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HUMAN ACTIVITY RECOGNITION: COMPARATIVE STUDY

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Abstract: Human Activity Recognition (HAR) can be described as the art of identifying and naming activities using Artificial Intelligence (AI) from the raw activity data collected by using different sources. It becomes essential to monitor the Activity of Daily Living of elderly people living alone by keeping track of their day to day activities. In this paper we have discussed various approaches along with their accuracy in percentage for Human Activity Recognition using UCI-HAR dataset. In the first part of paper the basic introduction of Human Activity Recognition is given. In second part details of every articles including Approaches which are used in those articles. In the last part of paper, we have given comparison for all approaches as per given in respective articles.

Index Terms - Human activity recognition, Deep learning (DL), Deep Convolutional Neural Network (DCNN), Convolutional Neural Network (CNN), Linear Discriminant Analysis (LDA) with the Artificial Neural Network, Hierarchical Hidden Markov Model (HMM), continuous hidden Markov model (CHMM), Support Vector Machine (SVM).

Introduction

Human activity recognition (HAR) gained significant importance in research community as it is a challenging time series classification task. In human activity prediction, firstly the sensor data is recorded for activities of specific subjects, then a machine learning model is trained to generalize the model for unseen data. There are lots of applications of activity predictions like behavior analysis, health and workout monitoring, gait analysis, interactive gaming, gesture recognition, video surveillance etc. HAR also has many applications to improve elderly people's living. For example, through continuous monitoring an effective HAR system can ensure the proper medication, physical activity as well as recognizing the diseased conditions.

Human Activity Recognition, which is a field of study that focuses on developing algorithms and techniques to automatically identify and recognize human activities based on sensor data. It combines elements from computer science, signal processing, machine learning, and pattern recognition to analyze data from various sources such as wearable sensors, smartphones, or cameras.[14]

The goal of HAR is to enable computers and intelligent systems to understand and interpret human activities in real-time or from recorded data. This has numerous applications in various domains, including healthcare, sports and fitness monitoring, security surveillance, smart homes, and augmented reality.[14]

HAR typically involves several stages in its process. Firstly, data collection is performed using sensors that can capture relevant information about human activities, such as accelerometers, gyroscopes, magnetometers, or GPS. This data is then preprocessed to remove noise, filter out irrelevant information, and extract meaningful features.[15]

After preprocessing, the data is fed into machine learning algorithms or pattern recognition techniques for activity classification. These algorithms are trained on labeled datasets, where human activities are annotated, to learn patterns and relationships between the sensor data and corresponding activities. Common machine learning approaches used in HAR include decision trees, support vector machines (SVM), random forests, and deep learning methods like convolutional neural networks (CNNs) or recurrent neural networks (RNNs).[15]
Once the model is trained, it can be used to predict or classify activities in real-time or on new, unseen data. The output can be a specific activity label, such as walking, running, sitting, or more complex activity sequences.
HAR has gained significant attention due to its potential to enhance numerous applications and improve user experiences. For example, in healthcare, it can be used to monitor patients' activities and detect anomalies or changes in behavior that may indicate health issues. In sports, it can help track performance metrics and provide personalized coaching recommendations. In smart homes, it can enable automated control of appliances based on user activities, optimizing energy consumption.
However, HAR still faces challenges, such as handling diverse activity contexts, dealing with noisy or missing sensor data, and addressing privacy concerns related to data collection and usage. Researchers continue to explore new algorithms, sensor technologies, and data fusion techniques to improve the accuracy, robustness, and real-world applicability of HAR systems.[14]

I. Related Work

One of the main challenges of activity prediction is to generalize the model for different problem, sensors, and activities. Activity signal may vary significantly for different human, even the same person may do the same activity differently in another time. Similarly, different activities may have similar signal pattern which may confuse the learning process. Other challenges include the computational cost to implement in embedded and portable devices, accurate data annotation, variety of complex daily activities, and ensuring privacy of the subjects. Traditional pattern recognition based HAR requires to extract problem specific features to fit a machine learning model.

Deep learning (DL) makes the task easy and adoptable by automatically learning the features. In a DL approach, it also can extract high-level features in deep layer that makes it appropriate for complex activity recognition. There are lots of new innovative ideas, and experiments are ongoing with model architecture to predict human activity more accurately [1]. The deep learning architectures used for HAR can be categorized into six major types: Deep Neural Network (DNN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Deep Belief Network (DBN), Stacked Autoencoder (SAE), and Hybrid Models.

In [2], they worked on 6 class activity of UCI-HAR dataset [3] and they stacked the raw signal row by row to form an image. Then applied the 2D Discrete Fourier Transform (DFT) to signal image and choose magnitude to form the activity image. They showed that the images vary for different activity and this visual difference indicates their potential for Deep Convolutional Neural Network (DCNN) to extract discriminate image features.

In [4], authors first divided activities into dynamic and static categories. Then used CNN models to discriminate between activities of a particular category. Their limitations is, for dynamic activity the CNN model performed better compared to the static activity.

In [5], they worked with CNN models and tried to get an optimized model by adopting the number of layers, filter size, pooling size, as well as tuned various hyperparameters. For complex activity recognition it is difficult for a single model to detect all activities accurately and effectively [6]. Thus, several hybrid approaches have been proposed over the last few years [7] [8].

One of the very first hybrid approach was the combination of Linear Discriminant Analysis (LDA) with the Artificial Neural Network proposed in [9]. This method first distinguishes between the static and dynamic state at lower level and then recognize more specific activities.

In [10] a Hierarchical Hidden Markov Model (HMM) with two-stage was proposed to recognize five types (stand, walk, stair up, stair down and run) of human action and three type of human activities (shopping, taking bus, and moving by walking).

Another approach is the twostep method using two-level Continuous HMMs (CHMMs) in [11]. In the first level two CHMM was used to identify the stationary and moving activities, and in the second-level six CHMMs used to classify six specific activities of UCI-HAR dataset.

In [12] author proposed a hybrid model combining the SVM and HMM and showed better performance than signle SVM or neural network.

In [13], author presented a hybrid method to effectively perform human activity recognition. The method first identifies the abstract activity by using a Random Forest classifier to identify the activities type as static and moving. For static activity's specific recognition they have used support vector machine and for moving activities we designed a deep 1D CNN. They have achieved an overall accuracy of 97.71% which is comparable to state-of-the-art performance.

Following table shows the PERFORMANCE COMPARISON ON UCI-HAR DATASET in given articles.

II. CONCLUSION

The

Model	Accuracy (%)
SVM [3]	96.37
SVM+HMM [16]	97.60
LSTM-CNN [17]	95.78
Bidirectional-LSTM [18]	92.67
CNN-LSTM [19]	93.40
1D CNN [5]	94.79
DeepCNN [2]	97.59
TFFT + CNN [5]	95.75
DeepConvLSTM [20]	95.80
Stacked Autoencoder [21]	92.16
CHMM [22]	93.18
Hybrid method[13]	97.66

comparative analysis of human activity recognition using various algorithms provides valuable insights into the performance and effectiveness of different approaches. The analysis involved evaluating the accuracy, efficiency, and robustness of multiple algorithms in recognizing human activities from sensor data.

Through the comparative analysis, it was observed that different algorithms have varying strengths and weaknesses in human activity recognition. Accuracy differs from algorithm to algorithm. Performance of Various methods like SVM, HMM, LSTM-CNN, Bidirectional - LSTM, Deep CNN, TFFT, CHMM on UCI-HAR Dataset are shown in this paper.

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