



A Novel Patient - Centric Intelli Care System

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Abstract

In recent years, mobile health (mHealth) has emerged as a powerful paradigm for real-time monitoring and analysis of physical activities using wearable sensors and smart devices. Human Activity Recognition (HAR) plays a pivotal role in this domain by enabling automated classification and prediction of user activities, contributing to improved healthcare services. This paper explores the development of an intelligent HAR system using the MHEALTH dataset, employing both machine learning and deep learning techniques. Specifically, a Random Forest (RF) classifier and a Long Short-Term Memory (LSTM) neural network were implemented and evaluated for their classification capabilities. Experimental results demonstrate that the RF model achieved superior performance with an accuracy of 97.13%, while the LSTM model attained an accuracy of 91.44%. The study highlights the significance of combining temporal and spatial features for efficient activity recognition and provides insights into model selection for real-world deployment in mobile health applications.

Keywords: Human Activity Recognition (HAR), Mobile Health (mHealth), Wearable Sensors, Activity Classification, Healthcare Monitoring.

1. Introduction

Mobile health (mHealth) has emerged as a rapidly evolving domain at the intersection of healthcare, behavioural science, and information technology. With the widespread adoption of smartphones and wearable devices, vast amounts of behavioural and physiological data can now be captured in real time and in natural environments [1]. This continuous monitoring capability has created new opportunities for understanding human behaviour and its impact on health outcomes, extending beyond the limitations of traditional clinical assessments that are often periodic and environment dependent [2]. Human behaviour plays a pivotal role in health management, influencing the onset, progression, and prognosis of both communicable and noncommunicable diseases. Chronic conditions such as diabetes, cardiovascular disorders, and mental health issues are strongly linked to lifestyle and behavioural patterns [3,4]. mHealth systems, equipped with embedded sensors and self-reporting tools, enable the measurement of key behavioural indicators such as physical activity,

sleep quality, dietary habits, stress levels, and social interactions [5]. When combined with advanced computational methods—including machine learning and artificial intelligence—these multimodal data streams facilitate accurate behaviour modelling, risk prediction, and personalized intervention strategies [6,7]. Human Activity Recognition (HAR) has emerged as a vital research domain within ubiquitous computing, machine learning, and artificial intelligence due to its wide range of applications in healthcare, sports, smart homes, surveillance, and human-computer interaction [8]. The primary objective of HAR is to automatically identify and predict various physical activities performed by individuals based on sensor data. With the proliferation of wearable devices, smartphones, and Internet of Things (IoT) technologies, vast amounts of multimodal data—such as accelerometer signals and gyroscope readings—are being generated, making HAR an increasingly feasible and impactful area of study [9-10]. Traditional methods for HAR

relied on handcrafted features and shallow learning models, which often struggled with complex, noisy, or overlapping activity data [11-13]. Recent advances in machine learning and deep learning have significantly improved the performance of HAR systems by enabling automated feature extraction, temporal pattern recognition, and adaptive learning from large datasets [14- 15]. The prediction aspect of HAR focuses on anticipating upcoming or ongoing activities before they are fully executed. Predictive HAR is crucial in applications such as fall detection for elderly care, proactive healthcare monitoring, adaptive user interfaces, and intelligent surveillance systems [16-18]. By predicting activities in advance, such systems can provide timely interventions, improve safety, and enhance user experiences [19-21]. This research aims to explore efficient approaches for predicting human activities using machine learning and deep learning techniques. It emphasizes improving recognition accuracy and ensuring real-time applicability.

2. Method

The task of Human Activity Recognition (HAR) from time-series sensor data necessitates models that can effectively capture both spatial patterns and temporal dependencies. Given the increasing availability of wearable sensors and mobile devices, robust computational techniques are essential for classifying physical activities in diverse and often noisy environments. To address this challenge, the present study employs two modelling paradigms: a machine learning-based approach using the Random Forest (RF) algorithm, and a deep learning-based approach leveraging Long Short-Term Memory (LSTM) networks. The Proposed architecture for activity prediction using the MHEALTH dataset is illustrated in Figure 1.

2.1. Tables

Table 1 Comparison of classification performance metrics for Random Forest and LSTM models

Algorithms	Accuracy	Test Accuracy	Precision	Recall	F1-score
Random Forest	97.13%	97.00%	97.01%	97.21%	97.04%
LSTM	91.44%	90.13%	92.54%	90.13%	90.62%

2.2. Figures

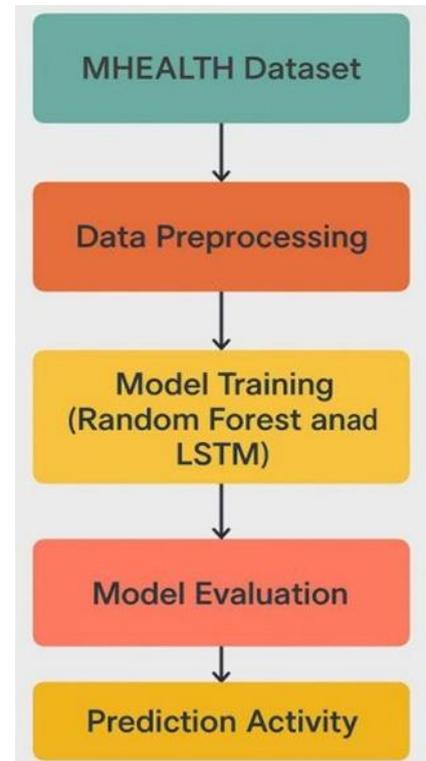


Figure 1 Proposed Architecture for Activity Prediction Using the MHEALTH Dataset

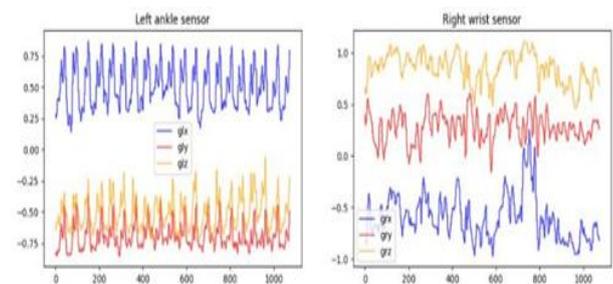


Figure 2 Gyroscope Signal Responses Obtained from the Left Ankle and Right Wrist Sensors

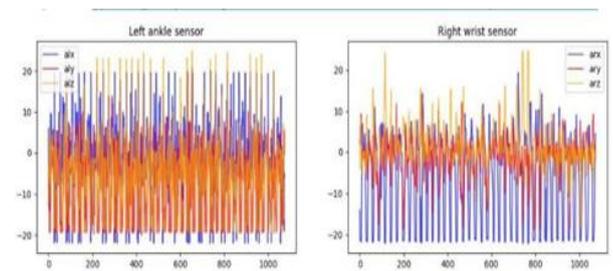


Figure 3 Accelerometer Signal Responses Obtained from the Left Ankle and Right Wrist Sensors

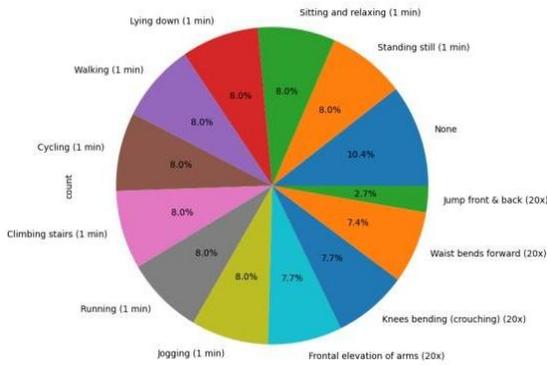


Figure 4 Distribution of the Activities in the Dataset

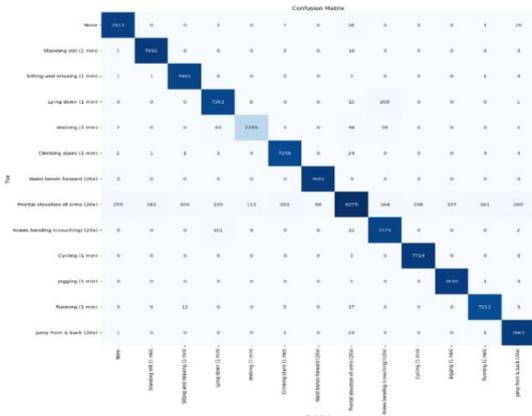


Figure 5 Confusion Matrix of the Random Forest Model.

3. Related Work

The widespread adoption of smartphones and wearable devices has enabled the collection of continuous behavioral data, supporting real-time monitoring of physical and psychological states. This section presents the experimental outcomes obtained from the implementation of the proposed machine learning and deep learning models for Human Activity Recognition (HAR) using the MHEALTH dataset. The goal of these experiments is to evaluate the classification performance of the Random Forest (RF) and Long Short-Term Memory (LSTM) models on diverse physical activities captured through multimodal sensor data. To ensure comprehensive evaluation, key performance metrics such as accuracy, precision, recall, and F1-score are used. The results highlight the effectiveness of each model in handling temporal and spatial patterns inherent in human activity signals. A comparative analysis is

conducted to understand the strengths and limitations of both approaches, providing insights into their real-world applicability in mobile health monitoring systems. Figures 2 and 3 depict the gyroscope and accelerometer signal responses obtained from the left ankle and right wrist sensors during various physical activities, whereas Figure 4 illustrates the overall distribution of the recorded activity labels. Figure 5 shows Confusion matrix of the Random Forest model. Table 1 presents the Comparison of classification performance metrics for Random Forest and LSTM models [22-31].

Conclusion

This research presents an intelligent human activity recognition framework utilizing both traditional machine learning (Random Forest) and deep learning (LSTM) methods on the MHEALTH dataset. The study confirms that Random Forest outperforms LSTM in terms of classification metrics and robustness. The RF model's simplicity, efficiency, and high accuracy. By leveraging multimodal sensor data and robust classification techniques, this work contributes to the development of intelligent healthcare monitoring systems that can operate effectively in diverse real-world conditions. The results reinforce the relevance of ensemble learning techniques in activity recognition tasks. Future work includes deploying the models on real-time mobile platforms and enhancing performance using additional sensor data and personalized learning techniques. Incorporating explainable AI will also improve transparency in healthcare applications.

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