# IoT-based Healthcare System for Real-time Maternal Stress Monitoring


Olugbenga Oti[1], Iman Azimi[1], Arman Anzanpour[1],
Amir M. Rahmani[2,3], Anna Axelin[4], and Pasi Liljeberg[1]

[1]*Department of Future Technologies, University of Turku, Turku, Finland*
[2]*Department of Computer Science, University of California Irvine, USA*
[3]*Institute of Computer Technology, TU Wien, Vienna, Austria*
[4]*Department of Nursing Science, University of Turku, Finland*
{olmoti, imaazi, armanz, anmaax, pakrli}@utu.fi, amirr1@uci.edu



***Abstract*—Excessive stress during pregnancy could cause adverse effects for the mother and her unborn baby, disrupting the normal maternal adaptation throughout pregnancy. Such conditions could be tackled to some degree via traditional clinical techniques, although an automated healthcare system is required for providing a continuous stress management system. Internet of Things (IoT) systems are promising alternatives for such real-time stress monitoring. In conventional IoT-based stress monitoring, stress-related data is collected, and the stress level is determined using a pre-defined model. However, these systems are insufficient for pregnant women whose physiological data are changing over the course of their pregnancy. Therefore, an adaptive monitoring system is needed to estimate stress levels, considering the maternal adaptation such as heart rate elevation in pregnancy. In this paper, we propose a stress-level estimation algorithm based on heart rate and heart rate variations during pregnancy. The algorithm is distributed in an edge-enabled IoT system. We test the performance of our algorithm using supervised and unsupervised learning via an unlabelled set of data from a 7-month monitoring. The monitoring was fulfilled for 20 pregnant women using wearable smart wristbands. Our results show a 97.9% accuracy with 10-fold cross validation using Random Forests.**



***Index Terms*—Internet of Things, Online Clustering, Edge Computing, Stress Monitoring, Maternal Monitoring**


## I. Introduction

There is a major concern about pregnancy-associated stress and anxiety, which are key risk factors for various pregnancy complications involving the health of mother and fetus [13], [32], [24], [14]. Maternal adaptations to decrease the stress level are important to enable a successful pregnancy although various maternal difficulties and environmental stressors can disrupt these adaptations. Several studies have tackled this subject, managing stress level during pregnancy with different medications and techniques [22], [12]. However, to support the conventional clinical methods, a personalized and automated healthcare system is highly required, providing stress monitoring for not only in-hospital environment but also everyday settings. Fortunately, recent advancements in Internet of Things (IoT) technologies have enabled the deployment of remote health monitoring systems in real-time applications, of which patient's health-associated parameters are continuously collected and analyzed to deliver health services.

Internet of Things is an advanced network of physical devices including embedded systems, sensors and actuators, leveraging shared pools of data, communication and computing resources to provide advanced services [4], [19]. In healthcare applications, IoT is conventionally decomposed into three main tiers [2]. In the first tier, data acquisition is implemented 24/7 using a sensor network consisting of a group of lightweight and wearable sensors. At the second tier, the gateways, located at the vicinity of the user, enable the connection between the sensor network and the remote computing resources (i.e., cloud servers). In addition, leveraging smart gateways for health monitoring has been recently proposed, allowing local data processing at the edge of the network [36], [35]. Third, the cloud server enables data storage and a wide range of health data analytics.

Continuous stress monitoring has been proposed, leveraging user's vital signs such as heart rate and heart rate variability to deliver the level of stress [3]. In the literature, such monitoring systems have been addressed from different perspectives. For example, Yoon et al. [42] tackled stress-related data collection designing a lightweight bio-patch. In addition, different models have been introduced to enable stress measurement particularly at work, detecting excessive stress and providing personalized coaching [6], [5], [28]. Moreover, other studies have introduced stress monitoring systems using the user's context information and physical activity collected via mobile sensors [34], [18].

These methods mostly detect the stress level using fixed rule-based methods or models generated from user's medical history. Therefore, they are inappropriate for long-term monitoring in particular for individuals such as pregnant women who experience physiological changes during the course of pregnancy. In consequence, an IoT-based stress monitoring system is required to determine the maternal stress level, considering the maternal adaptation such as elevation in heart rate during pregnancy. The changes in the cardiovascular system in a normal pregnancy could increase the average heart rate by 10 bpm to 20 bpm [10], [29], [20].

In this paper, we propose an IoT-based health monitoring system to continuously evaluate maternal stress throughout pregnancy. This system is empowered by an online k-means algorithm to determine the stress level leveraging real-time heart rate. Moreover, we provide a proof of concept and evaluate the accuracy of the proposed system using a case study on maternal health, in which 20 pregnant women have been remotely monitored for 6 months of pregnancy and 1 month postpartum.

Rest of the paper is organized as follows. Section II outlines the background and related work. The proposed method is presented in Section III. We indicate the implementation and results in Section IV. Finally, Section V concludes the paper.

## II. Related Work

### A. Maternal monitoring

Several studies have carried out maternal monitoring, however only a few have performed long-term monitoring. Chen et. al.[8] monitored pulse rate during nightly sleep, their goal was to measure individual changes in heart rate during pregnancy. Therefore, they had only two subjects; a pregnant woman and a nulligravida woman who was used as a baseline. The pregnant woman was studied from week 30 of her pregnancy to week 63 postpartum. The monitoring system consisted of a sensor board which was attached to patient's pillow to measure occipital pressure signals that occur as a result of heartbeats and movement, it also contained a bedside box that performed signal processing and thereafter sends the data to a database server via the internet. Moreira et. al. [31] explored the use of IoT in high risk pregnancies for long term monitoring of physiological data. They propose a system that uses body sensors to capture blood pressure and/or proteinuria levels in real time to predict the probability of having a hypertensive disorder. Their system also facilitates communication to health professionals when the prediction model (Naive Bayes Classifier) detects a change in the patient's condition. Carpenter et. al. [7] study the effect of exercise on Heart Rate Variability during pregnancy, 51 women participated in this study which was carried out from week 20 of their pregnancy to 12 weeks post partum. During this monitoring period, they had an exercise group and a control group, the exercise group attended weekly sport classes. Their heart rates were monitored using Heart monitors from Polar, Finland. In weeks $12-16$, $26-28$, $34-36$, both groups had an electrocardiogram (ECG) test during rest and exercise. They found that there was an increase in heart rate and a corresponding decrease in Heart Rate Variability (HRV) as the gestation progressed.

### B. Monitoring stress in real-time

There is continuing research on how to make stress level classification available through real-time monitoring. A chest device called Zephyr in combination with Amulet (a wrist-worn device) to collect continuous heart rate data was described in [6], in addition, they collect ground truth labels through an app on the Amulet by asking the user questions about their stress levels at least 32 times a day. They proceed by generating stress level classifications - high, medium and low, using an offline Support Vector Machine (SVM).

### C. Online machine learning with streaming data

There is a growing demand for online machine learning algorithms, particularly in systems that generate big data (e.g. IoT systems )[37], [15]. Seo et. al.[38] applied online machine learning in transportation research to reduce the amount of surveys required to estimate trip purposes. A naive Bayes classifier was implemented using GPS data from a mobile device and periodic surveys (dependent on confidence level of the algorithm). The algorithm was able to reduce the amount of surveys needed, they also found that the performance of the algorithm improved as more data was available.

## III. Proposed method

Based on the need to continuously monitor stress levels in pregnant women we developed a k-means algorithm that works in an online setting using streaming data from a wearable IoT device. This algorithm is designed to adapt to changes in heart rate that occur during pregnancy[7], [11], [21]. We focus on using k-means clustering because of its speed, accuracy, low memory requirement which makes it a candidate for an edge-based architecture, also, compared to other algorithms like Neural Networks, it does not require large amounts of data to perform well.

### A. Measuring stress level

Traditionally, Heart Rate Variability (HRV) analysis is used to indicate stress levels [33], [26], however, some studies have shown an inverse relation between Heart Rate (HR) and HRV [25], [23], [30]. Other studies have investigated the impact of stress on the heart rate and found that stress is indicative of an increase in heart rate [40], [41]. In these studies, the HR and HRV measurements are usually performed either at rest, during exercise or during sleep, this is because the heart rate changes during these periods. In this work, we focus on measuring heart rate at rest.

### B. Online k-means clustering algorithm

K-means clustering is one of the most commonly used approach for cluster analysis. Its popularity is due to its execution speed, simplicity and ability to produce good results. k-means is a numerical, unsupervised, fast and iterative method of finding patterns that may exist in raw data[39]. The k-means clustering algorithm is divided into two phases; the first phase is the initialization of the $k$ cluster centers ($k$ is fixed), in the second phase, each data point is assigned to its nearest cluster center using a distance measure (Euclidean distance), after adding the new point to a cluster $k_i$, the cluster center for $k_i$ is recalculated. For a finite set $P$ with $n$ points in $\mathbb{R}^d$, the k-means objective is to select $k$ cluster centers, $C$, that minimizes[9]:

$$\phi_x(C) = \sum_{x \in P} min_{c \in C} \|x - c\|^2 \tag{1}$$

In batch k-means, the algorithm terminates, when the cluster centers stop changing, whereas in online k-means clustering, the algorithm continues as long as the data points continue in the stream. Another difference between online k-means and batch k-means is that the former uses an online learning model such that the algorithm sees each data point only once[9]. We implement an online k-means clustering algorithm based on Lloyd's online k-means clustering with a modification made to the update for the centroids[27]. In addition to this, we modify the method of initializing the centroids, by using a batch k-means algorithm on a small subset of the data. The following is the pseudocode for the online k-means clustering algorithm[27]:

**Result:** Stress level classification - high stress, medium stress and low stress
**Initialize** clusters with all patient data from previous week[from cloud servers] using batch k-means;
**while** *true* **do**
  get new data point x;
  determine the closest center $z_i$ to x;
  update the cluster center $z_i \leftarrow z_i + \alpha(x - z_i)$ for $\alpha \in (0, 1)$;
**end**

**Algorithm 1:** Online k-means algorithm

Algorithm 1 is designed to be personalized to each patient, this is necessary because their baseline heart rates may differ. The algorithm is divided into two phases; the daily phase and weekly phase. The daily phase accounts for changes that may begin occurring during a day. As the algorithm receives new heart rate readings, it updates the model. However, the impact of the update is based on how consistent the "new" values are, this is how the model accounts for concept drift. In the weekly phase (beginning of the week), the model is updated, in order to account for all changes that occurred in the previous pregnancy week, thereafter, it continues to the daily phase.

### *C. Edge-based IoT architecture*

The proposed edge-based architecture is divided into 3 layers: sensors, edge devices, and cloud server. In the sensor layer, we use Garmin vívosmart 2 smart bands which are able to measure user's heart rate and activities. The edge devices are Android phones that receive data from a sensor device and transfer it to the cloud server which is a virtual private server (VPS). Since we are implementing our edge-based solution based on the previously recorded data, we store our data on the phone storage and we emulate the sensor-side incoming data by reading the phone storage, one vector of samples every 15 minutes. The cloud server stores all incoming data from all users eventually. The cloud server separates heart rate values into several categories based on the user's activity level and performs the k-means clustering algorithm to calculate the centroids of heart rates for each stress level when the user is at rest. It sends the centroids to the gateway for local processing and notification. The user's Android phone performs the test algorithm implemented by Python language via Qpython tool. Qpython creates a local web server and displays the results of local processing via a web application. Figure 2 shows the web application user interface.

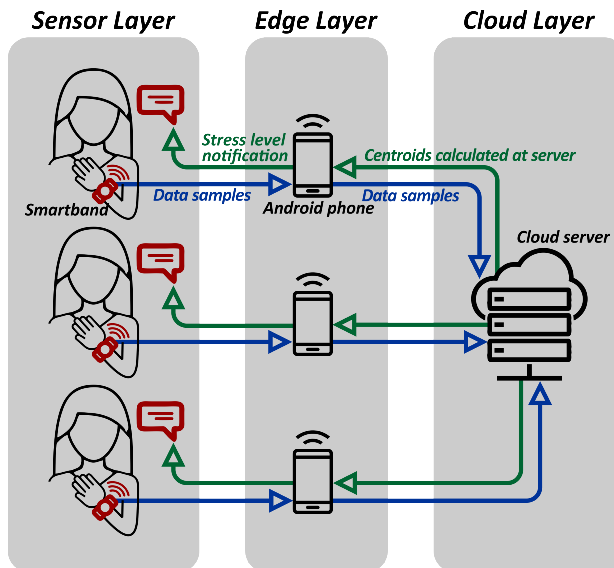


Figure 1. Edge-based system architecture

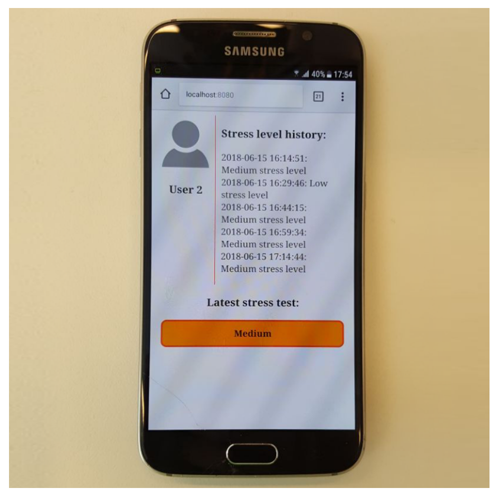


Figure 2. Qpython web application running on Android phone

In the proposed architecture (Figure 1) the cloud server collects data from all users and since every gateway device updates the centroids from the same source, then every user gets the stress level label comparing to all other users. Every 15 minutes, the edge device sends a new vector of samples to the cloud server and the server adds that vector to a database and computes a new set of centroids out of all vectors from the last week and returns them to edge device. The edge device is able to perform the test algorithm for a while using the latest set of centroids, therefore local processing in this architecture enables local notification even when the user's phone loses internet connection to the cloud server.

## IV. Implementation

### A. Study Design

*1) Data Extraction I:* We obtained data from a feasibility study on the use of an IoT-based system for pregnant women. The participants wore a Garmin vívosmart 2 device over a period of 7 months. We extracted the heart rate, activity and sleep information from the data, due to the fact that we only want to measure stress when the subject is at rest. This dataset contained about 60000 data points.

*2) Data Extraction II:* We obtained the second data set from a Garmin vívosmart 3 device which has a stress level classification of values ranging from $0 - 100$. We extracted the heart rate, sleep, activity and stress classification from the data, we used this data to test the performance of our algorithm in a supervised setting. This dataset contained about 600 data points.

### B. Results

Evaluating the performance of online k-means in the absence of labels remains an open research problem[9], [1]. The most common method of evaluation is to calculate the accuracy of the algorithm on a labelled dataset. In the absence of true labels for the dataset, there are several options, one is to attempt to reclassify the dataset with the labels generated from k-means using a classification algorithm[17], another method is to calculate the Sum of Squared Error (SSE) on each cluster, lower SSE values are associated with better clusters[1], [27] recommended a weighted squared distance from each point to its cluster, such that, the weights decrease exponentially in the age of the point at time $t$. In this paper, we employed three methods of evaluation, majority of our data did not have true labels, therefore, upon clustering the data points, we used Random Forests to evaluate the performance of the algorithm. For the other dataset, we used the true labels of stress levels generated from a recently released Garmin vívosmart device. And for both datasets, we obtain the weighted squared distance over time.

*1) Data with true labels:* The data from the male subject was from a Garmin vívosmart device that has a stress level classification of values ranging from 0-100. They indicate that values from 0 to 25 is a resting state, 26 to 50 is low stress, 51 to 75 is medium stress, and 76 to 100 is a high stress state[16]. Since we do not have a resting state classification in our paper, we combine the resting state and low stress, thereby, considering both as low stress states. To test the performance of the algorithm on this data, we begin by normalizing the ranges to our classification labels as described above and running the algorithm on this data set. We obtain an accuracy of **71.75%**, we consider this to be a good performance, the algorithm was designed to have the ability to adapt to changes in heart rate in each pregnancy week, despite the fact that this data is on a non-pregnant subject, it is able to adapt accordingly. To study the performance of the algorithm in more detail, we look at the confusion matrix, it shows the mistakes the algorithm makes in classifying each class. From

Table I
Confusion matrix for data with true labels

| | | Actual stress level | | |
|---|---|---|---|---|
| | | Low stress | Medium stress | High stress |
| Estimated stress level | Low stress | **315** | 87 | 0 |
| | Medium stress | 56 | **152** | 0 |
| | High stress | 7 | 35 | **3** |

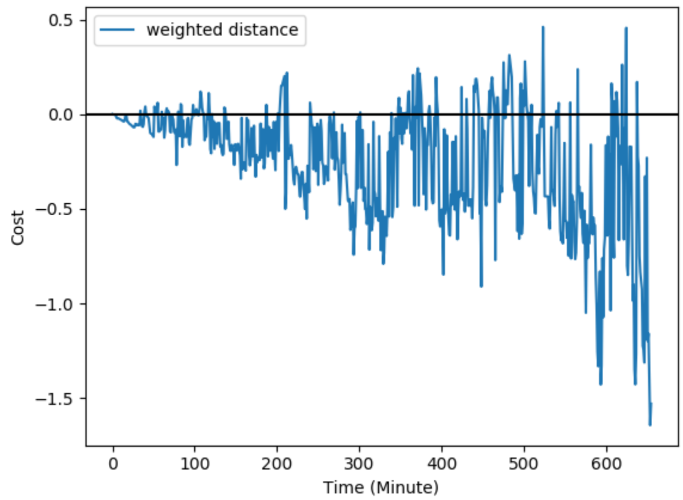


Figure 3. Cost of online k-means algorithm

Table I, the algorithm is able to predict low and medium stress more correctly that high stress, this is most likely a result of having limited samples for this class. We also note that low and medium stress have the most overlap. Further, high stress is often confused with medium stress states.

Asides, from the accuracy, we also calculated the weighted squared distance in the interest of visualizing how the algorithm adapts over time. As can be seen Figure 3, the weighted square distance errors shows that the online k-means algorithm is able to recover from changes in the data as seen in variation of high to low cost.

*2) Data without labels:* The focus of this paper is on predicting stress levels in pregnant women (in real time). We have obtained data from a Garmin vívosmart 2 device from 20 women over a period of 7 months, this data does not include a stress level classification. For this data, we use Random Forest to reclassify the labels derived from the online k-means algorithm. The performance was averaged using 10-fold validation across all weeks of pregnancy and summed over all patients, the accuracy is **97.9%**. Figure 4, shows an example of the clustering output for patient 1 throughout week 8. In addition to the accuracy, we also calculate the weighted distance error on a daily and weekly basis, the reason for this is that we expect changes to occur during the weeks of pregnancy, the algorithm should be able to adapt to such a change, for instance, if the algorithm has a rough start at the beginning of the week, it is able to see this as a concept drift and make changes accordingly.

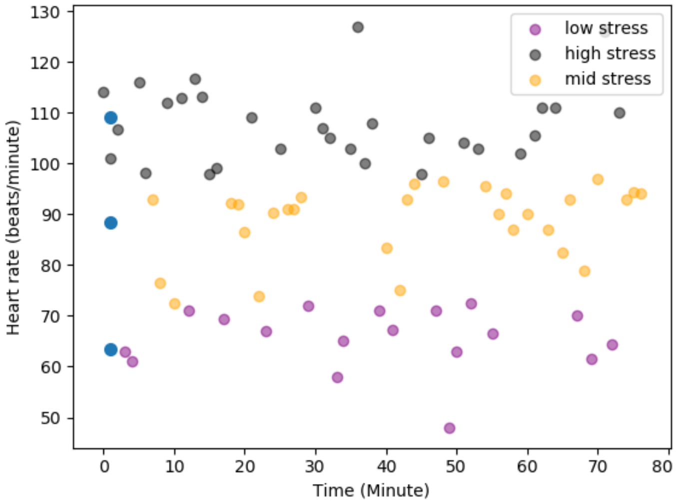


Figure 4. Output of online k-means clustering

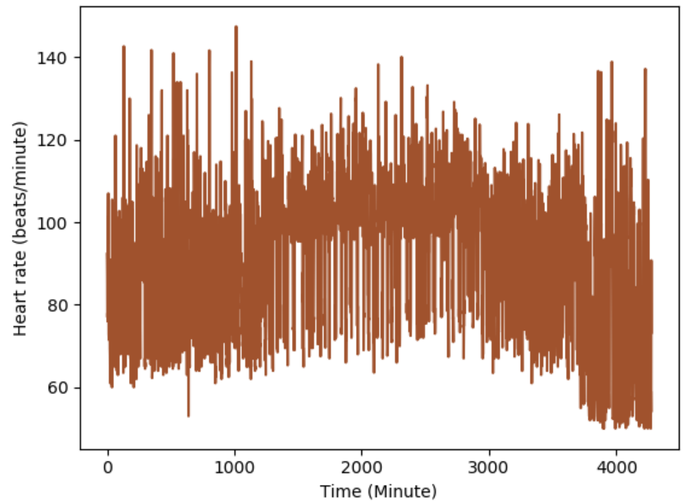


Figure 6. Gestational progression of heart rate for patient 2

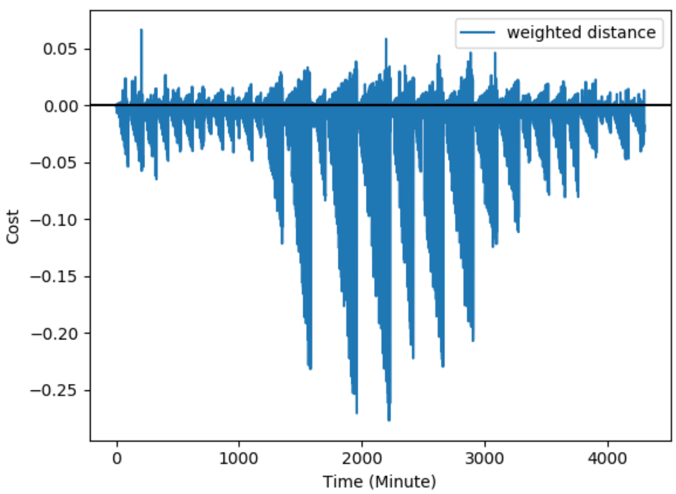


Figure 5. Cost of online k-means algorithm for patient 2

As shown in Figure 5, the algorithm performs as we expect, when there are consistent changes in the input (as seen in Figure 6), it is able to adjust to such changes hereby improving the cost.

### *C. Future directions*

In this study, we have been able to implement a real time stress level estimation algorithm that works in an online setting. Our results show that our model is able to adapt to expected changes in heart rate during pregnancy. However, one limitation of this work, is that we do not have true labels for the majority of our data, in the future, we would like to obtain true labels from a wearable device and/or subjective feedback from the patients. We have also proposed an edge-based IoT architecture for this algorithm, in the future, we would like to test the feasibility of implementing this architecture in our system.

## V. Conclusion

In this work, we presented a real time stress level estimation approach for pregnant women with a possibility of implementing the proposed model in an edge-based architecture. We obtained an accuracy of 71.75% on a validation dataset. Moreover, we examined the performance of the model on the main data (20 pregnant women) using a 10-fold validation Random Forest. We achieved an accuracy of 97.9%. Lastly, upon visualizing the progression of the cost over time, we indicated that the proposed algorithm is capable of considering the elevation of user's heart rates throughout pregnancy. We find these results promising, and believe that it has the potential to be used for stress monitoring during pregnancy. Upon integration into an edge-based architecture, it could be used by health professionals and pregnant women to improve stress management in pregnancy.

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