**LITERATURE ONE**

TITLE: A Comprehensive Framework for Wearable Module for Prenatal Health Monitoring and Risk Detection(2024)

Notes:

\*This paper proposes a modular health monitoring system for pregnant women, encompassing vital sign monitoring such as temperature, heart rate, oxygen saturation, blood pressure, and introduces a noninvasive Near-Infrared (NIR) blood glucose monitoring system, **employing a 2nd order polynomial regression model** for enhanced accuracy.

\* Rigorous evaluation using commercially available devices validates the system's reliability.

\* An **integrated SMS alert system** enhances communication in critical situations.

\*Addressing the challenge of differentiating between normal movements of mother and fetal kicks, the paper introduces a hybrid algorithm utilizing two Inertial Measurement Units (IMUs) for precise fetal kick detection.

\*Sustaining a low MMR demands continuous monitoring of the health of pregnant women

\*The main aim is to **predict health issues and develop a reliable alert system for possible pregnancy related emergencies**. The project focuses on designing a cost-effective, non-invasive device that connects with smartphones for consistent monitoring while maintaining the patient's health safety while ensuring the accuracy of each specific parameter.

\*This innovative system includes vitals monitoring such as **temperature, heart rate, oxygen** **saturation, blood pressure, blood glucose, and features such as fall detection.** It introduces an innovative algorithm for fetal kick detection, achieved through the usage of data from a secondary Inertial Measurement Unit (IMU).

Method Used:

\*We considered vital signs such **as temperature, oxygen saturation, heart rate, blood pressure, and blood glucose.** Additionally, we aimed to track fetal movement and detect unwanted falls.

\*Our central processing unit is the **ESP-32s microcontroller,** chosen for **its ability to collect and send data over the cloud through Wi-Fi.**

**\*To get accurate temperature readings, we selected the DS18b20 sensor.**

**\*For monitoring oxygen saturation and heart rate, we used the MAX30100 sensor.**

**\*. Addressing the discomfort of invasive blood glucose measurement, we propose a noninvasive solution using infrared light absorption technique. We have utilized a NIR 940mm led and a photodetector to detect the blood glucose level. The light absorbed by the glucose enriched blood is different from blood with less glucose level. This allowed us to measure the blood glucose level by comparing the output from the photodetector. However, in order to mitigate the noises, we have enclosed the glucose measurement system in a black box so that it cannot be affected by the external lights. This method allows continuous monitoring without the pain associated with traditional techniques which involves poking a needle every time we want to measure blood glucose.**

**\* For the blood pressure monitoring, we have used an off the shelf blood pressure monitoring device equipped with an EEPROM which stores the reading of the measurements.**

**\*The way the Blood pressure machine and the EEPROM chip communicates is by utilizing the I2C protocol.**

**\*The ESP-32-S which is acting as a slave device in the I2C bus listens for the incoming bits and processes it to get the blood pressure reading**

**\*The fall detection algorithm works with the use of acceleration parameters of MPU6050. If a sudden change is seen in the acceleration, then it is considered as the person has fallen.**

**\*In order to get the fetal movement, we have used another IMU named ADXL335.**

**\*If it is seen that after subtracting the MPU6050’s acceleration value from the ADXL335’s there is still a noticeable increase in the acceleration value, then the system flags it as a fetal movement**

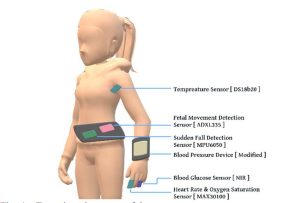
**\*Our system transmits user data after each 30- second interval except for blood pressure, activated manually or after a user-defined interval from the IoT server.**

**\*The system incorporates an alert system.**

**\*Whenever any vital sign shows any anomaly or if there is a fall detection, the system triggers the alert system, which consists of a push notification to the remote device and SMS to a predefined number using an API.**

**\*The designed user interface of the mobile application for maternal health monitoring is shown here. The system can also store the data in the database, and if the doctor wants to analyze the historical data, he/she can do it using the designated portal designed for the doctors.**

**\*** **The system has a feature that sends SMS when it detects any anomaly say temperature value is that high, an SMS is sent.**

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**RESULTS:**

**\*To validate vital monitoring parameters such as Temperature, Heart Rate, Oxygen Saturation, and Blood Pressure, the system underwent evaluation with a total of four volunteers.**

**(A)**

**-The reference device that has been used is a commercially available thermometer. The error metric used in the analysis is the Mean Squared Error**

**-For temperature measurement ,the system has a Mean Squared Error of only 0.0035 i.e combining that of all 4 volunteers.**

**(B)** **Accuracy Analysis of O2 Saturation and Heart Rate**

**-The reference device used is a commercially available pulse oximeter.**

**-The implemented oxygen saturation and heart rate measurement system has a Mean Squared Error of only 1.1 and 2.45, respectively i.e combining that of all 4 volunteers.**

**(C)** **Accuracy Analysis of Blood Pressure**

**-** **For blood pressure monitoring, the data taken is already from a commercially available blood pressure machine. However, as the machine is modified so, another commercial device is used as a reference device to analyze the data of the developed prototype.**

**-** **The implemented blood pressure measurement system has a Mean Absolute Percentage Error of 4.54% for systolic blood pressure and 5.43% for diastolic blood pressure.**

**(D)** **Development and Accuracy Analysis of Blood Glucose**

**-** **To develop the NIR-based blood glucose level monitor initially, we have taken a total of 40 readings from 8 different volunteers.**

**-** **A commercial blood glucose monitoring device is used as the reference.**

**-** **Based on the analysis, it is found that the proposed system has a MAPE of only 4.77%, and it can be utilized as an early indicator of any anomaly in the blood glucose trend.**

**Others:**

**\*** **For the fall detection, we have used the MPU6050. When a fall occurs, abrupt change happens in the values of the accelerometer in a very short time.**

**\*** **To detect the fetal kick, we have used the ADXL335 as the sensor responsible for detection, and it is placed on the abdomen of a pregnant woman based on the fetal orientation.**

**--Both are indicated by a spike.**

**Advancements :**

**- security measures for data protection**

**CONCLUSION : Implemented In Banglagesh**

**LITERATURE TWO**

Title: Wearable Technology Model to Control and Monitor Hypertension during Pregnancy

Notes:

\* In this paper, we proposed a wearable technology model to control and monitor hypertension during pregnancy.

\* Our proposed model also emphasizes the application of real-time data analysis for the healthcare organization

\*

1. The health parameters of the patient are collected through a wearable device

2. The data is received by a mobile application

3. The data is stored in a cloud database

4. The data is analyzed on real-time using a data analytics application.

\* The preliminary results showed an increased-on number of controlled patients by 11% and a reduction of maternal deaths by 7%, among other relevant health factors that allowed healthcare providers to take corrective and preventive actions.

\* Pregnancy complications related to hypertension, also known as a preeclampsia, represents a serious risk to the mother and the baby.

\* The common denominator of hypertension during pregnancy is the increase in blood pressure (BP) equal to or greater than 140/90 MmHg and when appropriately controlled could be a preventable risk factors.

\* This paper evaluates mobile and wearable technologies to control and monitor hypertension during pregnancy.

\* We decided to use the “V07” wearable device

\* SAP cloud platform (SAP HANA) is used.

\* We decided to use the Android operating system because it has a larger market of people and we can connect a wearable device without problems compared to an IOS.

Methodology:

MAIN FUNCTIONALITY

\*User domain (e.g., health parameters),

\*data domain (e.g., database servers and algorithms to interpret and store data that will be displayed to the doctors),

\* service domain (e.g., health providers’ services that use systems data to provide feedback to the patient).

First, a wearable device obtains patient health parameters, this data gets sent to a mobile device through an application, the data gets stored in a database in the cloud and finally the data is processed and analyzed through a data analytics application offered by the cloud provider.

**-This model focused on 3 users: patient, healthcare provider and the healthcare organization**

**\* The device captures her blood pressure, heart rate and patient steps.** **The data was collected every 30 minutes.**

**\*** **The wearable device is connected via Bluetooth with the mobile application all the data captured by the wearable will pass immediately to the cell phone and the memory of the wearable will be cleaned to obtain new data. This case occurs when the cell phone is not connected to the wearable, otherwise the data will be stored directly in the cell phone memory**

**\*The patient will be able to monitor his health anytime through the statistics shown in the application, besides this, he will be able to visualize the medicines that s/he must take, appointments and her/his treatment. The application is also developed to alert the health organization and the patient when an incident of high blood pressure is present, this alert also shows the location on google maps in which the patient is located**

**\*** **The variables such as weight, age and gestational age must be entered by the user manually in the application, each modification made will be recorded.**

**\*** **The stored data automatically transferred to the SAP HANNA database and the data will be deleted from the phone memory.**

**\*** **A data that is stored in the database is useful for the statistics to provide greater accuracy of patient's status to the doctor and health organization**

**RESULTS :**

**\*** **The Social Health Insurance Hospital also called EsSalud was the healthcare organization where the model was validated.**

**\*** **Prior to the implementation of the model, there were no records of controlling and monitoring cases of hypertension among pregnant women**

**\*** **We work with 20 pregnant patients who live in Lima and their gestational were between 3 months and 9 months. The study was conducted between October and December 2017.**

**\*** **The study received Ethics clearance by the Peruvian University of Applied Sciences and EsSalud.**

**ACTUAL IMPLEMENTATION**

**\*** **A wearable device and instructions of use wares given to each pregnant patient. The main recommendation was to not remove except when bathing or having to charge it. The charge of the device lasts approximately 90 minutes.**

**\*** **The wearable device sends all health parameters values obtained in a 30 minutes range (heart rate and blood pressure) to the mobile application, which is used as a mean to store data in SAP HANA database. It is important that mobile application is connected to internet and paired with wearable via Bluetooth.**

**\*** **We showed the healthcare providers how the data could be potentially analyzed and displayed. For example, one graphs showed all patients who had their blood pressure and heart rate controlled. A second graph indicated the analysis of the patients based on the healthcare parameters, and a third graph showed the month of gestation where higher alerts by pressure or high heart rate occurred. This preliminary information helped the healthcare providers to start developing new strategies to control and monitor these patients more efficiently and effectively**

**STRICT RESULTS:**

**\*** **Out of the total subject pool, we found that 70% of the subjects (14 pregnant women) had abnormal health parameters during the study.**

**\*** **It provided the healthcare institution with relevant information to start taking action on developing better strategies to control and take care of their pregnant population.**

**\*** **We found that in their thirtieth month, pregnant patients had a greater number of alerts for high blood pressure and high heart rate compared during their twentieth month of gestation.**

**\*** **Although, this finding was not surprising, it helped healthcare providers develop preventive and corrective actions starting from week 28th of pregnancy.**

**\*** **Prior this data, high blood pressure and heart rates alerts were thought to start on week 34 or 36 of gestation among health pregnant women. Even though, our goal was to increase the number of healthcare parameters to monitor and control preeclampsia in pregnancy, future studies should aim to have a more comprehensive measure of healthcare parameter to monitor and control not only preeclampsia but other alterations in pregnancy.**

**CONCLUSION:**

**\*The model was piloted in a healthcare center in Lima, Peru. The number of controlled patients was increased by 11% and the rate of maternal deaths was reduced by 7%**

**\*** **The pregnant patients expressed satisfaction with the model because they felt empowered by checking and monitoring their own health. They also found the technology non-invasive and easy to use. They also commented on the friendliness of the graphics and alerts. The doctors could treat their patients on time based on the values of their blood pressure and heart rate and start developing strategies to improve the care of this population. Finally, the organization verified the great impact that such a model could have on their business process as well as their final mission of improving health conditions.**

**NB: Data is uploaded to the cloud from the mobile device.**

**LITERATURE 3**

**Title: Long-Term IoT-Based Maternal Monitoring: System Design and Evaluation**

**Notes:**

**\*High-quality care during pregnancy is needed to identify possible complications early and ensure the mother’s and her unborn baby’s health and well-being.**

**\*** **In this paper, we present an Internet-of-Things (IoT)-based system to provide ubiquitous maternal health monitoring during pregnancy and postpartum.**

**\*** **The system consists of various data collectors to track the mother’s condition, including stress, sleep, and physical activity**

**\*** **We carried out the full system implementation and conducted a real human subject study on pregnant women in Southwestern Finland.**

**\*** **We also indicate the smartwatch, used in our study, has acceptable energy efficiency in long-term monitoring and is able to collect reliable photoplethysmography data.**

**FACTORS AFFECTING LONG-TERM USE OF IOT-BASED DEVICES**

**(1) feasibility and usability**

**(2) energy consumption and efficiency**

**(3) reliability and accuracy**

**\*** **The implemented system allows the monitoring of stress, sleep and physical activity of pregnant women.**

**\*** **We also integrated various AI-based and machine learning methods into the system in a holistic way, providing a data analysis pipeline. This pipeline contains deep learning-based quality assessment of data, personalized modeling, missing data imputation and anomaly detection**

**METHODOLOGY**

**1.** **In the perception layer, physiological well-being information is collected from mothers, exploiting various types of sensors.**

**2.** **Collected data are sent to the cloud layer through the gateway layer.**

**3.** **The cloud layer stores and analyzes the data and provides processed data for visualization.**

**4.** **The application layer visualizes health information to the users. It also enables the researchers to communicate with the mothers.**

**Actual Implementation:**

**\*** The Samsung Gear Sport smartwatch is selected in this study, considering access to raw data, battery life, configurability of the data collection, adequate built-in memory and waterproofness. The watch includes one built-in inertial measurement unit (IMU) and one PPG sensor.

\* We programmed the watch to collect the PPG signal for 12 min every second hour, considering the watch’s battery life. Acceleration data and daily activity data (e.g., step counts) provided by the watch are also acquired to track participants’ physical activity and sleep

\* We developed a cross-platform mobile application for smartphones to collect self-report data.

\* The participants were asked to measure their blood pressure at least once a week and send the data through the mobile application to the server.

\* Using the cross-platform application, we sent a self-report questionnaire to the participants to collect their background information. The questionnaire is designed to gain insights into their diagnosed diseases, previous miscarriage or preterm birth, lifestyle and perceived stress.

\* There are two types of gateway devices used in this monitoring. The first device is the smartphone. Our mobile application is a client–server application that uses the smartphone’s Internet connectivity to send data from the application to the server. The second gateway device is a WiFi router, providing Internet connection for the smartwatches during the monitoring.

\* We used Apache 2 , an open-source, cross-platform web server, and Flask for developing our server. Sockets Layer Application Programming Interface was also utilized to provide secure communication. In this setup, an authorized user can add, modify and delete the questions and schedule a time for certain notifications and reminders. The data are stored anonymously in the server to ensure the user’s privacy

\* The data management module receives data from the mothers through the mobile application and the wristbands. The server implements an authentication mechanism. Then, the validity of the received data is checked. The user is notified to re-upload the data in case of errors occurring. No personal data are sent to the server concerning the users’ privacy. Moreover, the users need to be authenticated and authorized for accessing the data.

\* Stress monitoring service in this system is provided by monitoring heart rate and HRV parameters(from the PPG signal).

**- The heart rate is extracted by counting the number of heartbeat peaks in the signal. Moreover, we obtain the HRV parameters by extracting the variation of inter-beat interval (IBI) in the PPG signal. The IBI is the duration of two successive heartbeat peaks in the signal.**

**- Sleep monitoring service uses hand movement and step counts data provided by the smartwatch to extract sleep parameters, including total sleep time (TST), sleep efficiency (SE) and wake after sleep onset (WASO)**

**- Physical activity monitoring service also leverages step counts and wearing time data to estimate the daily physical activity and sedentary time of the participants.**

**\*** **The data analysis module consists of various artificial intelligence and machine learning algorithms to assess the quality of data, detect anomalies, find trends and create personalized models.**

**\*** **Machine learning algorithms are exploited to train patients’ models, by which trends and changes are evaluated throughout the pregnancy and postpartum**

**RESULTS**

**\*** I**n this study, 28 women with high-risk pregnancies were monitored during pregnancy and three months postpartum using the presented system**

**\*** **The participants were recruited via advertisements in maternity clinics in Southwestern Finland and social media in 2019. Interested pregnant women contacted the researchers via email**

**\*** **The eligibility criteria for participants were:**

**(1) greater or equal to 18 years of age;**

**(2) 12–15 gestational weeks**

**(3) singleton pregnancy;**

**(4) previous late miscarriage (12–22 gestational weeks) OR previous preterm birth (22–36 gestational weeks)**

**(5) ability to understand Finnish. In addition, the participants had to have a smartphone (Android or iOS) and accept wearing a smartwatch from the recruitment until three months after the delivery**

**\*** **The eligible women were asked to participate in a face-to-face meeting with researchers, in which the details of the study procedures were provided. After the written informed consent, the devices, including a smartwatch and a blood pressure device, with instructions were delivered to the participants. In addition, a mobile application developed for this study was installed on their smartphones. Thirty-two pregnant women with high-risk pregnancies were recruited in this study. Four women withdrew from the study during the data collection period. Thus, the final sample size in this study was 28 pregnant women. Participants had a median of 13.4 weeks of gestation at the beginning of the monitoring**

**\*** **Six participants experienced preterm birth as their pregnancies lasted fewer than 37 weeks. One participant was not allowed to use the wristband at work, thus having a minimum average wearing time. Three participants were hospitalized due to pregnancy complications for several days, having a restriction in using the smartwatch. Moreover, the data collection was interrupted due to technical issues, e.g., server failures. The data of twelve participants were lost for (on average) four days. The watch wearing-time decreased on average during the pregnancy. In the postpartum period, the wearing-time increased for most of the participants during the first weeks. Two participants could not use the device after the delivery due to the restrictions of the Neonatal intensive care unit (NICU)**

**-** **The average wearing time during pregnancy was 17.01 ± 4.20 h/day.**

**\* The average usage of our cross-platform mobile application in the monitoring from two aspects: answering the daily questionnaires and uploading blood pressure values through the mobile application.**

**\***  **The watch was configured to record the PPG signal for 12 min every second hour, including 2 min of sensor calibration (i.e., unreliable data) and two 5-min recordings**

**\*** **We selected the sampling frequency of the PPG signals as 20 Hz to guarantee an acceptable accuracy of heart rate and HRV parameters.**

**Advantage: For this purpose, we chose a wearable device that can be easily used in indoor and outdoor activities**

**Disadvantage: However, the participants need to upload the data manually.**

**Conclusion: In this study, we first presented an IoT-based maternal monitoring system, providing services such as physical activity, sleep and stress monitoring throughout pregnancy and postpartum.**

**\*This system utilized various data collectors, including a cross-platform mobile application and a smartwatch, to collect bio-signals and self-report data. The collected data were stored and analyzed in the cloud server.**

**\*Our results show that participants, on average, used the smartwatch 17.01 ± 4.20 h/day during pregnancy.**

**\*** **Our findings show acceptable energy consumption of the watch in long-term monitoring as well as a reliable PPG-based analysis.**

**LITERATURE 4**

Title: Health Monitoring of Expectant mothers using Multiple Sensor Approach : “PregCare”

-A project done in Bangladesh in 2020.

Gap: The system uses her data to predict if she might develop high blood pressure in the coming weeks or months. Without this prediction, the condition might go unnoticed until it becomes serious. The program acts like an early warning system, helping healthcare workers make better decisions to protect both the mother and the baby.

-Details are not actually in English so typing was almost impossible. Refer to slides/pdf.

**LITERATURE 5**

\*TITLE: Explainable Early Prediction of Gestational Diabetes Biomarkers by Combining Medical Background and Wearable Devices: A Pilot Study With a Cohort Group in South Africa

\*The title describes a research study focused on predicting gestational diabetes (GDM) early using biomarkers, combining medical background information with data from wearable devices. Here's a breakdown of its meaning:

1. Explainable Early Prediction:  
   The study aims to predict the likelihood of developing gestational diabetes early in pregnancy. The term "explainable" suggests that the methods or models used for prediction are transparent and interpretable, meaning the reasons behind predictions are clear and understandable to medical professionals or patients.
2. Gestational Diabetes Biomarkers:  
   Biomarkers are measurable indicators of a biological state or condition. In this study, biomarkers related to gestational diabetes (such as glucose levels, insulin resistance, or other metabolic indicators) are used as key inputs for prediction.
3. Combining Medical Background and Wearable Devices:  
   The study integrates traditional medical data (e.g., patient history, clinical tests) with data collected from wearable devices (e.g., smartwatches or health trackers). Wearables might provide real-time insights like heart rate, activity levels, or sleep patterns, which could be correlated with gestational diabetes risk.
4. A Pilot Study With a Cohort Group in South Africa:  
   A pilot study means this is an initial, small-scale experiment to test the feasibility of the approach. The "cohort group" refers to a specific set of participants (likely pregnant women) in South Africa, chosen for the study.

Why It Matters:

The study explores how combining different types of data can improve early detection of GDM, which is crucial for timely intervention. By making the predictions explainable, healthcare providers can trust and act on the results more effectively, potentially leading to better outcomes for expecting mothers and their babies.

\* Mean Squared Error (MSE) and Mean Absolute Error (MAE) are two commonly used metrics to evaluate the accuracy of a regression model. Both measure the error between predicted values .

\* Glucose intolerance refers to a condition where the body struggles to efficiently process glucose (sugar), leading to higher-than-normal blood sugar levels. It indicates an abnormal response to glucose, often associated with an increased risk of developing diabetes, particularly type 2 diabetes**.**

\* BMI (Body Mass Index) is a simple and widely used measure to assess whether an individual has a healthy body weight relative to their height.

\* An **Oral Glucose Tolerance Test (OGTT)** is a medical test used to assess how well your body processes glucose. It is commonly used to diagnose **diabetes**, **gestational diabetes** (diabetes during pregnancy), and **impaired glucose tolerance** (prediabetes).

NOTES:

\* **Blood biomarkers** are measurable substances in the blood that indicate a biological state, condition, or process in the body. These can include molecules, cells, proteins, enzymes, or other compounds that provide valuable information about a person’s health or disease status.

**Types of Blood Biomarkers**

1. **Diagnostic Biomarkers**:
   * Used to identify diseases or conditions.
   * Example: Elevated troponin levels indicate heart damage in a heart attack.
2. **Prognostic Biomarkers**:
   * Predict the likely outcome or progression of a disease.
   * Example: High levels of C-reactive protein (CRP) suggest an increased risk of cardiovascular disease.
3. **Predictive Biomarkers**:
   * Help determine the effectiveness of a specific treatment.
   * Example: HER2 levels guide the use of targeted therapies in breast cancer.
4. **Monitoring Biomarkers**:
   * Track the progression of a disease or response to treatment.
   * Example: HbA1c for long-term blood sugar control in diabetes management.
5. **Risk Biomarkers**:
   * Assess the likelihood of developing a particular disease.
   * Example: LDL cholesterol as a biomarker for cardiovascular disease risk.

**Examples of Common Blood Biomarkers**

1. **Proteins**:
   * Albumin: Evaluates liver and kidney function.
   * Ferritin: Indicates iron storage and anemia.
2. **Enzymes**:
   * ALT/AST: Liver enzymes that reveal liver health.
   * CK (Creatine Kinase): Elevated levels can indicate muscle damage or a heart attack.
3. **Lipids**:
   * HDL (good cholesterol) and LDL (bad cholesterol): Indicators of cardiovascular health.
   * Triglycerides: High levels suggest metabolic issues.
4. **Hormones**:
   * Insulin: Regulates blood sugar levels.
   * TSH (Thyroid-Stimulating Hormone): Monitors thyroid function.
5. **Electrolytes and Minerals**:
   * Sodium, potassium, and calcium: Key for nerve and muscle function.
   * Magnesium: Important for muscle and nerve function, and bone health.
6. **Metabolic Markers**:
   * Glucose: Indicates blood sugar levels and diabetes status.
   * Uric Acid: High levels can signal gout or kidney issues.
7. **Inflammatory Markers**:
   * CRP (C-reactive protein): Signals inflammation.
   * ESR (Erythrocyte Sedimentation Rate): Non-specific indicator of inflammation.

**Importance of Blood Biomarkers**

1. **Early Detection**:
   * Biomarkers can reveal the presence of diseases before symptoms appear, enabling early intervention.
2. **Personalized Medicine**:
   * Help tailor treatments to individual patients based on their unique biomarker profile.
3. **Disease Monitoring**:
   * Track disease progression and effectiveness of treatments.
4. **Health and Wellness**:
   * Assess overall health and identify potential risk factors for future diseases.

**Challenges with Blood Biomarkers**

* Variability: Biomarker levels can be influenced by age, gender, diet, or other individual factors.
* Specificity: Some biomarkers are non-specific and may indicate multiple conditions.
* Cost: Advanced biomarker tests can be expensive.

Blood biomarkers are essential tools in modern medicine, helping clinicians make informed decisions about diagnosis, treatment, and prevention of diseases.

\* **Sedentary behavior** refers to any form of physical activity where the body is in a sitting or lying down position with low energy expenditure.

\* The objective is to use various types of data collected earlier in pregnancy (between 13 and 16 weeks) to **predict** whether biomarkers related to gestational diabetes will indicate a risk. This would allow for **early detection** and intervention before the standard GDM test is conducted.

\***CGM** stands for **Continuous Glucose Monitoring**. It is a system that provides real-time, continuous tracking of glucose levels in the body throughout the day and night. Unlike traditional blood glucose testing, which typically involves fingerstick tests, CGM allows individuals to monitor their glucose levels continuously, offering more detailed insights into blood sugar trends.

\* **PHQ** stands for **Patient Health Questionnaire**. It is a set of standardized screening tools used by healthcare providers to assess a patient's mental health, specifically to evaluate symptoms of **depression**, **anxiety**, and other mood or mental health disorders.

\* **Feature aggregation** is a technique in data preprocessing, particularly used in machine learning and statistical modeling, where multiple features (or variables) are combined or transformed into a single feature to simplify the model, reduce dimensionality, or capture higher-level patterns in the data.

\* **Data fusion with Coupled Matrix Tensor Factorization (CMTF) - Alternating Least Squares (ALS)** is a method used in data analysis and machine learning for combining different types of data (often from multiple sources or modalities) into a unified representation. This method is particularly useful when the data is complex and multi-dimensional, such as data that involves both matrices (2D data) and tensors (multi-dimensional data, such as time series or spatial-temporal data).

Let’s break down the components of the term:

**1. Data Fusion**

* **Data Fusion** refers to the process of integrating data from multiple sources or modalities (such as images, text, sensor readings, or databases) to create a more comprehensive and informative dataset. The goal is to leverage complementary information from these data sources to improve decision-making, prediction, or analysis.

Example: Combining temperature readings from multiple sensors, weather forecasts, and historical climate data to improve climate predictions.

**2. Coupled Matrix Tensor Factorization (CMTF)**

* **Matrix Factorization** is a technique where a matrix (2D array) is decomposed into a product of two or more smaller matrices, capturing latent factors that explain the relationships between data points.
  + **Matrix Factorization Example**: In collaborative filtering (used in recommendation systems), the matrix might represent users and items, and factorizing it uncovers latent features that explain user preferences

\* **Subcutaneous** refers to the **layer of tissue beneath the skin**. The term comes from the Latin words *sub* (meaning "under") and *cutis* (meaning "skin"). Subcutaneous tissue is made up of **fat cells** (adipose tissue), connective tissue, and blood vessels.

\* **Peripheral skin temperature** refers to the temperature of the skin on the outer parts of the body, such as the **hands**, **feet**, **fingers**, **toes**, **arms**, and **legs**. These areas are far from the body's core (which includes organs like the heart, lungs, and brain).

\* In the context of **machine learning**, **tensor order** is crucial because it determines how complex data is represented, processed, and analyzed. Machine learning models often work with multi-dimensional data, and tensors are used to represent this data. The **order of a tensor** (i.e., the number of dimensions) helps define the structure of the data, which influences the algorithms and methods used to process and learn from it.

\* **Streamlining data** refers to the process of making data more efficient, organized, and accessible for analysis or use. It involves simplifying and optimizing the flow, storage, and processing of data, often with the goal of reducing redundancy, improving data quality, and enhancing the performance of data-related tasks or systems.

\* The statement is describing a **regularization method** in machine learning or statistical modeling that is used to improve the performance and stability of a model, particularly when dealing with complex data. Let's break it down:

**1. Regularization Method:**

* **Regularization** is a technique used to prevent **overfitting** in a machine learning model. Overfitting occurs when a model learns not only the underlying patterns in the data but also the noise or random fluctuations, making it less generalizable to new, unseen data.
* Regularization methods add a penalty term to the model’s objective function (the function that the algorithm is trying to minimize, like the loss or error), which discourages the model from fitting the training data too closely. This encourages simpler models that are more likely to generalize well.

**2. Sparse Models:**

* **Sparsity** in a model refers to having many coefficients (weights or parameters) equal to zero. Sparse models are beneficial because:
  + They are **simpler**, with fewer features or parameters being used.
  + They help **improve interpretability**, as you can focus on the important variables.
  + They can reduce the risk of overfitting, as the model is forced to focus on only the most significant features.
* A regularization method that helps in achieving sparse models typically uses a penalty that encourages the model to **set many coefficients to zero**. The most well-known regularization techniques for creating sparse models are **Lasso** (Least Absolute Shrinkage and Selection Operator) and **Elastic Net**.

**3. Maintaining Stability:**

* **Stability** in the context of modeling refers to the ability of a model to produce reliable results, even in the presence of variations in the data.
* Regularization helps maintain stability by preventing the model from becoming too sensitive to small changes in the data. This is especially important in high-dimensional data, where small fluctuations or noise can lead to highly variable models.

**4. Handling Multicollinearity:**

* **Multicollinearity** occurs when two or more features (variables) in the data are highly correlated with each other, making it difficult for the model to distinguish their individual effects.
* When multicollinearity is present, the model may become unstable, and the coefficients (weights) for correlated features may fluctuate wildly or become highly sensitive to small changes in the data.
* Regularization methods, like **Ridge** regression or **Elastic Net**, can help **reduce the impact of multicollinearity** by penalizing large coefficients, thus stabilizing the model and preventing it from placing too much importance on highly correlated features.

**In summary:**

The regularization method being described helps in:

* **Achieving sparse models**: By penalizing complex models, it encourages simplicity and reduces the number of features used.
* **Maintaining stability**: The regularization keeps the model stable and prevents it from overfitting or being overly sensitive to data variations.
* **Handling multicollinearity**: By applying penalties to correlated features, regularization reduces the negative impact of multicollinearity, allowing the model to handle correlated data effectively.

This process is essential in machine learning, especially when working with datasets that have many features or complex relationships, ensuring that the model remains robust, interpretable, and generalizable.

\*Decision follows some conditions and if they are true, then give some output. Hence, it uses if-then statements.

Here’s a summary of what each of the biomarkers measures:

* **LDL (Low-Density Lipoprotein)**: Measures the **"bad" cholesterol** that can contribute to **plaque buildup** in the arteries, increasing the risk of **heart disease** and **stroke**.
* **HDL (High-Density Lipoprotein)**: Measures the **"good" cholesterol** that helps **remove excess cholesterol** from the blood and protects against **heart disease**.
* **Triglycerides**: Measures the level of **fat** in the blood, which is a source of **energy storage**. High levels are associated with **heart disease** and **metabolic syndrome**.
* **Cholesterol (Total)**: Measures the **total amount** of cholesterol in the blood, including **LDL, HDL**, and other lipids, which affects **cardiovascular health**.
* **HbA1c (Hemoglobin A1c)**: Measures the **average blood glucose level** over the past 2-3 months, helping to assess **diabetes** and **blood sugar control**.

**\*** **A macrosomic baby refers to an infant who is born with an abnormally high birth weight, typically defined as a birth weight greater than 8 pounds, 13 ounces (4,000 grams), regardless of gestational age. This condition is also referred to as fetal macrosomia.**

**\*The number of women developing GDM was reduced by a moderate lifestyle intervention in pregnant women identified as being at high risk for the disease…….A similar goal**

**\*There have been other studies as well, but none of them aimed at forecasting biomarker values based on medical backgrounds, physical activity recordings, and CGM values captured around gestational week 12. For instance, in [21], the authors conducted causal analysis on medical records and a prerecorded dataset. Similarly, in another study [22], a conceptual framework for a telemedicine system was proposed. However, neither of these studies involved the use of sensory devices or machine learning techniques.**

**\* CGM…………………..Glucose Continuous Monitoring**

**\*Explain use of each of these:**

* + **Feature Extraction, Aggregation and Selection was performed on collected data.**
  + **Data Fusion With Coupled-Matrix and Tensor Factorisation-Alternating Least Squares is performed.**