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**ABSTRACT**

Inertial motion data-based Human Activity Recognition (HAR) has seen significant growth in recent years in both academic and commercial settings. From an abstract standpoint, this has been caused by a speeding up of the development of intelligent and smart surroundings and systems that span every element of human existence, including healthcare, sports, manufacturing, and commerce. Such environments and systems demand and encompass activity recognition, which identifies one or more individuals' behaviours, traits, and objectives from a temporal stream of observations streamed from one or more sensors.

Human Activity Recognition (HAR) is classifying the activity of a person using responsive sensors that are affected by human movement. Both users and capabilities(sensors) of smartphones increase and users usually carry their smartphones with them. These facts make HAR more important and popular.

With the ageing of the population in many nations today, older people are increasingly likely to live alone and are frequently unable to receive assistance from family members. Elderly people are known to be vulnerable to falls and mishaps when engaging in daily activities. Through the Internet of Things (IoT), smart home technology has been designed to recognise the daily actions of elders, assisting lone elderly to live safely and pleasantly.

Since smartphones and their privacy are highly safeguarded due to the development of pervasive computer and sensor automation, sensor-based HAR is being utilised in smart devices more frequently. The focus of this project is therefore smartphone sensor-based HAR. This work focuses on the recognition of human activity using smartphone sensors using different machine learning classification approaches. Data retrieved from smartphones’ accelerometer sensor which is classified to recognize human activity. Results of the approaches used are compared in terms of efficiency and precision.

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