Comparative Study of Classifiers on Human Activity Recognition based on Feature Engineering

Abstract:

This paper presents a comparative discussion of classification approaches for human activity recognition tasks based on the feature subset through extensive feature selection works. The original dataset *Human Activity Recognition from Continuous Ambient Sensor Dataset* is collected from UCI machine learning repository and five specific activities (Watching TV, Reading, talking over Phone, Cooking, and Eating) have been selected from there for the purpose of this research. The scraped feature subset is run through four feature selection methods based on statistical significance of features and node impurity and four different feature subsets are produced from this step. Later on, Principal Component Analysis is applied on the four feature subsets to reduce feature space and five principal components are selected to cover more than 90% data variance of the feature subsets. And then, performance of five classifier models (K Nearest Neighbors, Decision Tree, Random Forest, Naïve Bayes and MLP classifier using Backpropagation) is evaluated against the five feature subsets (including the scraped dataset without feature selection). The selection of feature subset based on different approaches of feature importance creates a computational complexity and difference in outputs for each feature subset on each classifiers. The result shows that Multi-layer Perceptron using Backpropagation algorithm achieves better accuracy on human activity recognition on the five feature subsets. The research finding highlights the necessity of data preprocessing and significant feature selection for getting better accuracy score for noisy time-series data of HAR activity.

Introduction:

The advancement of Internet of Things (IoT) has paved the way for smart living in home spaces using intelligent system installed in the framework of home [1]. Smart intelligent appliances have been developed for convenient living style, which is gradually proceeding towards assisted living through interacting system space. Ambient Assisted Living [2] emerged with the aim of easing the life in indoor space for the independent elderly citizens, through the use of smart technology in home. AAL focuses on health care monitoring and user interaction [3], which requires the necessity of human activity recognition from Activities of Daily Life (ADL). Better performance of an AAL system installed in a home depends on the accuracy of the system to interact with user and to diagnose the activities to take actions accordingly. AAL infrastructures highly depend on wireless sensor networks [5] placed at home to collect stream of sensor data of human activities in the surrounding. In general, activity recognition is a context-aware system [6, 7], aimed to sense the surrounding activities and execute the system features consequently.

Sensor data for human activity recognition works are collected from wearable devices, smartphones and indoor infrastructure of wireless sensors [8]. The sequential or time-series datasets collected from the above mentioned systems are complex [9, 10] in terms of interpretation with comparison to computer vision based activity recognition. Time-series data for human activity recognition is checked for detecting change detection [11] or activity transition through calculating statistical metrics (e.g. Mean and Covariance). Robust activity learning technology is required in the IOT environment to provide proper services to its residents. By providing the information about activity transitions and insights on activity start/end times and durations, activity segmentation improves the robustness of these technologies. The beginning and ending point of each activity is known when recognizing activities from a pre-segmented data [12].

Proposing a daily human activity segmentation based on change point detection techniques in an online or streaming fashion, using unscripted data from smart homes, the performance of alternative segmentation and window based activity recognition algorithms were evaluated using pre-defined metrics. Results provide evidence that detecting activity transitions and utilizing segment features in activity recognition improve recognition performance while also providing activity boundary and transition insights.

The image/video datasets of human activity are easier to label and preparation of the dataset. Whereas the sensor collected raw dataset requires intensive feature engineering [13, 14] to achieve an optimum-cost computational algorithm with highest accuracy. The datasets are usually large and requires significant feature selection [15] to discard insignificant attributes and instances and produce a concentrated important feature subset. The feature selection approaches are based on statistical scoring on a threshold and node impurity calculation through GINI index. The common approaches include decision tree implementation for scoring of features and forest based categorization of features. Feature space reduction concentrates the dataset in execution reducing the dimension of dataset. It reduces the memory requirements and decreases computational complexity. Feature engineering of time-series data collected from sensors [16] is a necessity to achieve better recognition output through any advanced machine learning model.

This research work is motivated to classify five distinct activities (Watching TV, Reading, Taking on Phone, Cooking, and Eating) from the dataset of 12 pre-defined activities including unlabeled activity namely “other activity”. The dataset has been acquired from the UCI Machine Learning Repository dataset “Human Activity Recognition from Continuous Ambient Sensor Data Dataset” from Washington State University [11]. The motivation is to precisely classify the activities while reducing the number of parameters and selecting important features from original dataset based on statistical approach which will computationally efficient to make models. This originates from the idea to allow human activity recognition with a minimalist model for saving computation power so that real-life applications upon such model will be lighter. The sensors’ signals is preprocessed in original dataset, among them, features with statistically significant values have been selected for training, feature subset space has been reduced for less computational load and finally five different classifier models have been employed to evaluate activity recognition accuracy and a comparative study of performance is reported towards the end. The key finding of this research focuses on the significance of feature engineering for improving human activity recognition accuracy on different feature subsets. The results show variance in accuracy depending on the four feature subsets through five classifier models.

The major contributions of the proposed research are:

1. Feature Selection: Meaningful feature selection from the five-activity dataset through four feature selection approaches based on statistical significance score.
2. Feature Subset Generation: Four Feature subsets generation from the statistically significant features from the feature selection step
3. Dimensionality Reduction: Feature subsets space reduction through Principal Component Analysis (Five PCs) to prepare for the classifier computation
4. Classifier Performance: Five Classifier models are evaluated on the five feature subsets and compared for accuracy on activity recognition.

The rest of the paper is organized as follows. Section II presents the related works on human activity recognition. Section III presents data source and Section IV presents methodology where data preprocessing, feature selection approaches, and classifier models are discussed. Section V reports performance evaluation of the five classifier models on the feature subsets. In the following Section VI concludes the paper and gives direction of future works.

Related Work:

The research field of activity recognition considers the combination of embedded sensors, different environmental setups and algorithms to detect activity points. Probabilistic graph based Markov models, conditional random fields, Bayesian network [21, 12] are some of the state-of-the-art classification models for detecting activity from times-series data.

Distinct activities like Walking, Running, Standing, Sitting, Climbing Stairs and Falling) are classified in [13, 18] using accelerometer placed on the body. Recently smartphones with embedded motion detector and orientation sensors (Accelerometer and Gyroscope) are used as wearable device to recognize gesture and motion patterns [19]. Improvement in performance, increased accuracy and better results can be attained by the Deep Learning based approaches from raw sensor inputs.

In indoor HAR system, large range of activity are observed through embedded sensors at key location of activities. Environment sensors such as motion detector, light sensor, temperature and pressure sensors etc. are used to record stream of sensor data of activities in [4, 5].

In realistic activity recognition tasks, the recognizing activities are performed with interleaved activities [20, 21], embedded errors [19] and concurrent activities are performed by multiple individuals in the setup [6, 20]. Detecting activities in free movement setup, where the residents perform usual daily routines in a smart home environment [3, 6]. These recorded datasets requires manual labelling to segment and analyze the data.

Dedicated HAR architectures recognizes sequential and concurrent human activities using multiple sensor data at a time. Two key approaches are followed in HAR: “Data-Driven” and “Knowledge-Driven” technique [23]. Naïve Bayes (NB) classifiers, Decision Trees, Hidden Markov Models, Bayesian Networks and Support Vector Machine (SVM) classifier had been used as the Data-driven method in [23]. Existing works performed with data-driven technique utilize supervised approach using manually labeled data for training. The unsupervised approaches achieve low performance in comparison with the supervised approach in indoor home environment. Activities are classified with the prior knowledge of pre-recorded data of surrounding. Data-driven techniques are useful for detecting basic distinctive activities, on the other hand unsupervised approach is suitable for creating probabilistic models with good accuracy

Data Source:

The primary dataset of the project has been collected from UCI Machine Learning Repository [11], Human Activity Recognition from Continuous Ambient Sensor Dataset, published on September 20, 2019. This dataset recorded multiple sensor data placed at volunteer resident houses where the residents performed their daily activities with no direct contact with the data collector infrastructure. Ambient PIR motion sensors, door/temperature sensors, and Light Switch sensors are used to record activity data as event stream the sensors are located in different corners of resident houses to record event data. The classification task is to predict the activity that is occurring in the smart home and being observed by the ambient sensors. The sensors communicate using the ZigBee Pro protocol [5,6].

The motion sensors determine the time of motion occurrence in the range of the sensor. The motion sensor reports 1/0 depending on the record of motion activity. The transition period between turning the sensor on and off status is roughly 1.25 seconds. For continuous activity record beyond the threshold time, the sensor will not record 0 until 1.25 seconds after the activity has ceased. One example smart home layout is attached in Figure 1.The key features of the scraped dataset for our purpose is presented in Table 1.

The original dataset is built under the lead of Diane J. Cook from School of Electrical Engineering and Computer Science at Washington State University, and the other creators are Aaron S. Crandall, and Brian L. Thomas. [12]. Figure 1 shows the layout of sensor placement in the indoor environment for data collection in their proposed system.

Methodology:

This research work focuses on the comparative performance evaluation of the five classifier models on the generated feature subsets through extensive feature engineering from the scraped dataset of five activities from “*Human Activity Recognition from Continuous Ambient Sensor Data Dataset*” [4, 11].The research team has scraped the dataset for this research from the UCI dataset, for the five selected activities (Watching TV, Reading, talking over Phone, Cooking, and Eating). The attributes of the selected feature subset are presented in table 1. The proposed work is primarily divided into three major segments- Feature Selection, Feature Subsets Generation and Performance Evaluation of Classifier models. Figure 2 presents the basic workflow of this project

References:

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