A Novel Framework For Iot-Based Automatic Remote Health Monitoring Using Big Data Analytics

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Abstract: With the tremendous development in the field of Internet of Things (IoT), huge amount of data is being continuously generated. This data is termed as the big data. Processing of big data is a crucial task as it may be helpful for inferring useful information. The big data generated by IoT devices are processed using data analytics techniques that helps to analyse and explore the hidden information behind the big data. This system is especially useful in remote health monitoring systems in which data collected by medical sensors are processed and explored. In this research, we propose a new algorithm called IoT-based automatic remote health monitoring algorithm (IARHM), that can be used for monitoring the health conditions of patients from remote locations. In this framework, sensors like temperature sensor, pressure sensor, pulse rate sensor, cholesterol level sensor and sugar level sensor are used for collecting the medical data of the patients. These data are then transmitted to the cloud. In the cloud, these data are processed using the proposed IARHM algorithm to identify the health conditions of the patients. Any kind of abnormalities are immediately reported to the care takers so that immediate actions can be taken. The performance of the proposed algorithm is validated using metrics like accuracy, F-score, recall and latency. It was observed that, the proposed system achieved very high performance with minimal latency and hence can be easily implemented for real-time monitoring purposes. The main advantage of this framework is the remote monitoring capability of the system i.e., the patients can be monitored by the caretakers from remote locations. The proposed algorithm achieves a maximum recall of 97.59% and a maximum F-score of 96.83%.

Keywords: Data analytics, IoT, cloud, health monitoring, big data.

1. Introduction

The Internet of Medical Things (IoMT) is a recently trending research area that combines the medical industry with the Internet of Things (IoT) framework. This scheme provides continuous, real-time monitoring of patients from a remote environment. This system is used for integrating and enhancing the relationship between the caretakers and the patients [1]. Wireless sensor networks are commonly used for various remote sensing applications as they have the capability to acquire data from various remote locations. This technology has various advantages and is used popularly in the recent past due to which the overall cost of this technology has also decreased drastically. However, the main issue faced by this technology is the energy efficiency. This is due to the fact that, the method to switch off the devices when there is zero event is a crucial task [2]. To ensure privacy of medical data, block chain technology is being used. This technology ensures adequate privacy and security of the health care data. Since the health care data is highly sensitive, its privacy and integrity are very important. This is achieved by the integration of block chain technology with the medical domain [3]. In the block chain systems, the data is not handled using trusted third parties to ensure the security of the data. Thus, the data is delivered from the patients to the doctors and other research centres using block chain in a secure manner. Further, this scheme enables to provide sufficient scalability of the medical sensitive data [4]. The integration of IoT and medical industry has resulted in the emergency of smart health care systems. This system aids in the monitoring of patients suffering from various aliments like cardiac problems, brain issues, etc. Minimization of energy consumption and computational complexity are the major challenges of the smart health care systems [5]. Soft computing techniques are popularly used for the analysis of IoT data. These techniques helps to infer the details hidden in the big data using suitable algorithms [6]. In the smart health care systems, data are collected using various vision-based, wearable and embedded sensors. The data collected from these sensors are processed using various artificial intelligence and machine learning based algorithms [7]. These algorithms imitate the human brain and perform computations that helps in effective decision making. Big data analysis is used for the analysis of the data collected from these sensors. The computations are performed in the cloud where the collected data is stored [8]. This data is processed using algorithms like machine learning algorithms where classification is done using k-means clustering [6], support vector machine etc. The electronic health record (EHR) data must be carefully handled since even a minor alteration in this data can cause severe problems. To ensure the integrity of the electronic health record data, this data must be encrypted before transmission. Electronic re-encryption is popularly used for the encryption of this type of data to ensure that the data is safe and secure and is not seen or altered by any third party [9]. It has been found that the amount of health data transmitted through the cloud is increasing with a rate of 20%-40% each year. The integration of IoT with health care has enabled to perform even remote surgeries. Instructions are given by experts from various parts of the world [10]. This helps to bring the knowledge of medical experts from all over the world to perform crucial surgeries and other decision-making tasks. In this way, IoT is a biggest boon to the medical field. Further, using remote monitoring systems, patients are monitored in a real-time manner and alert signals are given to caretakers in case of emergency. This completely removes the requirement for continuous human intervention [11].

2. Literature survey

Talal et al. [12] has presented a review based on IoT for remote health monitoring of patients using body sensors. Various smart home security architectures were analysed and evaluated. Further, security requirements of the smart health care systems were discussed. The benefits of adopting the IoT-based health monitoring systems were outlined along with the drawback of these systems. Papers from the years 2007 to 2017 were analysed. Chandy [13] has performed a survey on the integration of IoT with the vision-based medical imaging technology. Here, the digitization of medical industry was discussed in detail. Furthermore, the application of IoT in medical field like patient monitoring, patient examination, medical imaging, lab result evaluation, database management etc were also evaluated. Different types of imaging techniques like MRI, CT, ultrasound etc., were also discussed. Rahman et al. [14] has presented a new scheme for patient monitoring with ECG sensor. The data acquired by the sensor is given to the Raspberry Pi module for further processing. From the Raspberry Pi module, the data is then transferred to the cloud. The information in the signal is represented in the form of a graph and is stored in the cloud. From the cloud, this data can be continuously monitored by doctors from the remote locations. Hossain et al. [15] has designed a methodology for smart health care system using sub-station. The sub-station equipment was integrated with the smart health monitoring system using Internet of Things framework. The main use of this equipment was the effective management of resources. The resource allocation was done in an effective manner using the sub-station. This helped to decrease the level of human intervention in the health monitoring. Saha et al. [16] presented a framework that combined three different smart systems namely, home automation system, alarm system and smart health monitoring system. This system was implemented with the help of sensor installed inside the home. The data acquired by the patients were stored in the cloud. This enabled remote access by the care takers and the doctors. The health parameters were continuously monitored and SMS signals were transmitted in case of emergency. Gutte et al. [17] utilized Raspberry Pi module for the health monitoring of patients. Different sensors like glucose meter, activity measuring sensor, pressure sensor etc were used for acquiring the health conditions of the patients. This data was continuously acquired and given to Raspberry Pi and then to the cloud. This system adopted low power sensors to minimize the power consumption so that they can be used for the real-time monitoring of patients. Verma et al. [18] proposed a scheme for the monitoring of student health. Here, the student diseases are predicted based on the health measurements collected from the students over a period of time. Dataset collected from 182 students were used for the training of the prediction model. Classification was done based on k-means clustering algorithm. Further, waterborne disease estimation was also performed using the proposed model. Ahmed et al. [19] has proposed a scheme for health monitoring of patients using wearable devices. The body temperature of the patients was continuously monitored. This value was transferred to the cloud. Using a microcontroller, the value was monitored. In addition to temperature, the heart rate of the patients was also monitored. Any deviation from the normal range was immediately reported to both the emergency care unit and the family members. Ali et al. [20] has proposed a scheme for smart health care using the Fuzzy ontology. The diabetics patients were monitored in this framework. The main drawback of classical ontologies is the inability to make appropriate diet predictions to the patients. This drawback was overcome in this work by the usage of Fuzzy ontology. In particular the Type-2 ontology was used here to make accurate predictions to help the diabetic patients. Jothi et al. [21] has presented a study on the data analytics in the health care domain. The usage of data analytics for the analysis of big data generated from medical IoT devices was discussed in detail. In addition, the main components of data analytics like exploring of data, defining the data, model creation and the analysis of model were discussed. The ways of improving the health care based on data analytics were also presented.

3. Proposed Methodology

The proposed methodology involves continuous monitoring of health conditions of individuals and transmission of alert signal to the care takers in case of emergency or abnormal conditions.

3.1. Data analytics using IoT-based big data

The data generated using IoT devices are huge. They have high volume and are referred as big data. This data is generated from devices like smart phones, smart homes, smart appliances, etc. The collected data contain numerous useful information. However, this information cannot be inferred unless they are processed. Hence, this data is processed using data analytics to understand the underlying information. The data analytics comprises of 4 main steps that include data collection, pre-processing, model generation and analysis. This is shown in Figure 1.

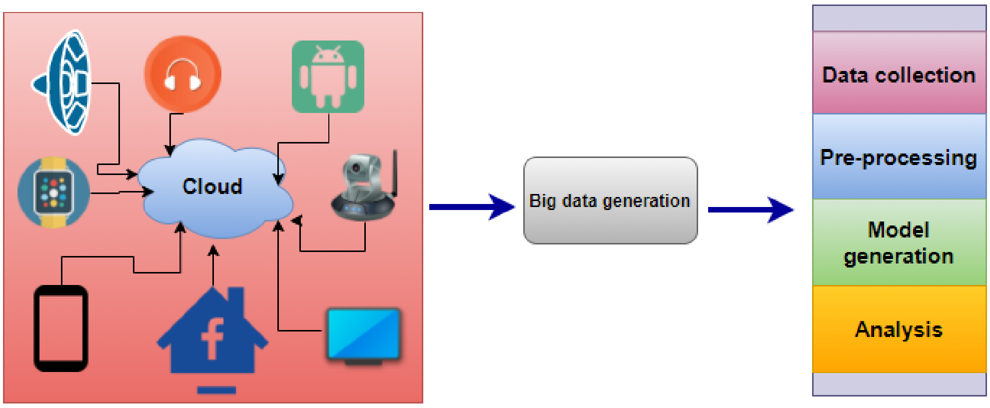

Figure 1. Data analytics using IoT-based big data

Figure 1 illustrated the data analytics using IoT-based big data. The first step is the collection of big data from numerous IoT devices that are connected to the cloud. The cloud acts as the best medium for data collection and data storage. The collected data are in various formats. Hence, this data must be pre-processed so that they can be converted to a suitable format that can be used for further analysis. The third step is the model generation. The pre-processed data are used for creation of useful models. These models represent a particular type of information. For instance, in case of classification applications, the obtained data are used for creating models that represent a particular class. The last step is the data analysis. This is done using the models created. The analysis can be used for applications like prediction, estimation, classification, forecasting, etc.

3.2. Proposed architecture of IoT-based remote health monitoring system

The proposed architecture of IoT-based remote health monitoring system involves the data collection from IoT-based medical sensors. The medical sensors include glucometer, pressure sensor, temperature sensor, oximeter, EEG, ECG etc.

Figure 2 shows the architecture of IoT-based remote health monitoring system. The first step is data acquisition. The acquired data is then transferred to the cloud. At the cloud, the acquired data is stored and processed. Processing is done to estimate any abnormal or emergency conditions to the emergency unit or the specific care takers. The data processing us done using a novel algorithm called IoT-based automatic remote health monitoring algorithm (IARHM). Using this algorithm, the normal and abnormal data collected from medical sensors are initially stored. This data is then used for the estimation of abnormal conditions in the test patients. The abnormal conditions are indicated using alert signal to the corresponding care takers.

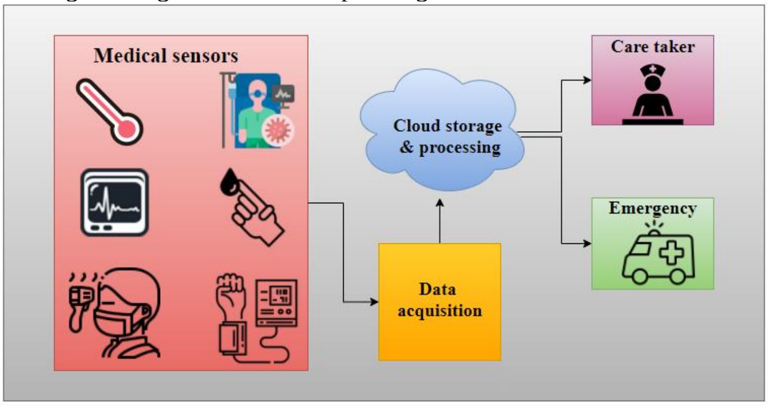

Figure 2. Architecture of IoT-based remote health monitoring system

3.3. Proposed IoT-based automatic remote health monitoring algorithm (IARHM)

The proposed IARHM algorithm involves the acquisition of data like normal temperature sensor values $T_1, T_2, \ldots T_n$, normal blood pressure values $P_1, P_2, \ldots P_n$, normal blood sugar values $S_1, S_2, \ldots S_n$, normal blood cholesterol values $C_1, C_2, \ldots C_n$, normal pulse rate values $PR_1, PR_2, \ldots PR_n$, abnormal temperature sensor values $T_1^{'}, T_2^{'}, ... T_n^{'}$, abnormal blood pressure values $P_1^{'}, P_2^{'}, ... P_n^{'}$, abnormal blood sugar $S_1^{'}, S_2^{'}, ... S_n^{'}$, abnormal blood cholesterol values $C_1^{'}, C_2^{'}, ... C_n^{'}$ and abnormal pulse rate values $PR_1^{'}, PR_2^{'}, ... PR_n^{'}$.

Using the sensor values, features like mean, variance, standard deviation, skewness and kurtosis are extracted. These values are used for the construction of normal and abnormal features using the normal and abnormal sensor data. The normal temperature feature vector is represented as $f_T^{\,N} = [\, f_T^{\,m}, f_T^{\,v}, f_T^{\,sd}, f_T^{\,sw}, f_T^{\,ku}]$. Similarly, all parameters are represented using the statistical feature values for normal data. For abnormal data (temperature), the feature vector is represented as $f_T^{\,A} = [\, f_T^{\,m'}, f_T^{\,v'}, f_T^{\,sd'}, f_T^{\,sw'}, f_T^{\,ku'}]$. Using the test data, similar type feature vector is then generated and is indicated as $f^{\,Test} = [\, f_{test}^{\,m}, f_{test}^{\,v}, f_{test}^{\,sd}, f_{test}^{\,sw}, f_{test}^{\,ku}]$. Then for each parameter, the alert signal is generated when the $\overline{f}_i^{\,N}.\overline{f}^{\,test} < \overline{f}_i^{\,A}.\overline{f}^{\,test}$ where i is the parameter and $i = T, P, S, C, \mathrm{P}R$ where, $\overline{f}^{\,test}$ is the normalized test feature vector, $\overline{f}_i^{\,N}$ is the normalized normal feature vector and $\overline{f}_i^{\,A}$ is the normalized abnormal feature vector. That is, when the correlation between the normal signal and test signal is less than the correlation between the abnormal signal and test signal, the alert signal is given.

Algorithm 1: Proposed IoT-based automatic remote health monitoring algorithm
Input:
Normal temperature sensor values $T_1, T_2, ... T_n$
Normal blood pressure values $P_1, P_2, ... P_n$
Normal blood sugar values $S_1, S_2, ... S_n$
Normal blood cholesterol values $C_1, C_2, ... C_n$
Normal pulse rate values $PR_1, PR_2, ... PR_n$
Abnormal temperature sensor values $T_1^{'}, T_2^{'}, ... T_n^{'}$
Abnormal blood pressure values $P_1^{'}, P_2^{'}, ... P_n^{'}$
Abnormal blood sugar values $S_1^{'}, S_2^{'}, ... S_n^{'}$
Abnormal blood cholesterol values $C_1^{'}, C_2^{'}, ... C_n^{'}$
Abnormal pulse rate values $PR_1^{'}, PR_2^{'}, ... PR_n^{'}$
Output:
Emergency alert signal
Algorithmic steps:
Construct the normal temperature feature vector as

$$f_T^{\,N} = [\, f_T^{\,m}, f_T^{\,v}, f_T^{\,sd}, f_T^{\,sw}, f_T^{\,ku}] \tag{1}$$

where, mean of the signal is computed as

$$f_T^{\,m} = \frac{\sum_{j=1}^{n} T_j}{n} \tag{2}$$

Variance of the signal is given by

$$f_T^{\,v} = \frac{\sum_{j=1}^{n} (T_j - f_T^{\,m})^2}{n} \tag{3}$$

standard deviation is computed using

$$f_T^{\,sd} = \sqrt{f_T^{\,v}} \tag{4}$$

Skewness is given by

$$f_T^{\,sw} = \frac{1}{n} \sum_{j=1}^{n} \left[\frac{T_j - f_T^{\,m}}{f_T^{\,sd}} \right]^3 \tag{5}$$

Kurtosis of the acquired signal is

$$f_T^{\ ku} = \frac{1}{n}\sum_{j=1}^{n}\left[\frac{T_j - f_T^{\ m}}{f_T^{sd}}\right]^4 \quad (6)$$

Construct the normal blood pressure feature vector as

$$f_P^{\ N} = [\, f_P^{\ m}, f_P^{\ v}, f_P^{\ sd}, f_P^{\ sw}, f_P^{\ ku}] \quad (7)$$

Construct the normal blood sugar feature vector as

$$f_S^{\ N} = [\, f_S^{\ m}, f_S^{\ v}, f_S^{\ sd}, f_S^{\ sw}, f_S^{\ ku}] \quad (8)$$

Construct the normal blood cholesterol feature vector as

$$f_C^{\ N} = [\, f_C^{\ m}, f_C^{\ v}, f_C^{\ sd}, f_C^{\ sw}, f_C^{\ ku}] \quad (9)$$

Construct the normal pulse rate feature vector as

$$f_{PR}^{\ N} = [\, f_{PR}^{\ m}, f_{PR}^{\ v}, f_{PR}^{\ sd}, f_{PR}^{\ sw}, f_{PR}^{\ ku}] \quad (10)$$

Construct the abnormal temperature feature vector as

$$f_T^{\ A} = [\, f_T^{\ m'}, f_T^{\ v'}, f_T^{\ sd'}, f_T^{\ sw'}, f_T^{\ ku'}] \quad (11)$$

Construct the abnormal blood pressure feature vector as

$$f_P^{\ A} = [\, f_P^{\ m'}, f_P^{\ v'}, f_P^{\ sd'}, f_P^{\ sw'}, f_P^{\ ku'}] \quad (12)$$

Construct the abnormal blood sugar feature vector as

$$f_S^{\ A} = [\, f_S^{\ m'}, f_S^{\ v'}, f_S^{\ sd'}, f_S^{\ sw'}, f_S^{\ ku'}] \quad (13)$$

Construct the abnormal blood cholesterol feature vector as

$$f_C^{\ A} = [\, f_C^{\ m'}, f_C^{\ v'}, f_C^{\ sd'}, f_C^{\ sw'}, f_C^{\ ku'}] \quad (14)$$

Construct the abnormal pulse rate feature vector as

$$f_{PR}^{\ A} = [\, f_{PR}^{\ m'}, f_{PR}^{\ v'}, f_{PR}^{\ sd'}, f_{PR}^{\ sw'}, f_{PR}^{\ ku'}] \quad (15)$$

From test data find test feature vector as

$$f^{\ Test} = [\, f_{test}^{\ m}, f_{test}^{\ v}, f_{test}^{\ sd}, f_{test}^{\ sw}, f_{test}^{\ ku}] \quad (16)$$

Let i represent parameter where $i = T, P, S, C, PR$

Send emergency alert signal if

$$\overline{f}_i^{\ N} . \overline{f}^{\ test} < \overline{f}_i^{\ A} . \overline{f}^{\ test} \quad (17)$$

where, $\overline{f}^{\ test}$ is the normalized test feature vector, $\overline{f}_i^{\ N}$ is the normalized normal feature vector and $\overline{f}_i^{\ A}$ is the normalized abnormal feature vector.

4. Results and Discussion

To verify the excellence of the proposed algorithm, various metrics like precision, F-score, latency, etc., were used in our research. For comparison we have used machine learning algorithms like k-nearest neighbour (k-NN), Naïve Bayes, support vector machine (SVM) and logistic regression (LR) algorithm.

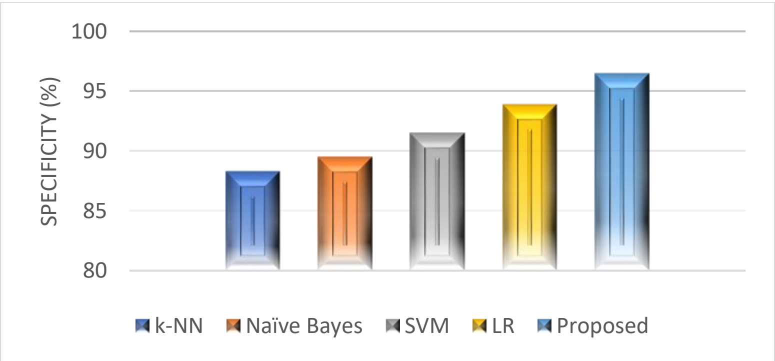

Figure 3. Variation of specificity

Figure 3 shows the variation of specificity with various algorithms like k-NN, Naïve Bayes, SVM, LR and the proposed IARHM algorithm. The k-NN algorithm attains a specificity of 88.32%, Naïve Bayes achieves 89.56%, SVM has specificity of 91.5%, LR attains 93.88%. However, the proposed IARHM algorithm attains a maximum specificity of 96.47%. This is due to the usage of effective correlation-based prediction system. Thus, it is evident that the performance of the proposed system is the best in terms of specificity.

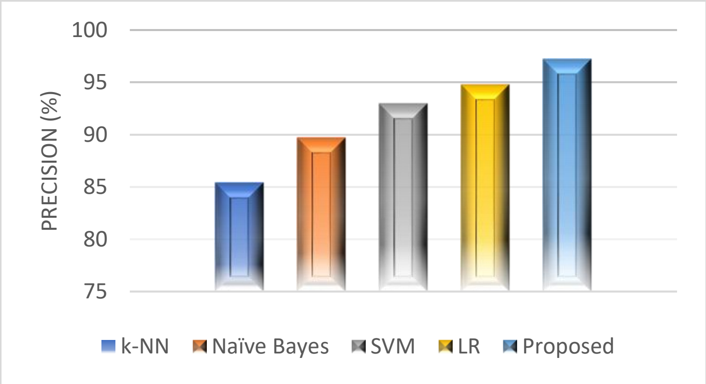

Figure 4. Variation of Precision

Figure 4 shows the variation of precision with various algorithms like k-NN, Naïve Bayes, SVM, LR and the proposed IARHM algorithm. The k-NN algorithm attains a precision of 85.43%, Naïve Bayes achieves 89.78%, SVM has precision of 92.99%, LR attains 94.81%. However, the proposed IARHM algorithm attains a maximum precision of 97.27%. This is due to the usage of huge amount of data for training the system. Thus, it is evident that the performance of the proposed system is the best in terms of precision as well.

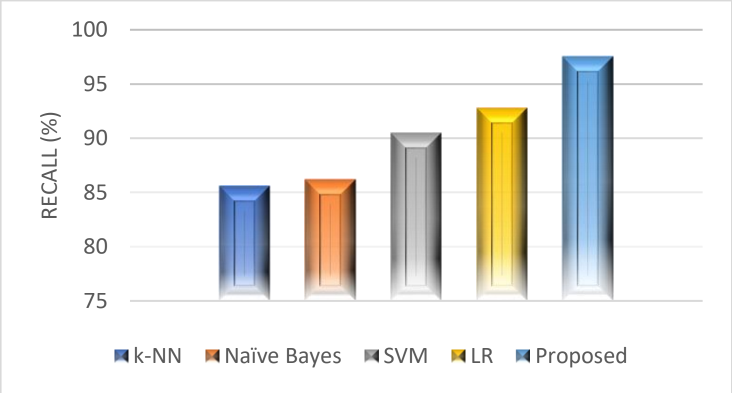

Figure 5. Variation of recall

Figure 5 shows the variation of recall with various algorithms like k-NN, Naïve Bayes, SVM, LR and the proposed IARHM algorithm. The k-NN algorithm attains a recall of 85.68%, Naïve Bayes achieves 86.24%, SVM has recall of 90.59%, LR attains 92.89%. However, the proposed IARHM algorithm attains a maximum recall of 97.59%. Thus, it is clear that the performance of the proposed system is the best in terms of recall as well.

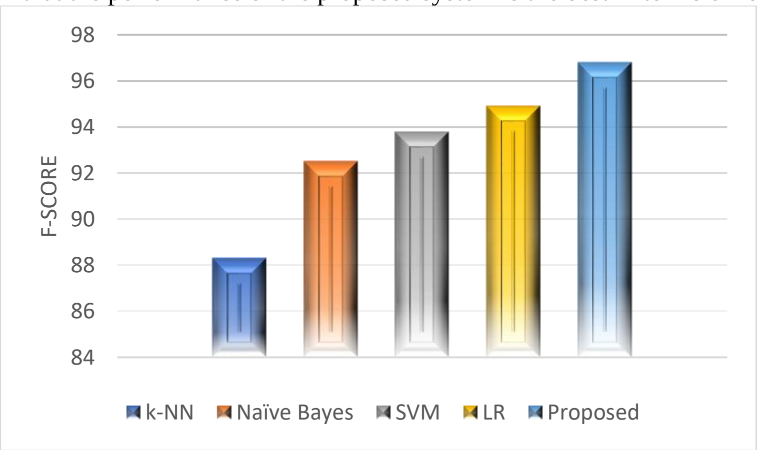

Figure 6. Variation of F-score

Figure 6 shows the variation of F-score with various algorithms like k-NN, Naïve Bayes, SVM, LR and the proposed IARHM algorithm. The k-NN algorithm attains a F-score of 88.39%, Naïve Bayes achieves 92.53%, SVM has F-score of 93.87%, LR attains 92.89%. However, the proposed IARHM algorithm attains a maximum F-score of 96.83%. Thus, it is obvious that the proposed IARHM scheme achieves best classification in terms of F-score.

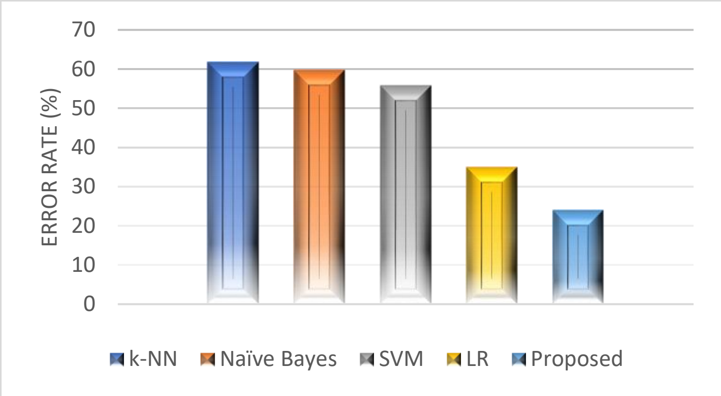

Figure 7. Variation of error rate

Figure 7 shows the variation of error rate of various classification systems. It is obvious that the proposed system achieves the minimum rate of 23.98%. The second least error rate was attained by LR with a rate of 34.92% and the third least error rate was achieved by SVM with a rate of 55.82%. However, k-NN and Naïve Bayes achieved error rate of 61.73% and 59.77% respectively. To further validate the recognition efficiency of the proposed framework, latency was computed for two important functions namely, latency for model creation and latency for the classification of test data.

Figure 8 shows the variation of Classification efficiency ratio of various classification systems. It is obvious that the proposed system achieves the maximum rate of 0.969. The second highest classification efficiency ratio was attained by LR with a rate of 0.872 and the third highest classification efficiency ratio was achieved by SVM with a rate of 0.843. However, k-NN and Naïve Bayes achieved classification efficiency ratio of 0.734 and 0.823 respectively.

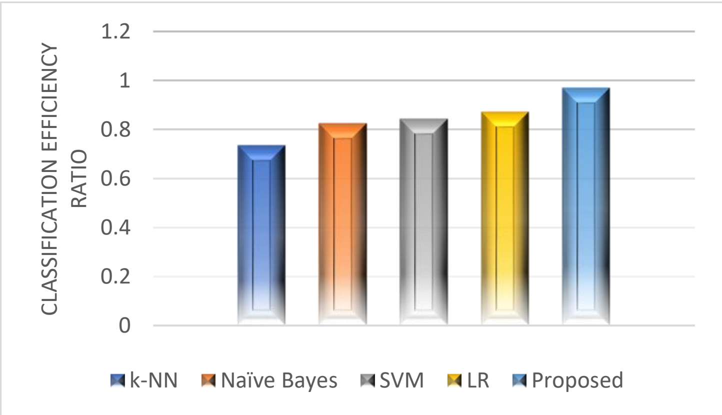

Figure 8. Variation of Classification efficiency ratio

To further validate the recognition efficiency of the proposed framework, latency was computed for four important functions namely, latency of data acquisition, latency for model creation, latency for the classification of test data and latency of alert signal indication. This analysis gives the time delay analysis of the proposed system and its comparison with other machine learning algorithms in the literature.

Table 1. Latency of data acquisition

No of patients	Latency of data acquisition (ms)				
	k-NN	Naïve Bayes	SVM	LR	Proposed

50	0.354	0.214	0.201	0.193	0.034
100	0.364	0.236	0.213	0.213	0.067
150	0.376	0.248	0.268	0.229	0.082
200	0.396	0.259	0.278	0.235	0.091
250	0.432	0.263	0.289	0.249	0.099

Table 1 shows the comparison of latency of data acquisition (in ms) using k-NN, Naïve Bayes, SVM, LR and the proposed IARHM scheme. It includes the total latency involved in the acquisition of various sensor data that are connected to the patients. Evaluation was performed for various number of patients like 50, 100, 150, 200 and 250. As the number of patients increases, the latency of data acquisition also increases. The average latency of data acquisition for k-NN is 0.3844 ms, for Naïve Bayes latency is 0.244, for SVM 0.2498 ms, for LR 0.2238 ms and for proposed system latency was 0.0746 ms. Thus, we infer that the latency of data acquisition is minimum for the proposed algorithm.

Table 2. Latency of model creation

No of patients	Latency of model creation (ms)				
	k-NN	Naïve Bayes	SVM	LR	Proposed
50	0.153	0.094	0.127	0.145	0.067
100	0.167	0.095	0.129	0.148	0.068
150	0.178	0.097	0.131	0.149	0.071
200	0.184	0.097	0.134	0.154	0.076
250	0.197	0.099	0.138	0.156	0.079

Table 2 shows the comparison of latency of model creation (in ms) using k-NN, Naïve Bayes, SVM, LR and the proposed IARHM scheme. Evaluation was performed for various number of patients like 50, 100, 150, 200 and 250. As the number of patients increases, the latency of model creation also increases. The average latency of model creation for k-NN is 0.1758 ms, for Naïve Bayes latency is 0.0964, for SVM 0.1318 ms, for LR 0.1504 ms and for proposed system latency was 0.0722 ms. Thus, we infer that the latency of model creation is minimum for the proposed algorithm.

Table 3. Latency of test data classification

No of patients	Latency of test data classification (ms)				
	k-NN	Naïve Bayes	SVM	LR	Proposed
50	0.161	0.081	0.131	0.156	0.054
100	0.169	0.083	0.133	0.159	0.057
150	0.171	0.086	0.136	0.161	0.062
200	0.183	0.087	0.139	0.164	0.069
250	0.192	0.091	0.148	0.166	0.071

Table 3 shows the comparison of latency of model creation (in ms) using k-NN, Naïve Bayes, SVM, LR and the proposed IARHM scheme. Similar to previous case, evaluation was performed for various number of patients like 50, 100, 150, 200 and 250. As the number of patients increases, the latency of test data classification also increases. The average latency of test data classification for k-NN is 0.1752 ms, for Naïve Bayes latency of test data classification is 0.0856, for SVM 0.1374 ms, for LR 0.1612 ms and for proposed system latency of test data classification was 0.0626 ms. Thus, we infer that the latency of test data classification is minimum for the proposed algorithm.

Table 4. Latency of alert signal indication

No of patients	Latency of alert signal indication (ms)				
	k-NN	Naïve Bayes	SVM	LR	Proposed
50	0.191	0.134	0.142	0.171	0.083
100	0.193	0.153	0.147	0.173	0.088
150	0.199	0.167	0.151	0.177	0.089
200	0.213	0.172	0.156	0.181	0.091
250	0.225	0.179	0.159	0.184	0.093

Table 4 shows the comparison of latency of alert signal indication (in ms) using k-NN, Naïve Bayes, SVM, LR and the proposed IARHM scheme. It is the total time taken to send the alert message to the caretaker in case of an emergency. As the number of patients increases, the latency of alert signal indication also increases. The average latency of alert signal indication for k-NN is 0.2042 ms, for Naïve Bayes latency of test data classification is 0.161, for SVM 0.151 ms, for LR 0.1772 ms and for proposed system latency of alert signal indication was 0.0888 ms. Thus, we infer that the latency of alert signal indication is least for the proposed algorithm.

5. Conclusion

A new algorithm called IoT-based automatic remote health monitoring algorithm (IARHM) was proposed in this research. According to this algorithm, the data generated by the IoT-based medical sensors are first acquired and stored in the cloud. This data is then processed. For the processing, two type of data are collected namely normal and abnormal data. Statistical features are extracted from both the types of data and are stored. When the test data is acquired, statistical features are again computed. Then the data is predicted based on the difference in the correlation between the trained signals and the test signal. That is, when the correlation between the normal signal and test signal is less than the correlation between the abnormal signal and test signal, the alert signal is given. The proposed algorithm achieved a maximum specificity of 96.47%, maximum precision of 97.27%, minimum model creation latency of 0.0722 ms and minimum test data classification latency of 0.0626 ms.

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