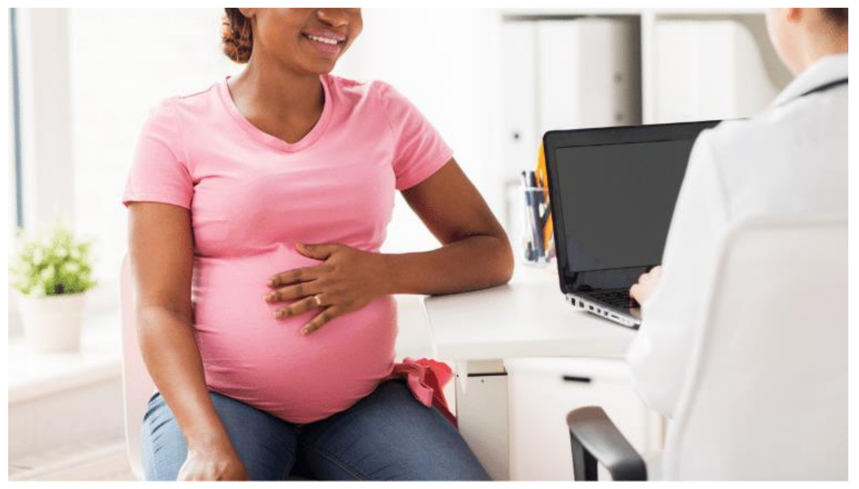
Maternal Health Monitor+: A Personalized Computational Framework for Early Detection and Intervention

Ashlyn Campbell
Georgia State University, Department of Computer Science, Atlanta, United States

Motivation & Background

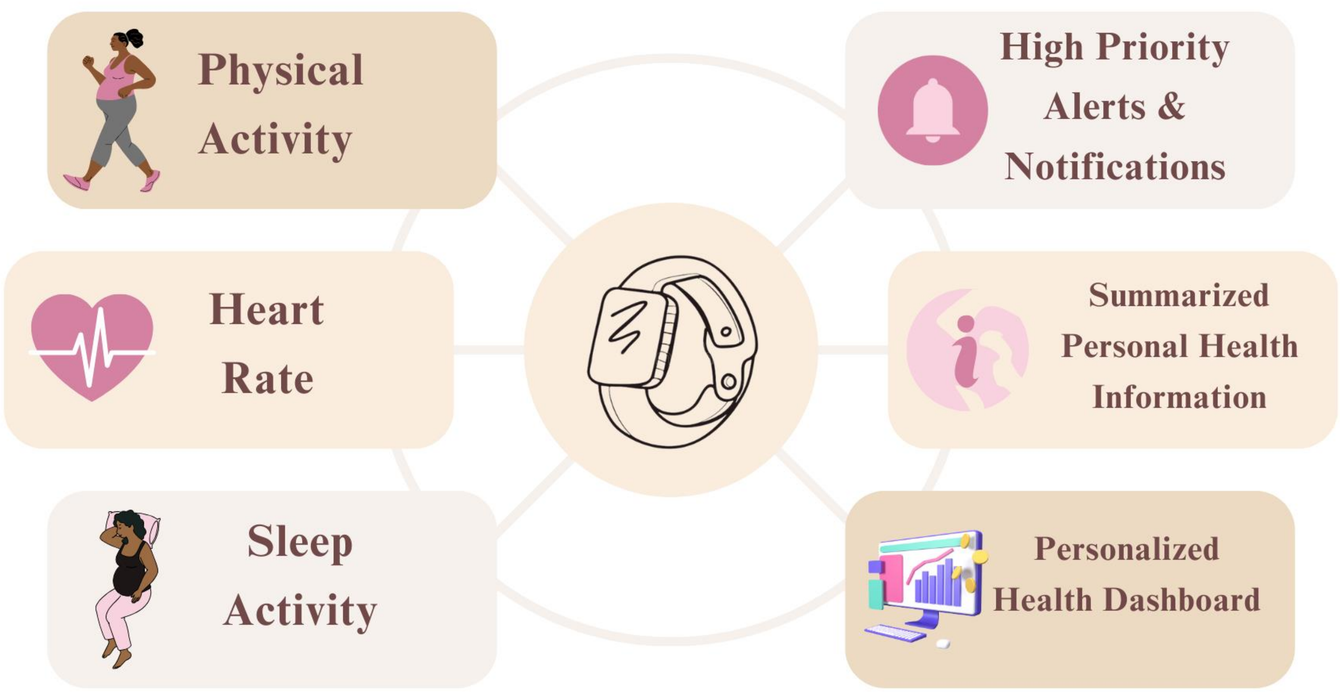
- Maternal health is a critical concern in lower income areas contributing to **95%** of maternal deaths in 2020 due to several factors such as, limited access to prenatal care, racism, age, and education level [1].
- In the United States, Black women have a maternal mortality rate of greater than **2.9** times higher than that of White women [2].
- Maternal Black women are at a **126%** higher risk of cardiovascular disease and **80%** greater risk of postpartum readmission [3].
- Today's market of wearable sensor maternal monitoring technology is costly, relies on two-way clinician communication, and **lacks education**.



Objectives

- Utilize Fitbit data trained **machine learning** models and threshold analysis to form connections in irregular pattern changes in heart rate, sleep, activity, and logged input leading to prominent complications.
- Enhance personal health education engagement by **bridging the information gap** through transformer summarization techniques.
- Effectively communicate personalized findings in a **mobile application** to participants through notifications, visualizations, and helpful resources.

Conceptual Design



Methods

- n = 14 distributed survey respondents with Amazon Mechanical Turk
- **Resting Heart Rate Calculation**
  i. Data is classified into 4 intensity levels and METs is captured to further classify heart rate at resting state.
- **Anomaly Detection in Heart Rate Risk Levels**
  i. Isolation Forest: The data space is randomly split into partitions to detect outliers in heart rate indicating the level of the anomaly score.
  ii. Local Outlier Factor: Local density amongst k=20 nearest neighbors is analyzed to determine outliers in a particular subset of the heartrate data classifying an anomaly score for each point.

$$\text{model } bin_{level} = \begin{cases} \text{low risk} & score > 0.25 \\ \text{medium risk} & score \geq -0.25 \text{ and } score < 0.25 \\ \text{high risk} & score < -0.25 \end{cases}$$

  iii. Standard Deviation Z-Score ($z = \frac{x-\mu}{\sigma}$): Standard deviation bins are determined by subtracting n heart rate values from the daily resting heart rate occurrence then further placed into anomalous levels using z-score.

$$std.bin_{level} = \begin{cases} \text{low risk} & z < 2 \\ \text{medium risk} & z \geq 2 \text{ and } z < 3 \\ \text{high risk} & z \geq 3 \end{cases}$$

- **Threshold Monitoring**
  i. Predetermined sleep, activity, and blood pressure system based on literature reviewed metrics to disperse daily notifications.
- **Extraction Summarization**
  i. Leverage transformers to retrieve and condense lengthy maternal health articles, sometimes exceeding 1000 words, sourced from the NHS API to generate concise summaries of less than 300 words, aiming to enhance accessibility and comprehension of personal health information.

Classification of Health Anomalies Using Machine Learning Models

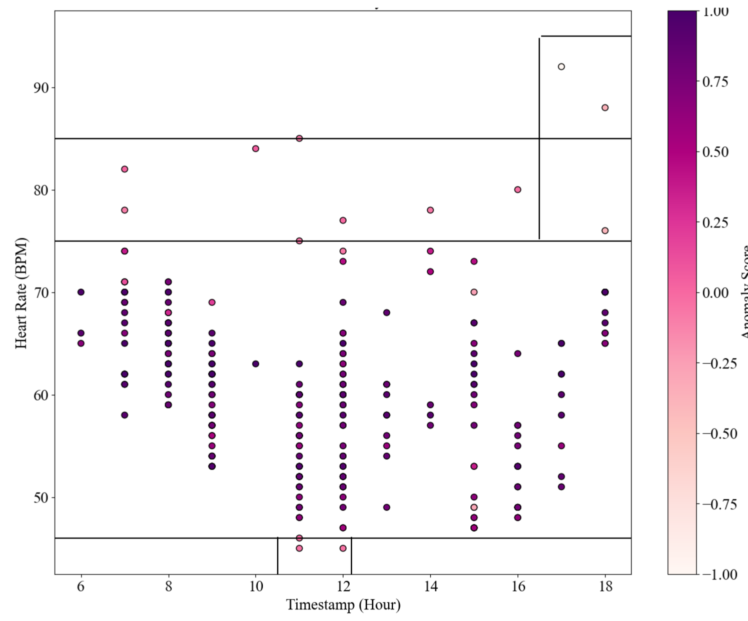


Figure 1 illustrates the application of Isolation Forest in identifying outliers within a participant's heart rate data over the course of a day, with anomalous data points outlined for clarity.

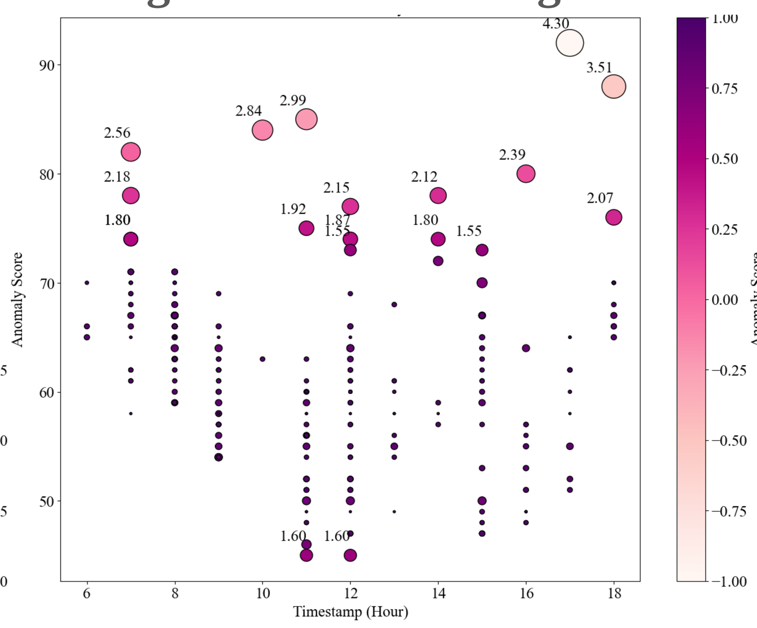


Figure 2 depicts the utilization of the Local Outlier Factor algorithm, which leverages local density, to identify outliers within a day of data points.

Preliminary Results

- The combination of Local Outlier Factor and Isolation Forest anomaly scores, along with Standard Deviation Z-Scores, reveals **overlapping risk assessments** in the medium and high-risk categories, underscoring the efficacy of anomaly detection methods working in parallel.
- The Isolation Forest algorithm identifies a significant number of anomalies at the **lower threshold** of heart rate readings compared to the Local Outlier Factor, indicating its effectiveness in detecting subtle irregularities.

Medium-Risk and High-Risk Level Distribution

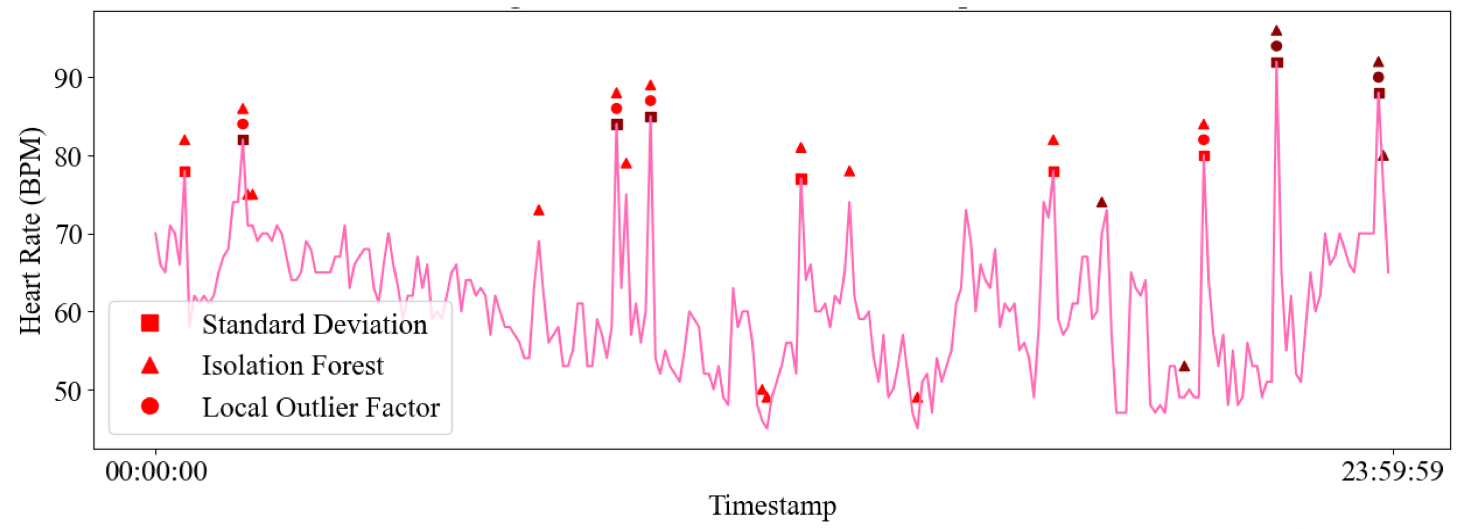


Figure 3 displays the medium (light red) and high (dark red) risk levels identified by three anomaly detection algorithms in the heart rate data of a single participant.

Distribution of Anomaly Score Risk Levels

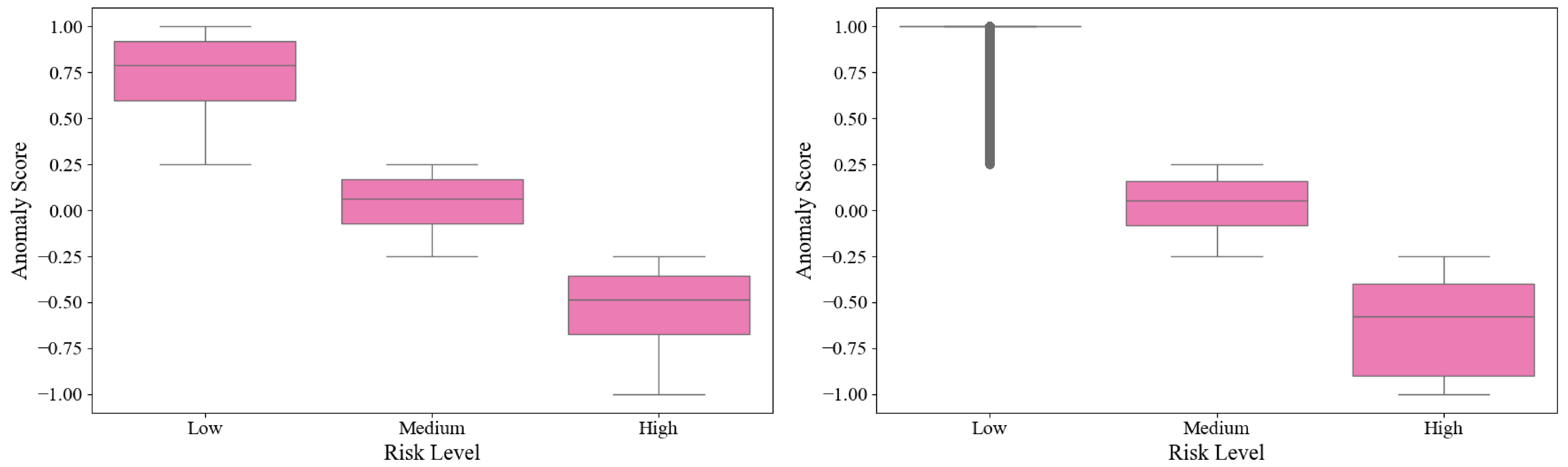


Figure 4 showcases the distribution of risk levels, depicted in Isolation Forest (left) and Local Outlier Factor (right) plots, categorized into low, medium, and high bins.

Future Work

Integration of the monitoring system and summarization model into a React Native mobile application for testing among a control group of pregnant participants residing in historically low-income areas.

Acknowledgements

Sincerest appreciation to Dr. Anu Bourgeois for her invaluable guidance and support throughout the course of this research project. Nicole Alicia, MD has provided gracious knowledge on the subject matter. This work is fully supported with the use of open-source datasets, libraries, and APIs.

References

1. World Health Organization. (2023, February 22). *Maternal mortality*. World Health Organization. https://www.who.int/news-room/fact-sheets/detail/maternal-mortality
2. Njoku, A., Evans, M., Nimo-Sefah, L., & Bailey, J. (2023). Listen to the Whispers before They Become Screams: Addressing Black Maternal Morbidity and Mortality in the United States. Healthcare (Basel, Switzerland), 11(3), 438. https://doi.org/10.3390/healthcare11030438
3. Aziz, A., Gyamfi-Bannerman, C., Siddiq, Z., Wright, J. D., Goffman, D., Sheen, J.-J., D'Alton, M. E., & Friedman, A. M. (2019). Maternal outcomes by race during postpartum readmissions. *American Journal of Obstetrics and Gynecology*, 220(5), 484.e1-484.e10. https://doi.org/10.1016/j.ajog.2019.02.016
4. Furberg, R., Brinton, J., Keating, M., & Ortiz, A. (2016). Crowd-sourced Fitbit datasets 03.12.2016-05.12.2016 [Data set]. Zenodo. https://doi.org/10.5281/zenodo.53894

Footnotes

1. Image 1. Retrieved from Health Affairs
2. Image 2. Retrieved from Scripps Health

Contact

Ashlyn Campbell
Georgia State University
acampbell89@student.gsu.edu

RISE in Computing