Chapter 8
XHAC:
Explainable Human Activity Classification From Sensor Data

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ABSTRACT

Explainable artificial intelligence (XAI) is a concept that has emerged and become popular in recent years. Even interpretation in machine learning models has been drawing attention. Human activity classification (HAC) systems still lack interpretable approaches. In this study, an approach, called eXplainable HAC (XHAC), was proposed in which the data exploration, model structure explanation, and prediction explanation of the ML classifiers for HAR were examined to improve the explainability of the HAR models' components such as sensor types and their locations. For this purpose, various internet of things (IoT) sensors were considered individually, including accelerometer, gyroscope, and magnetometer. The location of these sensors (i.e., ankle, arm, and chest) was also taken into account. The important features were explored. In addition, the effect of the window size on the classification performance was investigated. According to the obtained results, the proposed approach makes the HAC processes more explainable compared to the black-box ML techniques.

INTRODUCTION

Nowadays, millions of people and billions of objects use the Internet of Things (IoT) technologies. Besides, it is expected that these statistics will be exponentially increased in the future. IoT systems consist of hardware, software, data, and service components. Although the potential of their technology and the variety of their usage fields, the boundary of IoT components remains undetermined. In addition, it is challenging to process and analyze the heterogeneous data, which are produced by IoT.

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IoT systems interact with the physical environment through sensors, storing long-term data, and making data analyses to improve efficiency. Machine learning (ML) algorithms have been used in IoT systems for many purposes such as optimization, estimation, pattern recognition, data classification, outlier data detection, fault detection (Walter, 2019; Li et al., 2018; Dziubany et al., 2019; Zantalis et al., 2019). Besides, the search for optimal and explainable machine learning models has been undertaken in many different fields (Shanthamallu et al., 2017; Shafique et al. 2018). Especially the explainability is essential for multiple hardware/software components and systems that include heterogeneous sensor data.

Explainable Artificial Intelligence (XAI) has become a significant area of interest due to trust issues in the machine learning model's decision (Dosilovic et al., 2018; Rudin, 2019). XAI presents more explainable machine learning models without affecting their performance. Besides, it provides extra information, which can be understood by humans and therefore improves their trust in the models (Barredo-Arrieta et al., 2020). It improves the transparency of ML models by providing a human-understandable justification to the decisions.

Human activity classification (HAC) is the process of automatically and correctly categorizing the actions performed by the user by analyzing video or IoT sensor data. It is useful for understanding the behavioral patterns present in an environment, such as walking, standing, running, and eating. One of the main problems in the current HAC systems is providing results without interpretability. Although there are several studies covering HAC and XAI, it is still needed to investigate the XAI concept on the HAC in a more comprehensive way. Our study focuses on the topic in many respects, including data exploration, prediction explanation, and model interpretation. The proposed approach provides many properties such as interpretability, explainability, transparency, effectiveness, verifiability, scrutability, understandability, explainability, trust, and technical robustness.

The main aim of this study is to provide a basic, interpretable, and robust approach to HAC problems. For this purpose, an approach, called explainable human activity classification (XHAC), is proposed. In this study, the data exploration, prediction explanation, and model explanation of the four machine learning models have been employed to perform HAR with XAI using the MHEALTH dataset, including Decision Trees (DT), Partial Decision Tree (PART), Naive Bayes (NB), and K-Nearest Neighbors (KNN). It is aimed to improve the explainability of the HAC models' components such as sensor types and sensor locations. For this purpose, each sensor (accelerometer, gyroscope, and magnetometer) data has been considered individually. Besides, the locations of these sensors (ankle, arm, and chest) have also been examined. In accordance with the aims of this study, the following research questions were considered.

R1: Do raw signals give sufficient information about the related human activity?
R2: Is feature extraction necessary for human activity recognition? Which features provides the most meaningful information?
R3: In preprocessing phase, what is the importance of the window size in the performance of the human activity classification
R4: Which activities can be easily or hardly classified?
R5: Does the transparent machine learning models give accurate result in the explainable human activity classification? What is the effect of the sensor location on the model performance?
R6: How sensor type affected the human activity classification performance?
R7: No matter which sensor and machine learning model is considered, what is the best sensor location for human activity classification?