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NON-INVASIVE METHOD USED TO ESTIMATE HYDRATION LEVEL AND PHYSICAL PARAMETERS IN HUMAN BODY

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ABSTRACT

The heart is the most desired aspect of a human being's ability to survive in the world; at the same time, heart rate monitoring is becoming more common in the medical field, and heart analysis is an essential parameter of human health. In the medical sector, various heart rate measurement techniques such as ECG and pulse sensing system are available. This pulse analysis is based on the blood force of the heart artery. Since this artery is closed to the skin, the pulse can be easily detected. The proposed device uses an Arduino controller to measure the pulse rate at the fingertip and is based on the photo plethysmography theory. This approach analyses blood pressure differences, detects changes in blood pressure levels, and sends them to the controller.Since the heart beat happens as the whole body's blood is being pumped, the fingertip blood artery is also shifting. This form of shift is detected using a heartbeat sensor that is implanted in the finger to calculate the value and sent to the controller via serial communication system, which aids in the monitoring of the heart beat range. To detect blood volume, the sensor contains a photo diode and an infrared led. The infrared diode transmits infrared light to the fingertip, which passes through the blood within the finger's arteries. The light signal is analysed by the photo diode and reflected back to the computer, with the difference between the light signal being sent to the controller as a value. It is continuously processed during any blood circulation in the fingertip region, and the variation of light signal changes is sent to the controller through serial communication. To quickly distinguish the heart beat range, the reflected light is translated into the pulse range.

Keywords: Non-Invasive Hydration Level, Heartbeat Monitoring, Machine Learning

1. INTRODUCTION

In advanced healthcare systems, machine learning and sensing technologies have emerged as key players. They can be used to diagnose and manage diseases as intelligent, autonomous, and ubiquitous decision-making systems. The intelligence needed for such decision-making can be gathered using machine learning on the data. Healthcare data, such as a patient's medical history, medical test results, tracking system logs, and so on. There is now an enormous amount of digital healthcare data stored in medical databases that can be used to create intelligent healthcare solutions using machine learning. In addition, the use of smart sensor-based healthcare technologies has increased the amount of data obtained. Data can be produced continuously when used for monitoring and diagnosis. This data can be used by machine learning to provide seamless healthcare services in an autonomous manner.

It generally refers to the cellular to organ level maintenance of a stable human body's internal environment.Some key components of the human internal environment are maintaining appropriate temperature, pressure, and chemical composition. The human body is not only required to maintaining homeostasis but it is also required to perform some vital functions such as metabolism, respiration, digestion, reproduction, growth, exertion, etc. A key ingredient required for maintaining internal environment and performing the vital functions in humans is water. It is the major component of human body contributing about 63% to the total body weight and 90% to blood plasma. It is also a well-established fact that both dehydration and over-hydration both can disturb the equilibrium of the human body which can result in mild to severe medical implications.

The World Health Organisation estimated that nearly 4 billion cases of diarrhoea exist around the world. Dehydration can cause death in kids and the elderly. Therefore, it is vital to maintain appropriate hydration level is important for those people who suffer from diseases, children and elderly people as dehydration can cause an additional problem for them. It is, therefore, crucial to maintaining an appropriate hydration level in the human body. Dehydration may cause urological, a metabolic, neurological disorder, gastrointestinal or weakness, and over hydration may cause oedema, hyponatremia, etc.

Heartbeat Monitoring

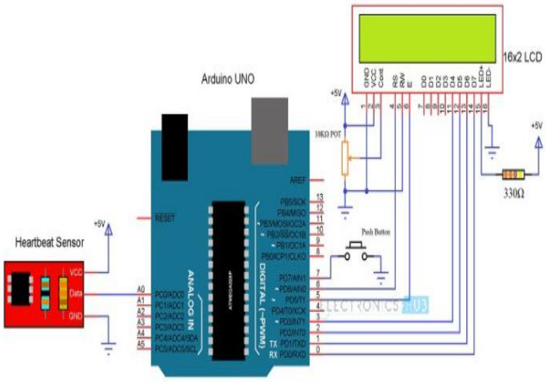
This paper presents a prototype for the monitoring of Heartbeat rate. A Heart Beat (HB) sensor is being developed for acquainting the input signals using Light Dependent Resistance (LDR) and Light Emitting Diode (LED). It senses the heartbeat of a person and converts it in the form of electrical signals and pulses. The signals are amplified using a signal conditioning circuit and processed by a controller. The frequency of the signal depends on the heartbeat rate; this lays down the basic principle of the HB measuring system. The user needs to put his/her finger in the HB sensor for acquiring the input signals. Although number of methods has been proposed and implemented in this domain yet the proposed system in this text provides a simpler and robust method for measuring the heart rate.

To monitor Heartbeat, make sure monitoring is enabled on your Elastic search cluster, then configure the method used to collect Heartbeat metrics. You can use one of following methods:

Internal collection - Internal collectors send monitoring data directly to your monitoring cluster.

Metric beat collection -Metric beat collects monitoring data from your Heartbeat instance and sends it directly to your monitoring cluster.

Legacy collection (deprecated) - Legacy collectors send monitoring data to your production cluster.



2. PROBLEM DEFINITION

The proposed system is based on the working of infrared light is passing to the blood value and analysis the heart rate. In this device is placed on the human fingertip and measure the heart rate through heart beat sensor and send the signal to the controller. First the sensor is fix into the human fingertip the blood is circulated to the fingertip at the time sensor infrared light is passing to the photo diode via blood value to measure the pressure of blood and this measured value is given to the Arduino controller. The controller analysis the sensed value and threshold value if any difference occurs in the output the controller sends the signal to user via, also the Arduino controller display the value of sensor output in the LCD display. The heart beat sensor having the photo diode and heart beat sensor, the working of this sensor is heart beat passed to the finger one side and the photo diode is receiving the signal and measure the pulse, blood count for 30 seconds.

METHODOLOGY

- Arduino Uno
- Lcd Display
- Power Supply Board
- Power Led
- Heart Beat Sensor
- Temperature Sensor
- Pulse Sensor

PULSE SENSOR

Pulse Sensor Amped is a plug-and-play heart-ratesensor for Arduino and Arduino compatibles. It can be used by students, artists, athletes, makers, and game & mobile developers who want to easily incorporate live heart-rate data into their projects. Pulse Sensor Amped works with either a 3V or 5V Arduino.

TEMPARATURE SENSOR

A temperature sensor is an electronic device that measures the temperature of its environment and converts the input data into electronic data to record, monitor, or signal temperature changes. There are many different types of temperature sensors. Some temperature sensors require direct contact with the physical object that is being monitored (contact temperature sensors), while others indirectly measure the temperature of an object .

Data Pre-Processing

Data is collected from five subjects in this research. Data of subjects are collected in two scenarios classified as hydrated and dehydrated. Moreover, data is also categorized based on physical postures sitting, standing and lay down. Data is recorded at a resolution of 16 bits in samples of 5 min to 15 min and the sampling rate is 1 MHz (maximum precision position on the BITalino Kit). The electro dermal activity GSR data used in this study is collected from five individuals after obtaining ethical approval using the EDA sensor available on the BITalino Kit. In particular, when the data is collected from the participants after the fasting of at least ten hours, it is labelled as dehydrated. Whereas data collected when the participant has been drinking water frequently and has had drank water within one hour before the data collection is labelled as hydrated. Therefore, the data used is for these two states (hydrated and dehydrated). Another aspect considered here is the impact of body posture on the electro dermal activity because it varies with body movements and change in body postures.

Feature Selection

The feature space F used in this study comprises the following features: After selection of features the identification of the right combination of features that can generate the best accuracy for the detection of hydration level is an important task. For a single posture-based data set (e.g., for the sitting and standing posture), the total number of combinations of features are tried and evaluated are

$$(2^{F} - 1)$$

where f is the number of features in the feature space.

Machine Learning

Machine learning has many classifiers which are divided into two categories (1) Supervised learning: used the label for data and identify important features in data (2) Unsupervised learning: is a clustering algorithm, unlabelled data. Specifically, supervised machine learning consists of two main categories (1) Regression algorithm which is used for continuous values in data (2) Classification an algorithm that is used for categorical values in data. In this study, supervised machine learning is used because the hydration level of individual is under the label of states. The model is trained with GSR data for hydration and dehydration state. In this paper, eight supervised classifiers have been used on collected data in different postures. Those classifiers are logistic regression (LR), random forest (RF), K-Nearest Neighbour (KNN), Naïve Bayes (NB), decision tree (DT), linear discriminant analysis (LDA), Ada boost classifier (ABC) and quadratic discriminant analysis (QDA). All the machine learning algorithms are tested on data and trained with all aforementioned extracted features. In this experiment, 70% of data is a training set and 30% is testing data of the model. Later, three-fold cross-validation is applied to training data, in which model is tuned for one data set and the remaining two data set is used for model training.

Non-invasive Glucose Measurement

Glucose measurement is mostly classified by the level of invasiveness of the sensing devices, which are usually classified as invasive (devices that are implanted in the patient's body or that invade the body to access a blood sample), minimally invasive (devices that painlessly invade a very small part of the patient's body, such as skin to collect a minimal sample, like a skin part, sweat, tear, and saliva), and noninvasively devices (devices that do not invade the patient's body).

Non-invasive blood glucose monitoring methods are based on measuring glucose concentration from its chemical, thermal, electrical, or optical sensing properties. Some other sensing properties can also be exploited for measurement since the human body shows different physiological responses to changes in glucose, such as electric and acoustic impedance, thermal conductivity, and electromagnetic response.

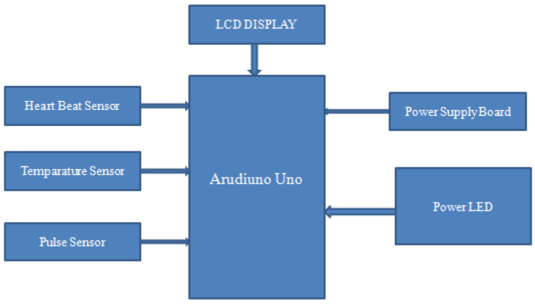
Usual classification of non-invasive methods is based on the used technology, although there are several authors that classify methods based on the subject they analyse, such as differentiation of media they target, including tissues (skin, aqueous eye humour, oral mucosa, tongue, and tympanic membrane) and fluids (sweat, urine, saliva, and tears).

Each measurement system is specified by its size that determines if it can be used in a specialized laboratory at the healthcare institution or as a part of a smart home system. In addition, it can be a pocket-size measurement device, such as those personal finger pricking devices or a wearable device, which is worn on the patient's body.

A specific method is used to process the sensed information and produce intermediate results, including transdermal and optical methodsor including nanotechnology. The way the information obtained intermediate results which are further processed may include a specific processing, such as multivariate analysis, multiregression, or various artificial methods, such as deep machine learning or neural networks, which are described in more detail in this paper.

Glucose measurement can be applicable for continuous and real-time monitoring or can provide only on-demand activation of a single measurement, treated to be just a substitute of the existing invasive methods. A measurement is defined to be a single measurement if it is activated on demand to access a sample and then to process a result, while the continuous measurement systems continuously take samples and calculate results.

Many non-invasive devices have been developed that purport to estimate central BP from different peripheral artery sites (e.g. radial, brachial, carotid arteries) using different principles of recording the pressure or surrogate signals (e.g. application tonometry, oscillometry, ultrasound, or magnetic resonance imaging) and different calibration methods to derive central BP.



CONCLUSION

Machine learning is now being used in the healthcare units for diagnosis and treatment. In this paper it is emphasized how different classifiers of machine learning are being used in the detection of the hydration level of the individual. It includes the collection of data through EDA for the modelling of classifiers. The data is collected for hydrated and dehydrated state of the body and different features are extracted and all classifiers are tuned and train on them for the detection of hydration level. On the basis of accuracy 91.3% it is found that random forest classifier is best of all other classifiers on a defined extracted features. As part of the future research direction, we plan to use deep learning classifiers such as convolutional neural network and long short-term memory to improve the performance of the approach.

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