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Individualized Maternal Sleep Quality Evaluation

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Abstract

Being pregnant is a special moment when many moms become aware of their lifestyle choices and how they affect the developing foetus. To detect potential issues early and guarantee the health and wellbeing of the woman and her unborn child, high-quality prenatal care is required. Up to this point, various researches have recommended maternal health surveillance programmes. However, they are either restricted to questionnaires and quick data gathering techniques or created for a specific health issue. Furthermore, no extensive studies have been conducted to examine the demands and difficulties. A thorough structure that enables ongoing monitoring of expectant mothers is necessary for maternal health. In this study, we offer a system that uses the Internet of Things (IoT) to continuously monitor maternal health throughout pregnancy and the postpartum period. The system uses a variety of data loggers to monitor the mother's health. We further point out that the smartwatch utilised in our study can gather accurate photoplethysmography data and has a respectable energy efficiency for long-term monitoring.

Keywords: Maternal health, Internet Of Things, long-term monitoring.

1. Introduction

The goal of maternity care is to protect the health and welfare of the pregnant woman and her unborn child. The baby's future development is greatly influenced by the mother's health both now and in the future. Additionally, health issues during pregnancy, such as hypertensive disorders or gestational diabetes, may mirror issues with health in the mother's later years. Preventing acute pregnancy issues in individuals as well as promoting long-term health at the population level requires maternity care. Pregnancy check-ups are necessary to identify anomalies and to stop further difficulties, harm, or even death. The main concrete measures to monitor during pregnancy historically have been blood pressure, blood glucose, and urine tests, as well as uterine growth and maternal weight increase. Maternity care providers must also offer counselling on other lifestyle and self-management issues, like exercise and sleep, in order to maintain a healthy lifestyle. These are not yet being carefully watched, though. Pregnant women's health needs to be continuously monitored in order to identify potential issues early and enhance health metrics. Additionally, regular monitoring of various health indicators permits the collection of precise quantitative information that can aid in improving understanding of pregnancy. Information and communication technology (ICT) breakthroughs are revolutionising how healthcare is provided. One such growing paradigm in contemporary ICT is the Internet of Things (IoT), which makes use of a variety of sensing, communication, and computing infrastructures to provide an advanced network of items anywhere and at any time. This paradigm can be integrated into healthcare services to provide remote health monitoring for people around the clock using big data analytics and artificial intelligence. Such a monitoring system can gather information from the user and the environment, send it to distant computers, analyse it, and then offer suggestions and feedback in line with the findings. Pregnant women can receive affordable health monitoring services via IoT-based solutions in typical circumstances. According to recent studies, these remote health monitoring devices can enhance maternal and foetal health outcomes during pregnancy and after delivery. Many attempts have thus far been conducted to provide remote health monitoring for pregnant women. Several studies leverage subjective methods, where mothers are inquired about their health and well-being. These methods are mostly restricted to scheduled phone-interviews and Internet-based questionnaires, which might be inaccurate. In other studies, various parameters such as blood pressure and weight are periodically collected from pregnant women at home. These works are also bounded to limited data collection. In addition, mobile applications and wearable electronics are utilized to continuously collect health parameters during and after pregnancy, targeting specific pregnancy-related issues such as sleep disturbances, physical activity and hypertension. Although the literature's current works use IoT-based systems to do remote maternal monitoring, they are only briefly evaluated during pregnancy, have limited sensing capabilities, and are primarily focused on a single health issue. Additionally, the practical difficulties of such maternal long-term IoT-based systems have not yet been researched. The literature has looked into the viability of a mobile application during pregnancy and a wristband during pregnancy and postpartum. In this study, we introduce a long-term Internet of Things (IoT)-based health monitoring system that will continually and remotely provide different services throughout pregnancy and postpartum. Our system uses a variety of subjective and objective data collection methods to monitor the health of moms. The data are then remotely stored and processed before being sent to the healthcare professionals. We implemented a complete system for a real human subject study that provided prenatal and postnatal health monitoring. The system in place enables the monitoring of pregnant women's stress levels, sleep patterns, and physical activity. We also created a data analysis pipeline by holistically integrating a variety of AI-based and machine learning techniques into the system. This pipeline includes personalised modelling, missing data imputation, deep learning-based quality assessment of the data, and anomaly detection. The difficulties in putting the proposed remote maternal monitoring system into use are then evaluated and discussed.

2. Background and Related Work

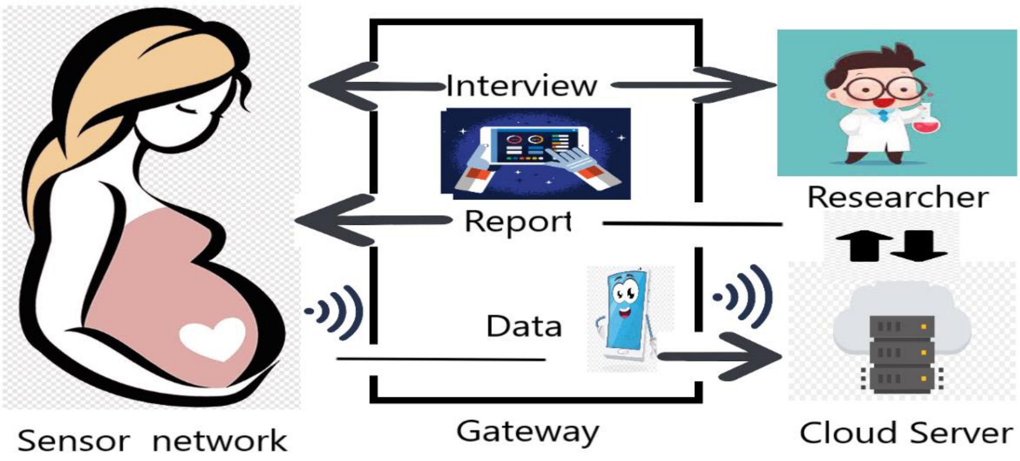
To guarantee both the mother and her unborn child's wellbeing, maternal health throughout pregnancy can be evaluated. Women are interested in keeping track of their health throughout pregnancy since it is a window into their future health. Given its significance for maternal health overall, sleep needs special consideration. Several hormonal and physiological changes that occur during pregnancy might be a factor in sleep issues. In the first trimester of pregnancy, for instance, sleep problems might be brought on by nausea, vomiting, or worry.

Sleep disruptions become more frequent and last longer as the pregnancy goes on. In the third trimester, frequent urination, backaches, leg cramps, and labour anxiety are major causes of poor sleep. Pregnant women are prone to insomnia.

The current study sought to determine how well women slept throughout each trimester of pregnancy using an actigraph and a questionnaire, and to explain how well they slept altered from the first to the third trimester of pregnancy.

Typically, questionnaires have been used to measure the quantity and quality of sleep during pregnancy. The benchmark for judging subjective sleep quality is the Pittsburgh Sleep Quality Index (PSQI). When compared to objective data, subjective approaches are inaccurate; pregnant women have both overestimated and underestimated their sleep duration.

Figure 1. The IOT-based System to Monitor Maternal Health



The gold standard for sleep monitoring is polysomnography (PSG). The PSG's cumbersome multisensor data gathering implementation limits its application to sleep labs and clinical settings. As a result, the procedure was often completed quickly in sleep research. Unlike the PSG, the actigraphy approach is simple to employ in non-hospital settings. For tracking sleep, contact-free sensors have also been suggested. Anomaly detection is discovering patterns or occurrences in data that deviate from anticipated behaviour is a problem.

Types of anomalies are point anomalies, contextual anomalies, collective anomalies.

3. Methods

3.1 Study Design

A monitoring system based on the Internet of Things that uses semi-supervised machine learning. The introduction of an Internet of Things-based device to continually monitor pregnant mothers. Architecture is divided into three main tiers. The sensor network first carries out data collecting in IoT-based systems that are close to the end users. The gateway, which is part of the second layer, serves as a link between the Internet and the sensor network. The high-performance computing infrastructure is part of the cloud server, which is the third layer.

Setup: For the data gathering, we only used wearable items (such smartwatches and wristbands) as sensor nodes. There were several gadgets on the market, including the Fitbit Charge, Microsoft Band, and Garmin

Vivosmart HR. We chose the Garmin Vivosmart HR after taking into account a number of elements, including the integrated sensors, battery life, small size, light weight, strap design, and waterproofness.

3.2 Participants and Recruitment

The monitoring was done on pregnant women in South Finland between May 2016 and June 2017 and also in Japan between February 2019 and May 2020.

A total of 21 women were registered in Japan, but one was disqualified because she had been hospitalised for a possible preterm delivery in the second trimester. Thus, 20 women who were available for the questionnaire survey and actigraph data in each of the three trimesters of pregnancy were included in the current analysis.

The surveillance was done on pregnant women who were primiparous and visiting one of two predetermined maternity outpatient clinics in Southern Finland.

Table 1. Information of the Participants

Statement	Type	Value
Age at pregnancy	-	27.5 ± 4.9
Pre-pregnancy BMI	-	25.0 ± 6.4
Quality of pre-pregnancy physical activity in week	Once or less	3 women
	Sometimes	5 women
	Almost daily	12 women
Quality of pre-pregnancy physical activity in a week	Light	8 women
	Moderate	11 women
	Vigorous	1 woman
Employment Status	At work	13 women
	Student	5 women
	Unemployed	2 women
Marital Status	Married or with partner	17 women
	Single	3 women
Educational Status	Below secondary education	4 women
	Secondary education	9 women
	College	4 women
	University	3 women
Smoking Status	Pre-pregnancy	7 women
	In-pregnancy	5 women

Following criteria was considered for the participants:

The participant must be at least eighteen years old. Her first kid should be due soon. There is only one pregnancy. The gestation period must be under 15 weeks. She speaks either English or Finnish. She has a laptop, a tablet, or a smartphone. The research comprised 20–40-year-old primiparous women who had given birth spontaneously, had no difficulties, and whose foetal heartbeat had been verified by ultrasound. They also had to be ready to give informed permission. Women who had trouble understanding Japanese and couldn't respond to the questionnaire in Japanese were not included in the research. Women who were deemed unsuitable for the study by the lead researcher or the attending physician at the research collaboration institution were also excluded.

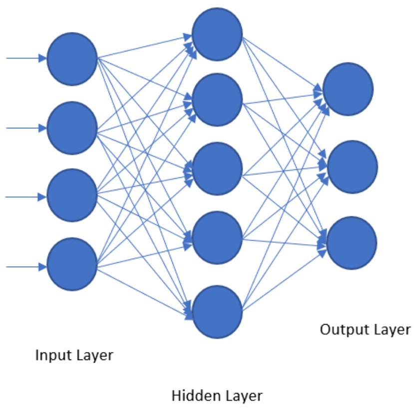
4. Assessment of the Participants

In Japan, both objective and subjective assessment was considered. During the first (10–14 weeks), second (16–27 weeks), and third (28–37 weeks) trimesters of pregnancy, the participant's data were gathered three times. The subjects also completed a questionnaire, and measures of their actigraph sleep activity during a seven-day period were taken.

The Pittsburgh Sleep Quality Index (PSQI-J) was utilised to measure sleep quality in Japan. The total score (0-21 points) is calculated by adding the scores of each component (0-3 points), with a higher score indicating more disturbed sleep. It is made up of seven factors related to the quality of sleep, including sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleeping medication, daytime dysfunction, and disturbance to daily life. The threshold is 6, with 6 or more scores indicating insufficient sleep. To measure health-related quality of life (QOL), the Medical Outcomes Study Questionnaire Short Form 36 (SF-36) was employed. The SF-36 is a universal assessment tool that does not restrict measures to people with particular illnesses or to signs of inadequate sleep. The state of one's health may be regularly monitored. There are eight subscales on the SF-36, and each has a score range from 0 to 100. Better circumstances are indicated by a higher score. The participants wore an actigraph wristwatch-style sleep measuring equipment from Sanita Trading Co. Ltd., Japan, round-the-clock, and their sleeping patterns were monitored for seven days. Participants tracked how long it took them to fall asleep and wake up using VAS.

In South Finland, for the assessment of participants, generally by feeding the sleep characteristics from the early phases of monitoring to a machine learning method, a customised model is created. From each sleep episode, eight objective sleep characteristics are retrieved. The attributes are: Sleep Duration, Sleep Onset Latency, Wake After Sleep Onset, Sleep Fragmentation, Sleep Efficiency, Sleep Depth, Resting Heart Rate, Heart Rate Recovery. In order to look at changes in sleep quality throughout pregnancy and postpartum, a personalised sleep model. is suggested. The user's sleep data are used to train the model at the start of the monitoring. The model is then applied to analyse the patterns and changes in the data from the remaining monitoring. A data instance or sleep event has several variables (i.e., characteristics), but no behavioural or contextual information is present. Because of this, we exclusively concentrate on Point Anomalies techniques, where a data instance can be chosen as anomalous in comparison to the other data instances but not the background information. Binary approaches are not suitable in this study since they provide the test instance a binary label (i.e., normal or abnormal) based on the outcome of the anomaly detection. Binary approaches include those based on support vector machines. Additionally, training data for rule-based approaches often has to include labels for both normal and anomalous classes. A test data instance's distance from its closest neighbours is also used by Nearest Neighbour algorithms (like KNN) to assess whether it is abnormal. However, the amount of the training data and the dimensionality of the features have a significant impact on how well they work. When the training set has little data, clustering algorithms are challenging to use. Statistical methods offer choices that are dependent on the presumptions. In high-dimensional data (like our dataset), the assumptions frequently do not hold true and cannot capture relationships between characteristics. Contrarily, artificial neural networks have been successfully used in a number of domains to detect anomalies. The most often utilised type of neural networks in semi-supervised and unsupervised contexts are replicator neural networks (RNN), also referred to as auto-encoders. However, when the training data amount is minimal, these strategies could perform poorly.

Figure 2. Replicator Neural Network



This problem is addressed by Bayesian network-based techniques, which include probability distributions into their models. The approach is a member of the class of compressed internal representation auto-associative neural networks. It records a nonlinear representation of the input data and makes an effort to create output that is identical to the input data. The weights of the network are optimised during training to reduce reconstruction errors of the training data. The reconstruction error is defined as follows for a given data instance:

$$\delta_i = \frac{1}{n}\sum_{j=1}^{n}(x_{ij} - O_{ij})^2 \qquad (1)$$

n is the data instance's feature count, xij is the input data instance, and oij is the RNN's output. For the specific data instance, the reconstruction error, δ_i may be utilised as the anomaly score.

Over the weights' space, the posterior distribution p(w|X, Y) is defined:

$$p(w|X,Y) = \frac{p(Y|X,w)p(w)}{p(Y|X)} \qquad (2)$$

where the model evidence is p(Y | X). However, Equation 2 cannot compute the posterior distribution since most real-world situations have unsolvable model evidence. To generate an approximating distribution, utilise a technique such as Variational Inference as follows:

$$q(w) = p(Y|X,w)p(w) \qquad (3)$$

In Equation 2, q(w) should be as near as feasible to the real posterior distribution p(w|X,Y). Therefore, it is necessary to reduce the two distributions Kullback-Leibler (KL) divergence[3].

$$KL(q(w)||p(w|X,Y)) = \int q(w)\log\left(\frac{q(w)}{p(w|X,Y)}\right)dw \qquad (4)$$

Equation 4 is still difficult to solve since it still incorporates the model evidence. As a result, Evidence Lower Bound (ELBO) is used instead of the KL divergence. Up to a logarithm constant, the ELBO is the KL divergence that is negative. As a result, minimising the KL divergence is equivalent to maximising the ELBO, allowing us to approximate the genuine posterior distribution:

$$\int q(w)\log p(Y \mid X, w)dw - KL(q(w)\|p(w)) \leq \log p(Y \mid X) \qquad (5)$$

We maximise the objective in Equation 5 in our Bayesian RNN.

5. Results and Conclusion

In Japan, 21 women were recruited; one was disqualified because she had been admitted to the hospital during the second trimester of her pregnancy due to a possible preterm delivery. Thus, the 20 women from whom we could get the questionnaire survey and actigraph data during all three trimesters of pregnancy were included in the current studies. The average age of the participants was 30.3±3.6 years. The average gestational age of the participants at the time the data were gathered in the first, second, and third trimesters of pregnancy was 10.7±1.1, 24.1±1.0, and 34.5±1.1 weeks, respectively. In the third trimester of pregnancy, there was an 8.5±2.4 kg weight increase from non-pregnant. Thirteen women were employed during the third trimester of pregnancy, whereas 19 women were employed during the first. Regarding minor annoyances, women reported that pollakiuria, low back pain, haemorrhoids, heartburn, and leucorrhea in the third trimester were significantly more difficult circumstances when compared to the first and second trimesters. Women also reported that morning sickness and dizziness/lightheadedness during the first trimester of pregnancy were the most difficult among the three trimesters. The subjective sleep evaluation using PSQI scores revealed no significant variations between the three trimesters, however the third trimester's high average score of 6.3±1.8 surpassed the cut-off mark of 6.0. This research has several restrictions. The sample size was tiny, to start. Only 20 individuals could be included in the study because to the limitations and lockdown brought about by the coronavirus outbreak in 2019. Second, there was no comparison with pre-pregnancy sleep efficiency. Future research with a bigger cohort and information on pre-pregnancy sleep is necessary. Pregnant women frequently experience sleep issues, which get considerably worse as the pregnancy goes on. The quality of sleep is considerably impacted by minor pregnancy issues. It's crucial to assess the risk factors for decreased sleep quality in pregnant women and to provide them the right kind of assistance so they can sleep comfortably and make up for lost sleep quality.

In South Finland, Due to the changes in the maternal body throughout pregnancy and after delivery, the quality of the mother's sleep changes. Such sleep changes should be carefully observed because insufficient sleep might cause a number of pregnancy problems. Traditional studies can't address this issue since they can only use a few specific methods of data collecting. In order to completely examine mother sleep changes during pregnancy and after delivery, we undertook an objective longitudinal research in this work. To remotely monitor expectant mothers around-the-clock, an IoT-based solution was devised. To track changes in maternal sleep patterns, a number of sleep variables were retrieved.

Additionally, we suggested a Bayesian RNN method to create a customised sleep model for every person using her own data. The sleep model was used to generate an anomaly score that represented the degree of changes in maternal sleep quality. We obtained data from 20 pregnant women over the course of 7 months, however we only used 172.15±33.29 days of each person's valid sleep data from 13 pregnant women in our sleep study. The sleep model was developed for each individual using data from the start of the monitoring, and it was then tested using the remaining pregnant and postpartum data. The results revealed that, compared to the middle of the second trimester, sleep problems increased throughout pregnancy (2.87 times) and after birth (5.62 times). Using precise quantitative measures and analysis of daily data from pregnant women, this study demonstrated that sleep quality reduced during pregnancy and after delivery with a high degree of confidence.

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