode visual class discriminative information that can be extracted by processing 1D biomedical signals. The work utilized the approach of converting the signals to images using Gramian Angular Summation Field (GASF), in which the time series is normalized in the range of $[-1, 1]$. The obtained signal is subsequently transformed to a polar coordinate from a cartesian coordinate, retaining the biomedical signal's temporal data. Afterward, every time point is matched with a neighboring point for finding the correlation between adjacent points, which is done by applying the trigonometric cosine function, $\arccos(\cdot)$. The correlation obtained by applying this function creates the Gramian matrix of dimension $[m, m]$, where m is the number of sample points of the 1D biomedical signal. Let $S = \{S_1, S_2, \dots, S_n\}$ represent the biomedical signal with m -samples, and signal S can be rescaled within the values $[-1, 1]$ evaluated from the Eq. (17) below:

$$S_0 = \frac{S_i - \min(S)}{\max(S) - \min(S)} \quad (17)$$

Afterward, the angle is calculated as given in Eq. (18):

$$\alpha = \arccos(S_0) \quad (18)$$

The summation of the angle between the adjacent features (i, j) is used to calculate the correlation among them, leading to the Gram matrix called Gramian Angular Summation Field as shown in Eq. (19):

$$GASF = [\cos(\alpha_i + \alpha_j)] \quad (19)$$

5.4. Classifier

The mRMR based feature set is given as an input to the widely utilized and preferred ML-based classifiers, namely SVM and KNN. The classifiers' performance is compared using performance metrics involving sensitivity, specificity, and accuracy to provide a more efficient classification process. A 10-fold cross-validation strategy is utilized to compute different comparisons among the dataset. Specifically, the entire dataset is partitioned into 10 different subsets, and then, randomly, one subset is selected for testing while the remaining 9 subsets are used for training purposes. The entire process is repeated 10 times to clear any biasing possibility during data partitioning in a cross-validation process. To avoid biasing in fold selection, the complete 10-fold cross-validation procedure was repeated 20 times using different participants' partitions. The averaging of results from each simulation was evaluated to compute the final result.

6. Results and discussion

The section represents the results obtained from the proposed model's execution on the simulation environment using contiki-cooja simulator. The bands are connected to the Micro-controller board that fetches the real-time data through the band and performs accuracy analysis from the computing device. Once the calculation part is over, the calculated results are then forwarded to the base station using a

wireless module. The 1D biomedical signals are converted into images as shown in Fig. 4.

The proposed framework’s efficiency is evaluated in two scenarios, viz. the accuracy of the results and the network evaluation. The accuracy of the results measured using performance metrics such as accuracy, precision, and recall. Further, network evaluation is done using network parameters viz. Transmission power, power consumed in the different modes of the network, and total power. The detailed result evaluation is divided into the following sections:

6.1. Accuracy of the model

The model is trained on the collected dataset to classify the patients into an infected and non-infected category. Simulations are done using R Software. The results are analyzed in terms of sensitivity and specificity. The sensitivity, also known as True Positive Rate (TPR), represents the correct prediction of positive cases, i.e. when the patient is infected. On the other hand, specificity, also known as true negative rate (TNR), represents the model’s ability to predict the non-infected cases i.e., when the patient is healthy. The trained data, tested data, validation data, and prediction for disease prediction are illustrated in Fig. 5. The model’s performance is determined in the given Fig. 5 by using the training and testing data for the classification of COVID-19 patients in Table 3. The performance rate comes out to be 0.035332. The trained model is finally evaluated in terms of the specified metrics viz. accuracy, specificity, and sensitivity. The sensitivity value is calculated to be 92.33 %, and the specificity value is 92.20 %. The accuracy of the model is calculated to be 96.33 %.

The effect of different combinations on the classification performed using SVM and KNN is shown in a tabular form in Table 4.

The running time achieved by two classification methods (SVM and KNN) for the proposed and KMCCA approaches for the testing and

training phase is summarized in tabular form in Fig. 6.

The running time is lower for a testing phase in all the samples compared to the training phase. For the proposed approach with SVM classification, the entire algorithm took 26.32 s compared to KNN (31.98 s). The reduced running time reflects the proposed approach’s reduced computational complexity despite integrating different fusion methods.

The comparison of the performance of both the classifiers is also carried out using ROC curves, as shown in Fig. 7. The higher value of $AUC = 0.988$ for the proposed method with SVM classifier as compared to KNN classifier (0.958) and KMCCA + SVM (0.945) and KMCCA + KNN (0.919).

6.2. Network evaluation

The analysis is done in two modes, i.e., active mode and non-active mode. By active mode, we refer to the mode when COVID-19 patients are detected in the building and thus require the transfer of data packets to the base station. On the contrary, the non-active mode is referred to mode when there are no patients detected in the building and thus don’t require any packets exchanged during a single network round. However, the non-active mode also consumes some power to keep the network alive. The detailed results on different scenarios are elaborated below:

6.2.1. Transmission power in the network (mW)

For evaluating the transmission power consumed in the network, a client-server network is created. Here, the edge computing device, which calculates the number of COVID-19 patients, acts as a client, and the base station acts as the server. Both the scenarios of power consumption viz. with and without COVID-19 patients are evaluated. Fig. 8 represents the comparison in the transmission characteristics. From Fig. 8, it is evident that transmission power consumed during detection

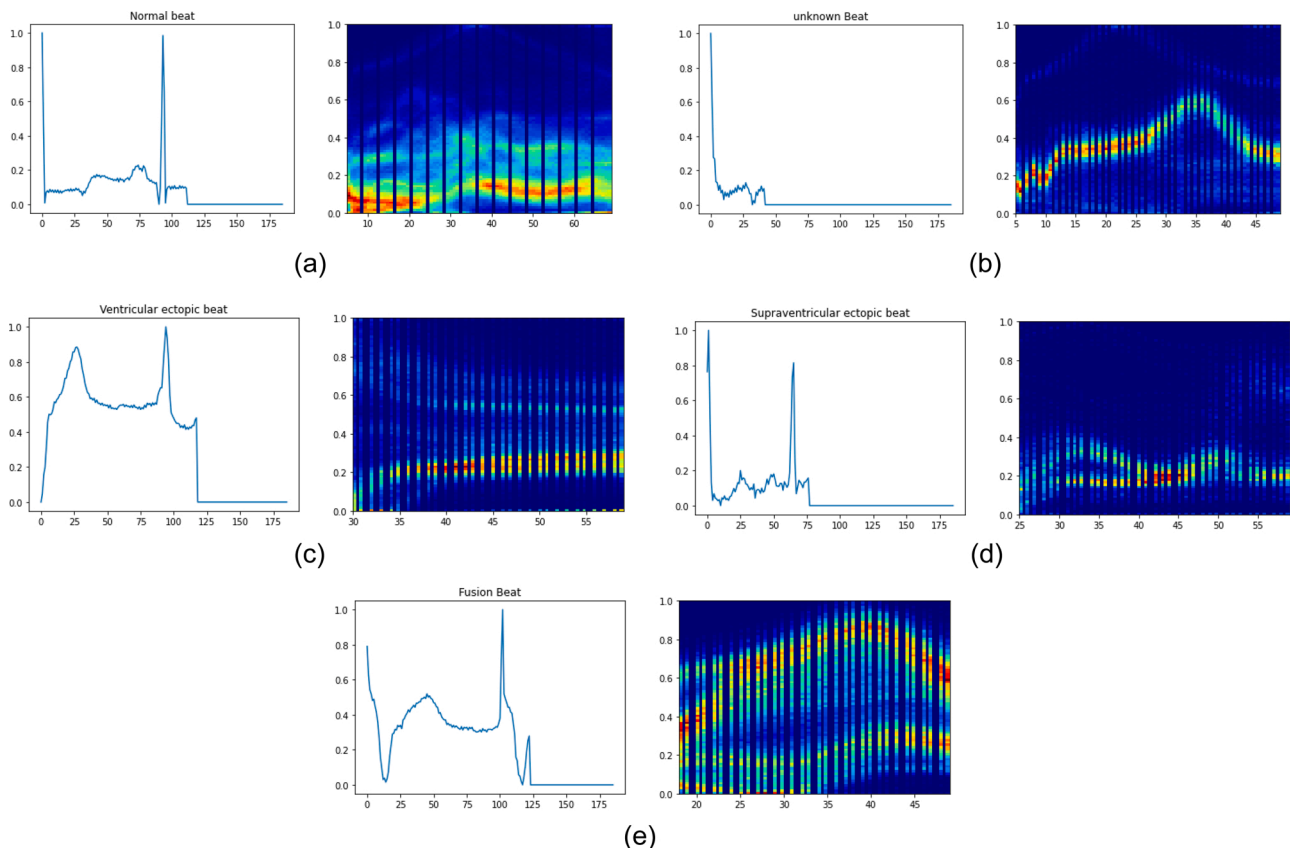


Fig. 4. (a): Conversion of Normal Beat ECG Signal into Image (b): Conversion of Unknown Beat ECG Signal into Image (c): Conversion of Ventricular Ectopic Beat ECG Signal into Image (d): Conversion of Supraventricular Beat ECG Signal into Image (e): Conversion of Fusion Beat ECG Signal into Image.

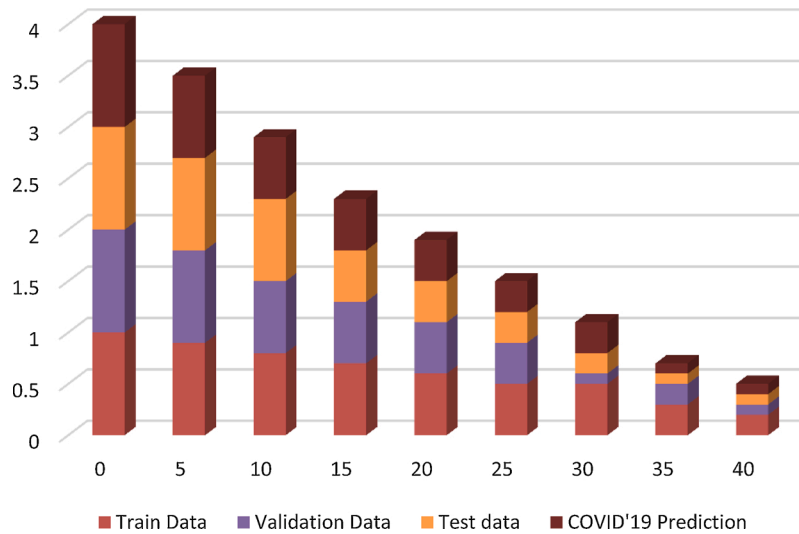


Fig. 5. Trained Data in the band for AI-related to COVID-19 Forecast.

Table 3
Trained Data in the band for AI related to COVID-19 Forecast.

Iteration	Train Data	Validation Data	Test data	COVID-19 Prediction
0	1	1	1	1
5	0.9	0.9	0.9	0.8
10	0.8	0.7	0.8	0.6
15	0.7	0.6	0.5	0.5
20	0.6	0.5	0.4	0.4
25	0.5	0.4	0.3	0.3
30	0.5	0.1	0.2	0.3
35	0.3	0.2	0.1	0.1
40	0.2	0.1	0.1	0.1

of COVID-19 patients for 1st round, i.e., after 60 s, is 0.68548 mW as compared to 0.282046 mW without any such patient detected. This reduced power consumption for no COVID-19 patient is due to reduced data transfer in such a scenario. However, if a COVID-19 patient is detected, the readings of all the sensors are communicated to the base station and hence require increased power.

6.2.2. Power consumed in the different modes of network (mW)

The power consumption is calculated based on power trace output in all the client and server mote’s working modes. Working mode refers to the state in which the node is currently during simulation. These modes are CPU, Low power mode (LPM), Transmit (Tx), and Listen mode(Rx). The graph of power consumption for each simulating scenario viz. with

COVID-19 patients and without COVID-19 patients is shown in Figs. 9 and 10, respectively. Fig. 9 shows the power consumed in milli-watt in each of the working modes of the client node. This power consumption is measured with COVID-19 patients. Here, the transmitting node sends all parameters one by one to the receiving node at regular intervals (i.e., 1 s). Whereas Fig. 10 shows power consumption in milli-watt by client or sink node in all of the working modes without COVID-19 patients. The comparison drawn between two approaches regarding power consumption shows that total power consumed with COVID-19 patients is 1.2 mW as compared to .9 mW for no patient. This proves the efficacy of the proposed model regarding power consumed. Even during the detection of COVID-19 patients, when the number of packets is being sent to the receiver node, power consumption is not much higher and is thus power-efficient.

6.2.3. Total power consumed (mW)

The results regarding total power consumption are depicted in Fig. 11 for both scenarios. For a scenario that detects COVID-19 patients, each sensor’s readings are sent to the remote receiver node at a regular interval of 1 min. Here, computation of the total number of readings collected from the various sensors is done at the sink node itself. On the contrary, without COVID-19 patients, each sensor’s values are fetched only once at MCU, which is sent to the remote receiver node at regular intervals. The authors establish that power consumption without patients in 10 iterations (intervals) is 1.326 mW from the simulation of power consumption.

Table 4
Comparison of the Performance Metrics (Sensitivity, Specificity, and Accuracy) of SVM and KNN classifiers in fusing different combinations of feature sets.

Feature Index	Fusion Method	Classifier	Sensitivity (%)	Specificity (%)	Accuracy (%)
ECG	Single Modality (no fusion)	SVM	0.90	0.80	0.87
		KNN	0.87	0.82	0.84
SVM		0.83	0.79	0.82	
KNN		0.76	0.8	0.78	
PPG	DCA fusion	SVM	0.78	0.82	0.80
		KNN	0.77	0.74	0.76
SVM		0.76	0.81	0.79	
KNN		0.72	0.73	0.75	
Temperature	MDCA fusion	SVM	0.97	0.89	0.94
		KNN	0.93	0.87	0.90
SVM		0.96	0.89	0.92	
KNN		0.94	0.85	0.89	
Accelerometer	MDCA fusion	SVM	0.98	0.95	0.97
		KNN	0.94	0.92	0.93
SVM		0.97	0.89	0.94	
KNN		0.93	0.87	0.90	
ECG + PPG	MDCA fusion	SVM	0.96	0.89	0.92
		KNN	0.94	0.85	0.89
SVM		0.98	0.95	0.97	
KNN		0.94	0.92	0.93	
Temperature + Accelerometer	MDCA fusion	SVM	0.98	0.95	0.97
		KNN	0.94	0.92	0.93
SVM		0.97	0.89	0.94	
KNN		0.93	0.87	0.90	
ECG + PPG + Temperature + Accelerometer	MDCA fusion	SVM	0.96	0.89	0.92
		KNN	0.94	0.85	0.89
SVM		0.98	0.95	0.97	
KNN		0.94	0.92	0.93	

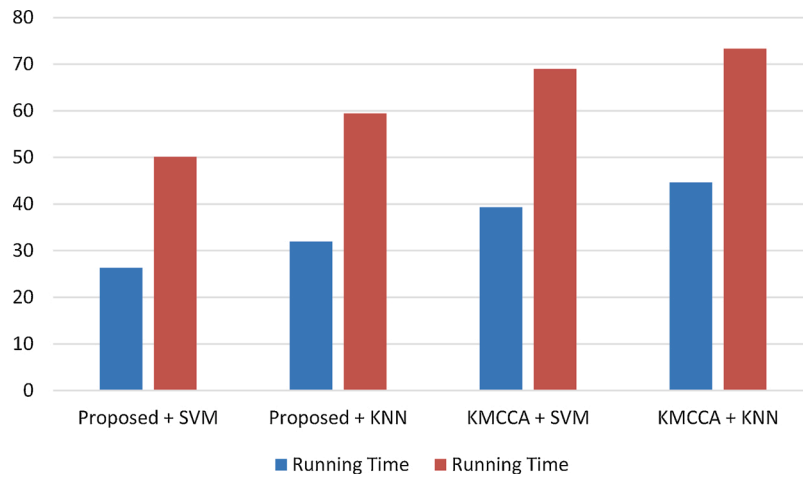


Fig. 6. Running time (Seconds) of different methods consumed in the classification of COVID-19 Prone Patients.

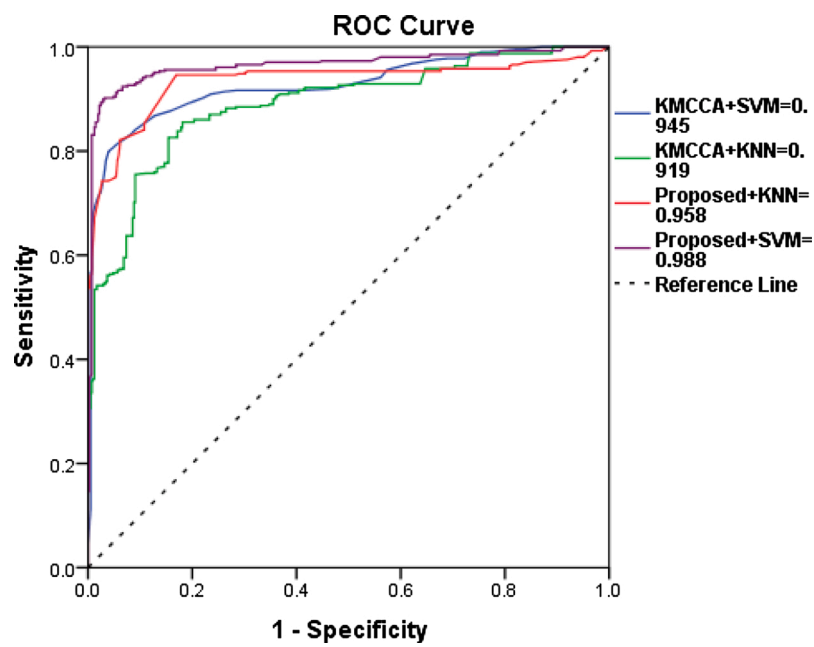


Fig. 7. Performance Comparison using RoC Curves.

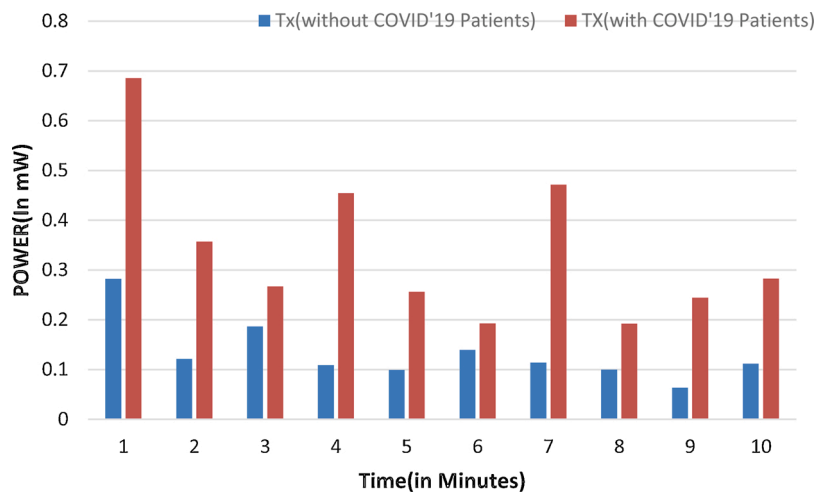


Fig. 8. Comparison of transmitting power in both simulating scenario.

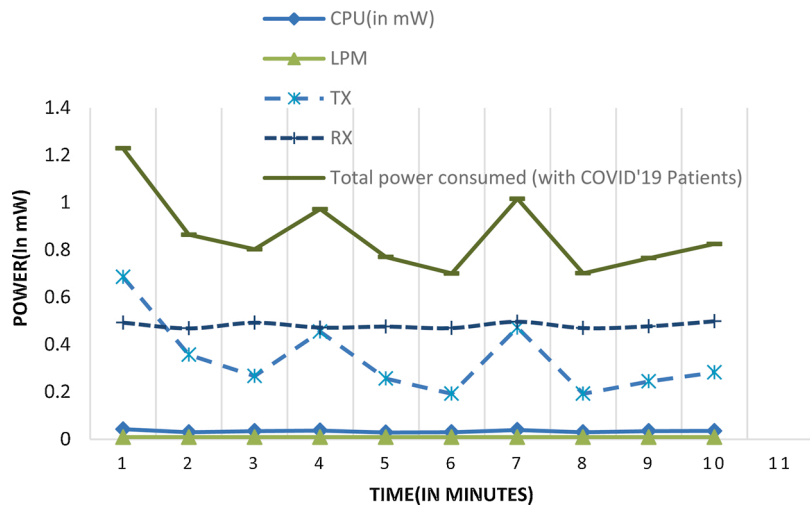


Fig. 9. Power Consumption with COVID-19 patients.

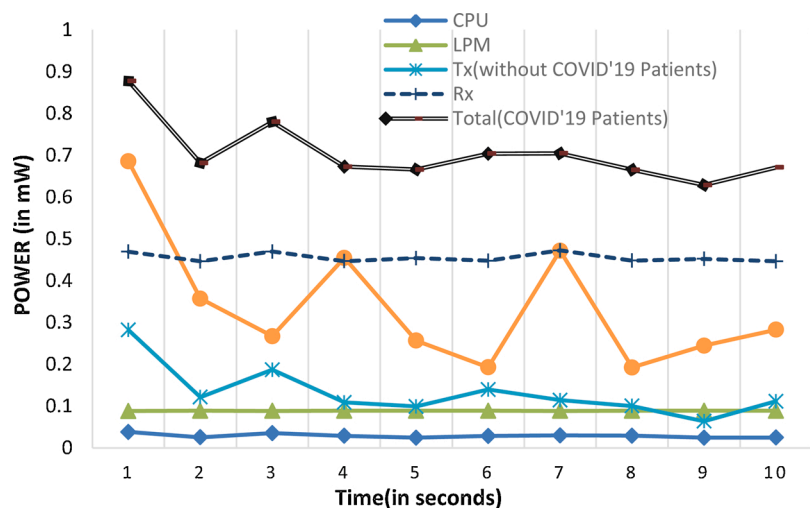


Fig. 10. Power Consumption without COVID-19 patients.

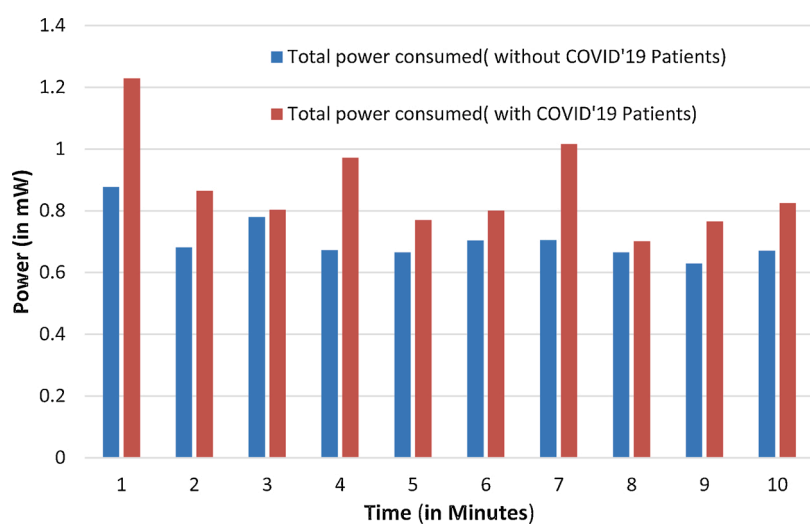


Fig. 11. Comparison of total power in both simulating scenario.

On the contrary, if any patient is detected, this power consumption is 3.404 mW. Hence, the power consumed in 10 iterations in the transmission is 2.078 mW. Also, the total power consumed in 10 iterations is nearly 8.646 mW.

7. Conclusion

IoT solutions in the medical domain provide a seamless environment by monitoring remote patients and providing medical help to distant locations by integrating different 1D biomedical signals into a single domain. During the COVID-19 pandemic situation, remote patient monitoring has become an absolute necessity as medical services fell short of pharmaceutical help. This work proposed an IoT ontology-based remote patient monitoring system that can help contain the spread of virus and treatment using sensory 1D Biomedical Signals such as ECG, PPG, temperature, and accelerometer. The research work aims to provide information regarding Corona Patients/suspected Corona patients in any locality to cohorts (colleagues, family members, visitors etc.). Three leading technologies are used to develop the IoT patient monitoring application described in this paper: RFID, microcontrollers, and sensors.

Along with that, the ontology related to COVID-19 may be incorporated. Here, the efficiency of the proposed model is validated in terms of accuracy and power consumption. During simulation of the proposed model, it becomes evident that the model gives an accuracy of 96.33 %. Additionally, it is also observed that the proposed model is also efficient in terms of power consumption. The obtained accuracy and energy efficiency establishes the effectiveness of the proposed model.

CRedit authorship contribution statement

Nonita Sharma, Monika Mangla, Sachi Nandan Mohanty, Deepak Gupta, Prayag Tiwari prepared the manuscript and the idea and experiment. Mohammad Shorfuzzaman and Majdi Rawashdeh contributed to manuscript preparation as well as the idea. Finally, Deepak Gupta, Prayag Tiwari, Mohammad Shorfuzzaman, and Majdi Rawashdeh did the proofreading.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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