**LEICESTER LIFESTYLE AND HEALTH RESEARCH GROUP**

**Human Activity Recognition using Self-supervised learning AI Architectures for Wearable Accelerometers in Free-Living Scenarios**

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**Section 2 – *Project Information***

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| **Project Title** | **Human Activity Recognition using Self-supervised learning AI Architectures for Wearable Accelerometers in Free-Living Scenarios** |
| **Project Summary** | |
| **Project Highlights:**   |  |  | | --- | --- | | 1. | Development of AI for automated labelling of free-living data from wearable accelerometers according to learnt behavioural profiles. | | 2. | Prediction of behavioural profile diversity over time for individuals using the AI architecture on data from both high-resolution and relatively inexpensive retail accelerometers with a focus on reducing health inequality. | | 3. | Application and testing of the algorithms in an epidemiological context (e.g type 2 diabetes) on large cohort studies with free-living accelerometer data. |   *Aim:* This project applies recently developed self-supervised learning architectures for time-series analysis from the field of deep learning AI and validates these for automated labelling of behavioural profiles contained within free-living accelerometer datasets.  *Background:* Wearable tri-axial accelerometers have been demonstrated as a useful technology for monitoring human activity levels and generating behavioural feedback for preventing chronic disease and comorbidity (Bull *et al.*, 2020). Activity levels, sleep and sedentary behaviour are routinely classified from accelerometer data based on signal magnitudes and/or orientation, but deeper insights may be obtained by identifying specific activities and their complex temporal relationships – so-called human activity recognition (HAR). For instance, deeper understanding of behaviour profiles across sub-types of type 2 diabetes could support personalisation of interventions and disease management (Henson *et al.*, 2024).  While accurately recognising and interpreting human activities from wearable accelerometer time-series data for patients in the community offers potential to unlock valuable insights for improving healthcare and healthy ageing, accurate time-resolved HAR in a free-living context is challenging. There is a lack of ‘ground truth’ data in free-living contexts and many datasets are collected in artificial laboratory settings with limited wider application to lifestyle research. Moreover, traditional data analysis (e.g. probabilistic and statistical) methods can struggle with the complexity of these data to capture the variability and the rich repertoire of human behaviour in the free-living context. Hence there has been a call to apply recent advances in AI to tackle large unlabelled free-living accelerometery datasets to unlock behavioural insights.  *Methods:* Self-supervised learning architectures (e.g. Figure 1) are attractive for addressing this issue due to their ability to handle and unlock insights in large-scale unlabelled data. These promise a reduced need for manual labelling, improved generalisation, performance gains on downstream tasks, capture of complex temporal dependencies, adaptability to real-world variability, the potential for personalisation and scalability (Zhang et al., 2024).  *Expected outcomes and impact:*  The potential to unlock novel insights from existing free-living accelerometery datasets, paving the way for personalised healthcare interventions and improved disease management strategies. | |
| **References** | |
| Bull FC, *et al.* World Health Organization 2020 guidelines on physical activity and sedentary behaviour. *Br J Sports Med.* 2020 Dec;54(24):1451-1462. doi: 10.1136/bjsports-2020-102955  Henson J, Tziannou A, Rowlands AV, Edwardson CL, Hall AP, Davies MJ, Yates T. Twenty-four-hour physical behaviour profiles across type 2 diabetes mellitus subtypes. *Diabetes Obes Metab.* 2024 Apr;26(4):1355-1365. doi: 10.1111/dom.15437  Yuan H, *et al.* Self-supervised learning for human activity recognition using 700,000 person-days of wearable data. *npj Digit. Med.* 2024 7,91 doi: 10.1038/s41746-024-01062-3  Zhang K *et al*. Self-supervised learning for time series analysis: taxonomy, progress, and prospects, *IEEE Trans Pat Analysis and Machine Intell.* 2024 46(10), 6775-6794, doi: 10.1109/TPAMI.2024.3387317 | |