Cyber-Healthcare Kiosks for Healthcare Support in Developing Countries

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Abstract. Cyber-healthcare can be described to be virtual medicine applied in reality. It involves the use of healthcare professionals consulting and treating patients via the internet and other modern communication platforms and using different techniques and devices of the Internet-of-Things (IoT) to automate manual processes. This paper aims to revisit cyber-healthcare and its applications in the health sector in the developing countries with the expectation of (i) assessing the field-readiness of emerging bio-sensor devices through a cross-sectional pilot study that benchmark the arduino sensors against manually captured vital signs using calibrated devices and (ii) comparing unsupervised and supervised machine learning techniques when used in Triage systems to prioritise patients.

Keywords: Cyber-healthcare · Internet-of-Things · Patient condition recognition · Disease identification · Patient prioritisation

1 Introduction

The internet of things consists of physical devices embedded with sensors, software and communication capabilities thus resulting in an ability for sensing the environment of the physical devices and enabling information exchange between devices (devices-to-devices (D-2-D) communication) and between human and devices (devices-to-human (D-2-H) communication). With technological advancements in the internet of things and healthcare, cyber-healthcare has become an interesting industry to combat various health care problems in developed and developing countries.

The application of cyber-healthcare would rely on the introduction of sensor networks for health data capture. These sensor networks would allow the monitoring and capturing of vital parameters which would then be processed and thereafter condition recognition would be performed using artificial intelligence techniques as suggested in [3]. Data capture using sensor networks can be non-invasive or invasive. It can also be based on different technologies such as using

G. Mendy et al. (Eds.): AFRICOMM 2018, LNICST 275, pp. 185–198, 2019.
https://doi.org/10.1007/978-3-030-16042-5_18

body sensor networks (BSN) or fixed sensors. While different protocols have been used for the dissemination of information, cyber-healthcare relies on specific protocols that have been engineered to meet healthcare data requirements. These include ZigBee, Bluetooth, WiFi [1] and many other emerging communication protocols.

By capturing patient vital signs, mapping of these signs as patient medical records can occur and patient prioritisation and disease identification can be performed as well as dissemination of these records to required parties through cloud infrastructure [4]. The focus of cyber-healthcare lies in the digitalisation of all clinical work, whether it be imaging, physical therapy, medical supply provision and more [3]. Although the clear advantage of cyber-healthcare includes addressing the supply-demand issue caused by an ever-increasing population, other important benefits of cyber-healthcare include its cost and time saving aspects. However, besides the ethical problems that may arise with information processing and interoperability, issues such as the field readiness of e-health bio-sensor devices used to monitor vital parameters exist. Furthermore, while many studies have been conducted to perform patient prioritisation, none of them have confirmed which is the best between supervised and unsupervised machine learning when performing patient condition recognition.

This paper revisits the application of cyber-healthcare for patient condition recognition as a service offered to citizens through healthcare kiosks located in the rural areas of the developing world. The objective of this paper is to assess the field-readiness the sensor devices used in these kiosks and compare different machine learning solutions to the issue of patient condition recognition. The rest of the paper will do so by focusing on the following sections: the Cyber-healthcare kiosk model in Sect. 2, a deployment scenario for rural areas and its validation in Sect. 3 and finally Sect. 4 contains our conclusions.

2 The Cyber Healthcare Kiosk Model

A network of wind/solar powered Cyber-healthcare Kiosks is presented in Fig. 1. It is designed to monitor patients' vital well-being through their vital signs, including blood pressure, blood oxygen levels, temperature, position, glucose levels, air flow, and heart rate. It allows medical tests to be scheduled and the results reported to a clinician without a traditional office visit. Furthermore, the collected results may be processed by a patient condition recognition that uses machine learning techniques to provide decision support to the healthcare professionals. As a community support tool, the Cyber-healthcare kiosk gives all citizens access to easy, convenient and affordable evaluations of their health on a regular or recurring basis. Some of its benefits include (i) providing tracks/reports trends daily, weekly, monthly which can be integrated into regional health information systems for planning and management (ii) providing quick, easy-to-read results with are free from errors resulting from manual data capture (iii) increasing communication and sending data remotely to enable information sharing and access to remote health expertise (iv) saving time and lowering health visit costs

(v) availing resources for multiple users/clinician sharing (vi) supporting early detection of health concerns and (vii) allowing integration with electronic health records.

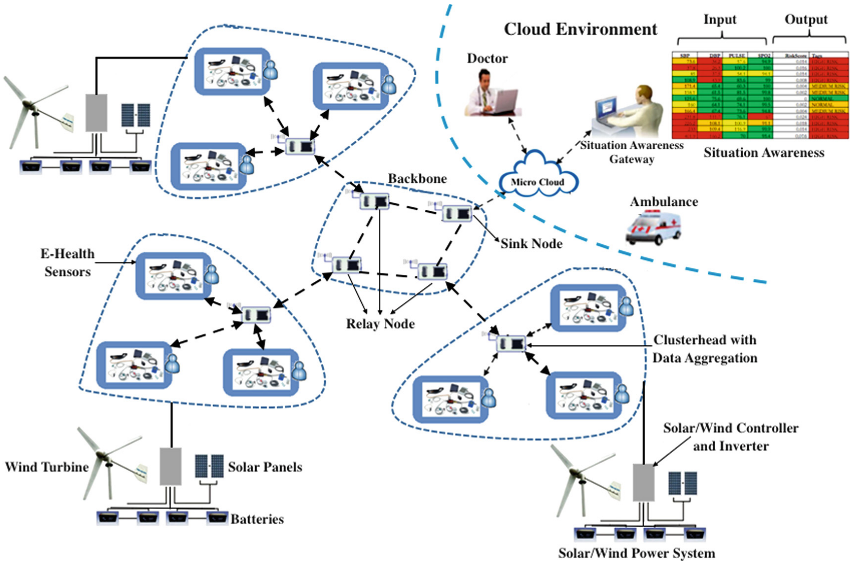

Fig. 1. Cyber-healthcare Kiosk network

2.1 The Cyber-Healthcare Framework

Figure 2 depicts a framework derived from the Cyber healthcare kiosk model in Fig. 1. It reveals a process transformation from vital signs collection to service delivery through different applications. The framework borrows from (i) the general Internet-of-Things (IoT) its multi-layer architecture with different layers describing the functionalities of different digital platforms and (ii) the four layer architectures in [4,23,24] but with focus on healthcare and using solar/wind powered Cyber-Healthcare kiosks. These include:

A sensing platform at the bottom of the architecture used to collect physiological signals as a well as the voltage and currents collected by the solar/wind battery system. The environmental conditions where the solar/wind system is operating will also be accounted by including environmental parameters such as temperature, humidity and air pressure in the measurements.

A dissemination platform layered above the sensing platform to enable communication of the sensor yields to places where these readings are processed and further decisions are taken about the health system. Such platform may be developed using different technologies and protocols such as WiFi, ZigBee, Bluetooth, GSM and many others depending on the health system's communication requirements.

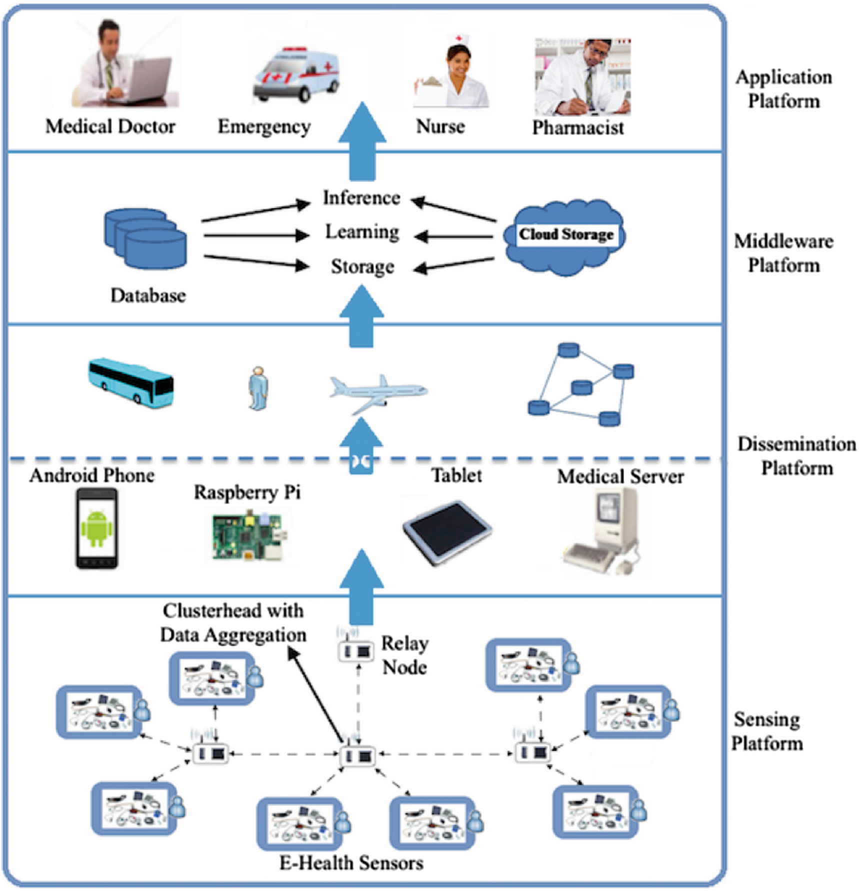

Fig. 2. Cyber-healthcare framework

A Middleware platform that serves as cement between the lower and higher layers of the framework and hides the complexity of the lower layers to the application layer. In that platform, situation recognition operations such as Triage and any form of medical support such as disease identification is carried out.

The application platform where different medical applications are integrated to the cyber-healthcare kiosk to provide different services to the users through different applications. These include pharmaceutical controls, hospital management and many others which are not necessarily directly connected to sensor networks.

The focus of this paper lies on the sensing platform where different bio-sensor devices are used to capture patients' vital signs and the middleware platform where machine learning algorithms are used to achieve patient prioritisation.

2.2 The Cyber-Healthcare Sensing Platform

Different bio-sensor devices are used to measure different vital signs. These include

The **pulse oximetry sensor** uses a noninvasive method of indicating the arterial oxygen saturation of functional haemoglobin. Oxygen saturation is defined as the measurement of the amount of oxygen dissolved in blood, based on the detection of Hemoglobin and Deoxyhemoglobin. It is useful in any setting where a patient's oxygenation is unstable.

The **nasal airflow sensor** is used to measure airflow rate to a patient in need of respiratory help.

The **patient position sensor (Accelerometer)** monitors five different patient positions: standing/sitting, supine, prone, left and right. In many cases, it is necessary to monitor a patient body's positions and movements because of their relationships to particular diseases (i.e., sleep apnea and restless legs syndrome).

The **glucometer sensor** is a medical device for determining the approximate concentration of glucose in the blood. A small drop of blood, obtained by pricking the skin with a lancet, is placed on a disposable test strip that the meter reads and uses to calculate the blood glucose level.

The **body temperature sensor** allows measurements of body temperature. It is important to measure body temperature since a number of diseases are accompanied by characteristic changes in body temperature. Likewise, the course of certain diseases can be monitored by measuring body temperature, and the efficiency of a treatment initiated can be evaluated by the physician.

The **electrocardiogram (ECG or EKG) sensor** is a diagnostic tool that is routinely used to assess the electrical and muscular functions of the heart. The electrocardiogram (ECG) has grown to be one of the most commonly used medical tests in modern medicine. Its utility in the diagnosis of a myriad of cardiac pathologies ranging from myocardial ischemia and infarction to syncope and palpitations has been invaluable to clinicians for decades.

The **skin conductance (Sweating) sensor** uses the galvanic skin response (GSR) method of measuring the electrical conductance of the skin, which varies with its moisture level. This is of interest because the sweat glands are controlled by the sympathetic nervous system, so moments of strong emotion, change the electrical resistance of the skin. Skin conductance is used as an indication of psychological or physiological arousal.

The **blood pressure sensor** measures the pressure of the blood in the arteries as it is pumped around the body by the heart. When the heart beats, it contracts and pushes blood through the arteries to the rest of the body. This force creates pressure on the arteries.

The **electromyogram (EMG) sensor** measures the electrical activity of muscles at rest and during contraction. EMG is used as a diagnosis tool for identifying neuromuscular diseases, assessing low-back pain, kinesiology, and disorders of motor control. EMG signals are also used as a control signal for prosthetic devices such as prosthetic hands, arms, and lower limbs.

2.3 The Cyber-Healthcare Middleware Platform

Patient' condition recognition involves the identification of patient's signs and symptoms. This allows a gain of insight into the patient's condition and allows patient prioritisation, an important healthcare factor targeted by cyber-healthcare. Healthcare professionals will be better aided by this "human-assisted-decision-making" system resulting in more efficient decision making and ultimately better patient care and health outcomes. The focus of this work lies on patient prioritisation. It is based on the traditional triage system, involves the analysis of patient's condition and prioritising urgent cases. The aim of the traditional triage system was to categorise patients into groups according to urgency of their medical condition in warfare situations [6]. Triage scores have evolved, however, and have become key players in emergency departments all over the world with various scores such as the Australian triage scale, the Manchester triage scale as well as Canadian triage scale being applied in their respective locations. In Southern Africa, the South African Triage Scale, founded in 2004, is used to assign triage early warning scores (TEWS) to infants, children and adults in emergency situations [3]. These scores which focus on observed physiological parameters have often resulted in a mis-triaging of patients due to various factors such lack of human resources to carry out the triage, lack of adequate triage training as well as human error [7]. Patient prioritisation with cyber-healthcare was proposed in [8] as a four components system including: (i) a database with storage of patient medical records as well as physiological parameters received from bio-sensors (ii) a scoring system adapted from WHO standardised table of vital parameter risk zones (iii) a server application allowing data analysis so that situation awareness is performed and (iv) a visualisation application which would provide an interface between cloud, the whole system and users. The process of patient prioritisation has been described in a paper by Bagula et al. and has included the following: Data capturing in various forms including crowd sourced data on mobile phones and bio-sensed data followed by local and/or remote processing of the collected information to allow data analysis, distribution and decision making [3]. The use of cyber-healthcare to bring about patient prioritisation may be a solution to the mis-triaging of patients as the elimination of human error due to various reasons will occur. Furthermore, a paper by Muhammed Mahtab Alam looking at various environments where sensors can be worn has shown that the sensor's ability to monitor physiological parameters (heart rate, stress level), body motion (posture, orientation) as well as surrounding environment (toxic gases, humidity), allows it to be used in settings that may lie outside of the normal hospital environment but where triaging is required [9]. These settings include rescue and emergency management where sensors can be used to better predict and manage life threatening situations as well as in mobile workforce safety and health management where construction workers fitted with sensors can be tracked and notified about possible health hazards such as carbon monoxide [9]. Therefore, although these sensors may be used to bring about patient prioritisation, they may also be used as preventative tools thereby decreasing the burden of healthcare on healthcare departments and the economy. Four patient prioritisation machine learning techniques were compared to evaluate their efficiency and time complexity. Their characteristics are described in Table 1.

Table 1. Machine learning characteristics

Characteristic	Multivariate linear regression	K-means clustering	Knowledge based	Support vector machine
Use of the algorithm	**(i)** Detecting patient deterioration **(ii)** Generates warnings when threshold values are reached and **(iii)** Generates priority list from all patient data in order to perform patient prioritisation	**(i)** Detecting patient deterioration and **(ii)** generates warnings when threshold values are reached	Generates priority list from all patient data in order to perform patient prioritisation	**(i)** Detecting patient deterioration **(ii)** Generates warnings when threshold values are reached and **(iii)** Generates priority list from all patient data in order to perform patient prioritisation
Scoring	**(i)** Uses the knowledge based system to score the training data before training (in other words it is an improved expert system knowledge based algorithm) and **(ii)** Algorithm learns from the data, calculates the weights for each variable or generates a linear hypothesis which it uses to score the vital parameters	A patient status index is calculated from the data provided; k clustering means are calculated from history data	Uses knowledge base to score the patients (the algorithm uses expert knowledge to score the patients)	**(i)** Uses the knowledge based system to score the data before training and **(ii)** Algorithm learns from the data, with input and output. From examples, the algorithm can predict output for any other input if given enough examples to train it

3 Deployment Scenario and Validation

Two set of experiments were conducted to complement the models proposed in [1,3,8] with (i) an additional assessment of the field readiness of the bio-sensor devices used in our study and (ii) a comparison of supervised and unsupervised machine learning techniques when performing patient prioritisation. The underlying deployment scenario consists of a smart village with bio-sensing devices used to collect patients' vital signs in Cyber-healthcare kiosks which are networked to transmit the vital signs to a situation awareness gateway/server where patient condition recognition is performed following the illustration of Fig. 1.

3.1 Sensors Field Readiness

The most common method used to test sensor-field readiness has been to perform experiments and comparing the results with other devices that have been declared field ready according to recognised standards. The experiments were conducted by looking at readings of bio-sensor devices to see whether results would be within normal ranges of such group of individuals. In cases where results were not within normal ranges, calibrations were performed to obtain realistic values, given that the sensors were prototype sensors. This research could have been improved largely by collecting vital signs of participants at various points of the day e.g. morning or after gym and analysing this information whilst taking into consideration the normal behaviour of the vital signs in each case [1]. This paper complements the work done in [1] by a cross sectional pilot study conducted on masters students at the university of Western Cape. Opportunity sampling was done to recruit participants due to the pilot nature of the study. Vital parameters were monitored by Arduino sensors as well as manually and data was compared to assess the field-readiness of the Arduino sensors. Data was analysed using Pearson's correlation coefficient. The experimental results are reported below:

Systolic Blood Pressure: As revealed by Fig. 3, the mean systolic blood pressure fell within the normal range for all participants except participant three who had a systolic blood pressure greater than 120 mmHg. The Pearson correlation coefficient is 0.984449.

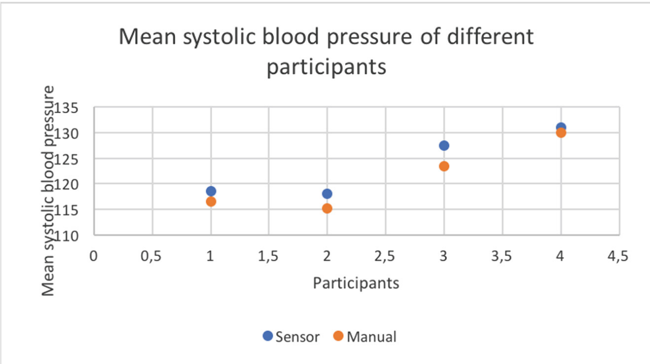

Fig. 3. Systolic blood pressure

Diastolic Blood Pressure: Figure 4 reveals that the mean diastolic blood pressure for all participants was normal. Pearson's correlation coefficient is 0.778418.

Oxygen Saturation: As shown in Fig. 5, the oxygen saturation for all participants fell within the normal range of 94–100% except those taken by the manual sats monitor for participants one and four. The Pearson correlation coefficient is 0.946335.

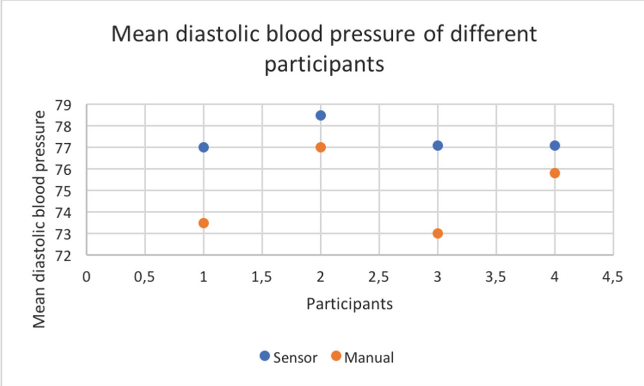

Fig. 4. Diastolic blood pressure

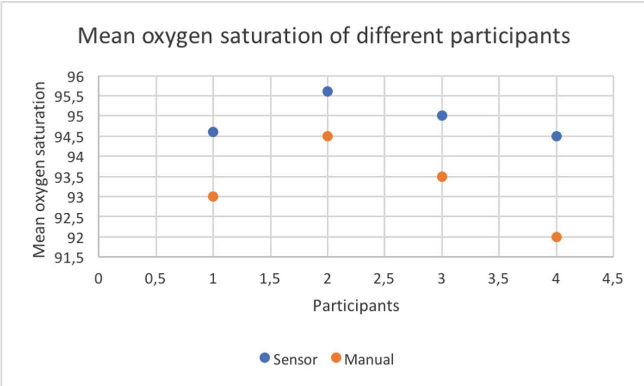

Fig. 5. Oxygen saturation

Heart Rate: The results displayed in Fig. 6 revealed that all heart rates fell within the normal range of 60–100. The Pearson correlation coefficient is 0.999676.

Temperature: The experiments conducted on temperature are reported in Fig. 7. They reveal that all temperature readings were within the normal range. The Pearson correlation coefficient is 0.46992.

A summary of results is presented below:

Blood Pressure Results Summary: The Pearson correlation coefficient for systolic and diastolic blood pressures of 0.984449 and 0.778418, respectively, revealed a strong correlation between the values received when using the Arduino sensors vs the manual sphygmomanometer. Therefore, the sensors ability to detect blood pressure may be described as similar to the manual sphygmomanometer. Studies looking at the accuracy of blood pressure readings in

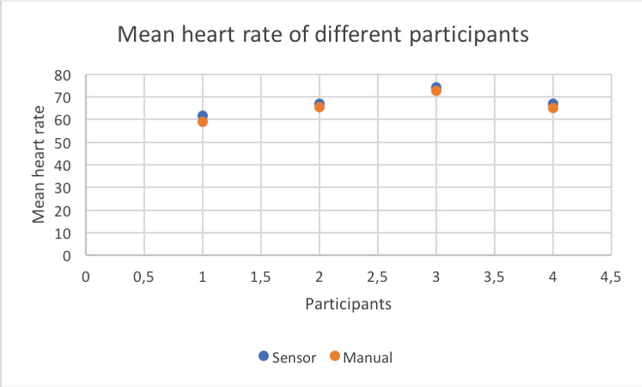

Fig. 6. Heart rate

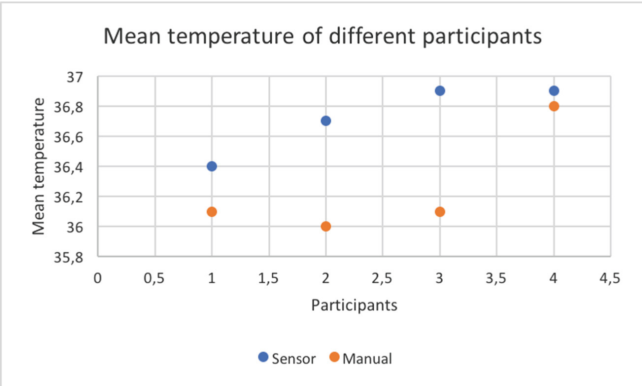

Fig. 7. Heart rate

sphygmomanometers vs digital devices have shown that using a stethoscope and sphygmomanometer produces more accurate results than when taken with digital devices18. Therefore, the strong correlation between the sensors and the manual sphygmomanometer show that the sensors are reliable.

Oxygen Saturation Results Summary: There was a strong correlation between the values received from the Arduino sensors and that of the pulse oximeters. A study by Milner and Matthews looking at the accuracy of pulse oximeters revealed that many pulse oximeters are inaccurate due to flaws with the mechanical electrical integrity or due to emission spectra inaccuracy. This study only examined a small proportion of pulse oximeters used in a few hospitals in the UK and may not necessarily be a true projection of the pulse oximeters used within this pilot study. Therefore, although the adequacy of the pulse oximeter used in the study may still be in question, it may be stated that the sensors, when compared to the pulse oximeter used in the study, produces similar results [17].

Heart Rate Results Summary: There was a very strong correlation between the heart rate taken by the sensors and that taken manually. Although manual palpation of heart rate may factor in human error, the palpation of heart rate for one full minute and ensuring supine position of participants, as mentioned in a study by Kobayashi, was done to decrease human error [18].

Temperature Results Summary: There is a moderately positive correlation between the values taken by the Arduino sensors and thermometer. This may be due to the type of thermometer used (auditory thermometer) as well as various other reasons such as an underlying ear infection, wax build up or the angle at which the thermometer was held.

3.2 Patient Prioritisation

The comparison of the four machine learning techniques described in Table 1 is reported in Table 2. Table 2 reveals through experimental results that the K-means clustering is slower than the other algorithms and through analysis that it presents issues of convergence. It should hence be less preferred compared to supervised learning techniques.

Table 2. Machine learning performance

	Multivariate linear regression	K-means clustering	Knowledge based	Support vector machine
Efficiency	**(i)** Not affected by amount of data and **(ii)** Algorithm is able to learn data patterns and generates a hypothesis	Affected by the amount of data, algorithm becomes slow if a large number of cluster centers are required, may also fail to converge (requires a lot of data to train without problems)	Not affected by amount of data	Algorithm is able to learn data patterns and predict a label
Time complexity	0.01425 min	0.237 min for 10 cluster centers	0.0034167 min	0.1701666 min

4 Conclusion and Future Work

A Cyber-healthcare kiosk model with its underlying multi-layer IoT-based framework has been presented in this paper and its relevance revealed through a study of the field readiness of the bio-sensor devices used by the model and the application of machine learning techniques complementing the model with patient prioritisation.

4.1 Summary of Results

Field Readiness. The field readiness study aimed at finding a correlation between vital parameters taken by Arduino sensors vs manual detection was assessed. The results revealed strong correlations between manually derived vital parameters and those taken by Arduino sensors. These results revealed that strong correlations existed for the measurements of blood pressure, heart rate and oxygen saturation whilst a moderately positive correlation existed for the temperature measurement. However, even though sensor reliability was displayed, the lack of condition variability testing and possible measurement bias may be factors that influenced results and should be looked at in future studies. Findings from this study indicate that with further testing these sensors could be used in public health facilities to provide accurate and reliable readings which may be used in medical decision making to bring about better health outcomes.

Machine Learning. Four different machine learning techniques were compared to assess the relevance of using the unsupervised learning (K-means clustering) technique compared to three supervised learning techniques: multi-linear regression, knowledge based and support vector machine. The analysis and results revealed that supervised learning techniques were faster in terms time complexity and were a better fit for patient prioritisation compared to the unsupervised learning technique.

4.2 Study Limitations

Some of the limitations of the work presented in this paper include:

Population: Due to the pilot nature of the study, a small sample was used to carry out the sensor readiness experiment. A larger sample would have increased reliability of the results. Lack of variability in population (various ages, different health statuses, various ethnicities) meant that there was very little variation in results.

Condition Variability Testing: Sensor operability in variable conditions was not tested. This would have provided greater knowledge about performance of the equipment in different conditions.

Human Error: Human error in the manual capturing of information must be considered as this may have affected the results received thereby decreasing reliability of results.

Measurement Bias: Measurement bias is a factor that may have come into play as vital parameters were taken manually and values may have been over- or underestimated.

4.3 Future Work

Future work will extend the work presented in this paper to cater for the limitations described above and consider traffic and network engineering aspects of the Cyber-Healthcare framework to enable efficient sharing of the health information among patients and medical practitioners.

Moving the traffic from the Cyber-healthcare kiosks to the local cloud where the situation recognition server performs patient condition recognition is a challenging aspect of the Cyber-healthcare model which can be solved by enhancing connection-oriented traditional traffic engineering techniques such as described in [19] to set traffic pipes between kiosks and cloud with the possibility of carrying both classic and IoT traffic and or emerging traffic engineering techniques such as in [20] and route discover mechanisms [21] to carry only IoT traffic from kiosks to the situation awareness server. Furthermore, the organisation of the network of Cyber-healthcare kiosks is another challenging issue that can be tackled by network engineering techniques borrowed from [22]. These techniques are an avenue for future research. Using drones for the transport of blood samples and data between Cyber-Healthcare kiosks is an effective way of adding value and enhancing the services provided to citizens in a smart village. The implementation of such services following the model and framework described in [25] is another direction for future work.

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