TinyDigitalExposome: The Opportunities of Multimodal Urban Environmental Data and Mental Wellbeing on Constrained Microcontrollers

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Abstract

The increasing level of air pollutants (e.g. particulates, noise and gases) within the atmosphere are impacting mental wellbeing. In this poster, we define the term 'TinyDigitalExposome' that takes us closer towards understanding the opportunity between environment and wellbeing using constrained microcontrollers. Specifically, we propose the opportunity of collecting particulate matter to infer mental wellbeing states whilst can have in the real-world.

Introduction

Air quality is a vital component of a healthy environment and plays a crucial role in the wellbeing or both humans and ecological systems. However, in recent years, the issue of air pollution has become a pressing global concern with the World Health Organization finding that 91% of people are living in places where the guidelines levels for air quality are often exceeding and the use of non-clean fuels and household emissions in the atmosphere are causing over 4.2 million deaths each year (1).

Personal sensors to measure individual exposures such as air pollution, noise, outdoor temperature, physical activity and blood pressure have been a positive way forward in monitoring due to their ability to collect data continually and in real-time helping to reveal early health conditions. With the high prevalence of sensor data streams combined and the possibility for an individual to continuously wear sensors, the data has the potential to show the exposure an individual encounters as we as predict early health conditions.

Figure 1.

DigitalExposome

The term 'Digital Exposome,' (2) serves as a conceptual framework utilizing multimodal mobile sensing technology to explore the intricate connections between environment, personal characteristics, behaviour, and mental well-being. DigitalExposome is primarily made up of two parts: data collection and data analysis with both aspects using technological advances to accurately calculate the exposome and therefore close the gap in relationship between the environment and human physiology.

PCA Factor Maps help understand the relational impact between different variables, with reducing information loss. It is worth noting, that most of the body attributes EDA, HR and HRV are all at the top of the figure, whilst the environmental variables PM1, PM2.5, PM10 and Reducing gases are in the middle as depicted at Figure 2.

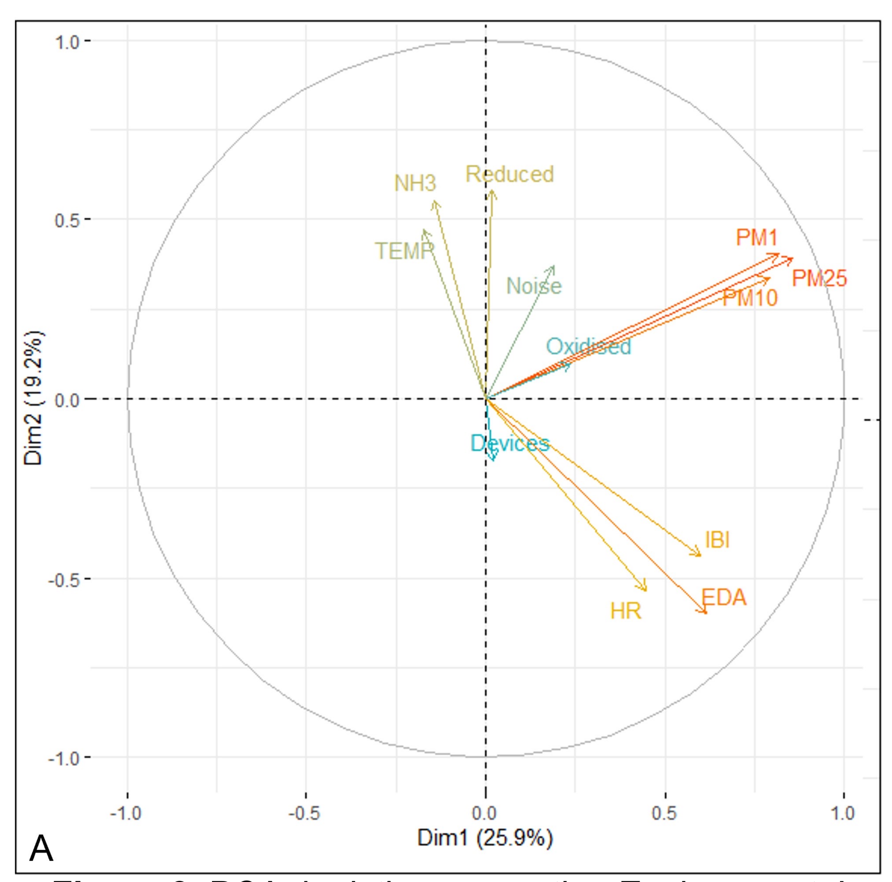

Figure 2. PCA depicting presenting Environmental and Physiological Variables.

Figure 3 demonstrates the variable importance of wellbeing against levels of PM2.5 within the environment. results of this indicate that high levels of PM2.5 are more commonly associated with a negative wellbeing, shown by participants choosing (1-Very negative wellbeing) on the device. Whereas less association is apparent where participants labelled '5' (very positive wellbeing), the levels of PM2.5 were much lower.

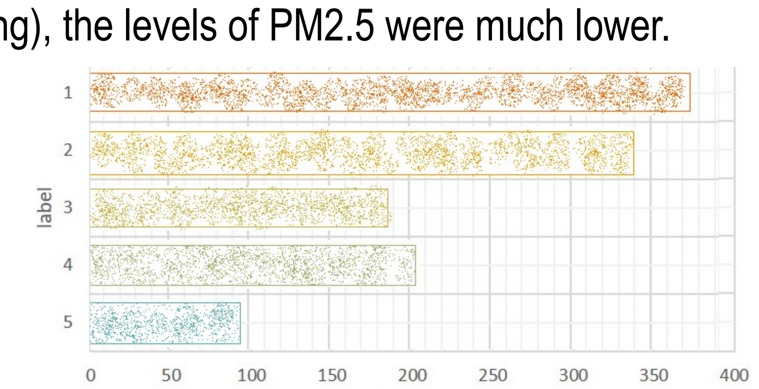

Figure 3. Depicts the relationship between wellbeing and Air Quality.

Figure 4 presents the F1-scores for each of the classification models trained using standard statistical features. Random Forest was the best performing model achieving an F1-score of 0.76, outperforming the other statistical models by 0.09 and the CNN which is frequently used for wellbeing classification by 0.13.

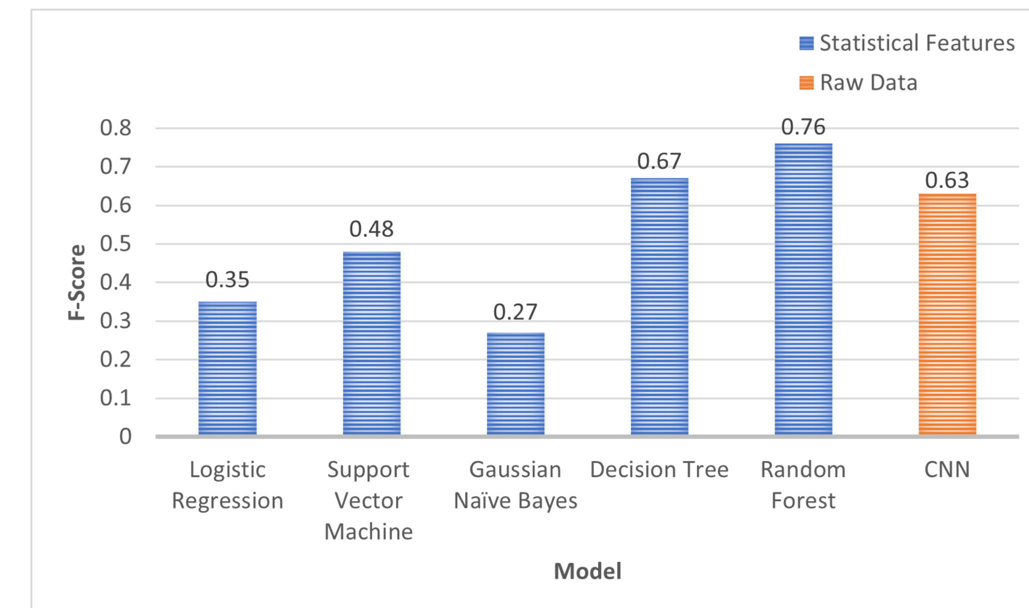

Figure 4. Comparison of classification models trained using statistical features and raw data from a CNN.

The results indicate that wellbeing can be inferred using environmental data alone, achieving an F1-score of 0.67 while well-being can be inferred from physiological data with 0.61. It is interesting to note that air quality pollution data when combined with physiological data outperformed the model trained using the environmental data alone, demonstrating the benefits of this data in classifying wellbeing.

This has also been the case in our other work in semantic enriched trajectories to understand at a personal level the impact of urban environment on mental wellbeing (3).

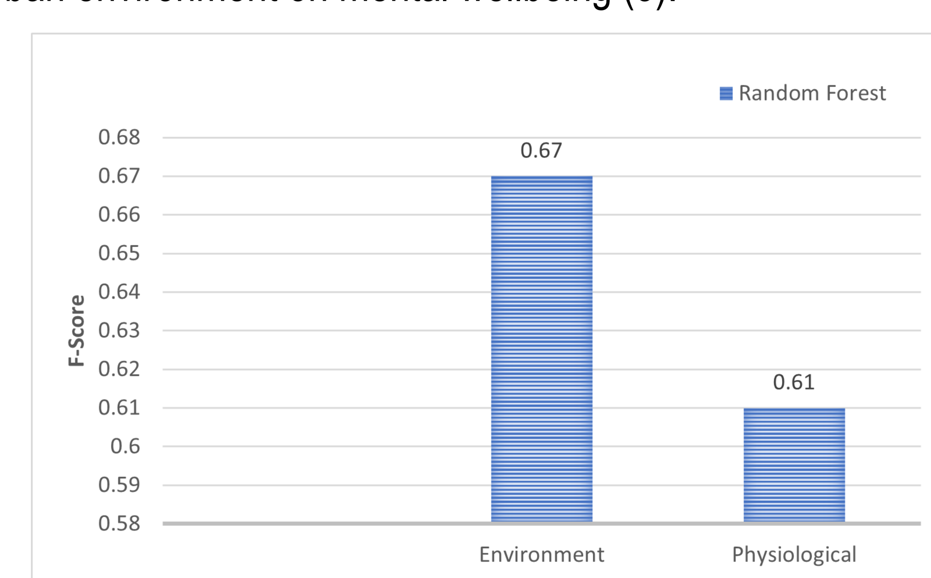

Figure 5. Comparison of Random Forest combined with CNN when trained using only the environmental or physiological data

Opportunities - TinyDigitalExposome

As demonstrated in our previous work, environmental factors can classify wellbeing states alone which could be applied in a TinyML format. In this next section we define 'TinyDigitalExposome' as a significant opportunity and step forward to unravel the relationship between environment air quality and mental wellbeing.

For this we propose the following technologies:

- Arduino Nano 33 Sense
- Particulate Matter Sensor
- Nitrogen Dioxide Sensor
- Carbon Dioxide Sensor
- LED indicators of air quality levels
- 5V battery

Figure 6, demonstrates the system technologies combined together using the technologies of an Arduino Nano and numerous particulate and gaseous sensors.

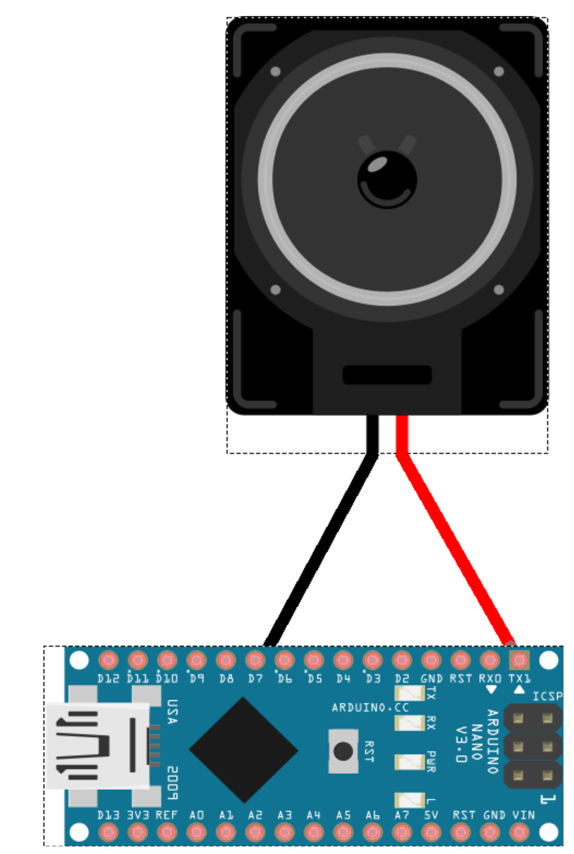

Figure 6. TinyDigitalExposome made up of a Arduino Nano 33 and Particulate Matter Sensor.

References

(1) Organisation, W. H. (2018). *Ambient air pollution*. WHO; World Health Organization. http://www.who.int/airpollution/ambient/en/

(2) Johnson, T., Kanjo, E., & Woodward, K. (2023). DigitalExposome: quantifying impact of urban environment on wellbeing using sensor fusion and deep learning. *Computational Urban Science*, *3*(1), 14. https://doi.org/10.1007/S43762-023-00088-9

(3) Thomas Johnson, & Eiman Kanjo. (2023). Episodes of Change: Emotion Change in Semantic Trajectories of Multimodal Sensor Data. *IEEE Annual Conference on Pervasive Computing and Communications Workshops (PerCom).*

DigitalExposome

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