Recent Trends in Machine Learning for Human Activity Recognition - A Survey

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Abbreviations: AR, Activity Recognition; HAR, Human Activity Recognition.

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Abstract

There has been an upsurge recently in investigating machine learning techniques for Activity Recognition (AR) problems as that have been very effective in extracting and learning knowledge from the activity datasets. The techniques ranges from heuristically derived hand-crafted feature-based traditional machine learning algorithms to the recently developed hierarchically self-evolving feature-based deep learning algorithms. AR continues to remain a challenging problem in uncontrolled smart environments despite the amount of work contributed by the researcher in this field. The complex, volatile, and chaotic nature of the activity data presents numerous challenges which influence the performance of the AR systems in the wild. In this article, we present a comprehensive overview of recent machine learning and data mining techniques generally employed for AR and the underpinning problems and challenges associated with existing systems. We also articulate the recent advances and state-of-the-art techniques in this domain in an attempt to identify the possible directions for future activity recognition research.

Keywords Activity Recognition, *Data Mining*, Machine Learning, Transfer Learning, Deep Learning, Active Learning, Wearable Sensors

1 Introduction

Extracting knowledge from the raw data, in general, has provided useful information in various fields. Human activity is unique, as the information inferred from raw activity data has been proved to be critical in functional and behavioral health monitoring (activities of

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daily living, sleeping, eating etc.), game console designing, personal fitness tracking, sports analytics to name a few. Data mining and machine learning approaches have proven to be effective than the classical mathematics and statistical techniques in extracting knowledge and discovering, learning and inferring activity from data. Human Activity Recognition (HAR) refers to the automatic detection of various physical activities performed by people in their daily lives. A HAR system helps recognize the activities performed by a person and provide informative feedback for intervention. Ambulation activities like walking, jogging, walking upstairs, walking downstairs are performed on daily basis (Lara and Labrador, 2013). Fitness related activities are popular among the young adults and also allows them to keep track of their fitness on a daily basis. Functional activities such as taking telephone calls, sweeping, preparing food, taking out the trash, folding clothes, combing hair, washing hands, brushing teeth, wearing jackets, shoes, answering the door, writing a check are the activities that every person does regularly. Inferring and assessing such functional and behavioral activities, help decipher the personal health and wellness (Alam et al., 2016a; Akl et al., 2015). Table 1 describes the list of existing works and the datasets, along with the specific activities and the application areas pertaining to the proposed HAR systems.

In AR, an activity can be captured using a variety of sensors with different modalities such as video cameras, wearable physiological and motion sensors, RADAR (Khan et al., 2016), acoustic sensors (Khan et al., 2015; Pathak et al., 2015), Echo (Amazon Echo, 2018), everyday objects (e.g., HAPIfork (HAPIfork, 2018), food scale (SITU-The Smart Food Nutrition Scale, 2018)), and device-free sensing (e.g., Wi-Fi (Ma et al., 2016)) etc. In addition, ambient sensors such as infrared motion detectors and magnetic sensors have also been used extensively for AR (Cook et al., 2013). Although video camera based HAR systems are popular for different security applications, they pose numerous challenges related to privacy and space constraints in smart environments. For example, if the video camera is placed in a common area, like in a corner of a room to capture the movements of a subject within its field of view, it may also capture the movements of people who are not the subject of interest such as the caregivers or the family members. These infringes their privacy and raises security concerns over collecting such videos. However, the most commonly used set of sensors, i.e., the wearable sensors help eliminate the problem of privacy and security concerns for activity monitoring(Roy et al., 2013). Wearable sensors like accelerometer and gyroscope are worn on various parts of the body, and they provide 3-axis acceleration and orientation, respectively. Despite the fact of eliminating privacy and security concerns, the wearable sensors also pose a set of unique challenges such as intra-class variability, inter-class similarity, class imbalance, finding the precise start and end time of each activity (San et al., 2017) heterogeneities across the sensing devices, and device positioning. Experiments to record data are usually conducted with multiple participants, and the data captured for the same activity set from different participants may not be of similar nature. Therefore, the intra-class variations become prominent. Moreover, the data pertaining to two different activities (like running and jogging) could be of similar nature, which poses inter-class variability. Class imbalance may occur when an activity is being performed for a longer duration than others, for example, a walking activity may be performed by the participant for a longer duration than a jogging activity. It is also difficult to find the precise point of start and end time of an activity episode given that the sensors usually have higher sampling frequency (hundreds of samples per second). Despite these challenges, wearable sensors are used in the majority of the studies and researcher have been designing the appropriate methodologies and experiments to mitigate these issues. In this study, we discuss the wearable sensors based HAR systems in the context of new and old machine learning and data mining methodologies needed to solve some of the underpinning challenges as mentioned previously.

HAR remains as one of the most challenging domain for the researcher owing to the complexity involved in recognition of activities and the number of inhabitants present. Initial research on HAR has considered HAR to be a conventional pattern recognition problem (Wang et al., 2017a). Traditional techniques like SVM, Hidden Markov models have been extensively used in the activity recognition systems, however, there is a recent shift in the use of machine learning and data mining techniques since the popularity of deep learning. The traditional methods (shallow learning) requires feature engineering from the data, which is heuristic driven and heavily dependent on human knowledge of the domain (Yang et al., 2015). This restricts the model developed for one domain to extend to another. In addition, it is also suitable for recognizing low-level activities such as activities of daily livings, however, it is nearly impossible to capture complex movements which involves sequence of several micro activities using shallow learning (Faridee et al., 2018; Yang, 2009). However, deep learning methods learns the features directly from the data hierarchically which eliminated the problem of hand-crafted feature approximations. In addition, deep learning such as Convolutional Neural Networks have been successful in learning complex activities due to its properties of local dependencies and scale-invariance which is elaborated by Wang et al. (2017a). HAR poses critical challenges associated with annotation of the ground truth, recognition of activity in presence of multiple users, heterogeneity of sensing devices, faulty sensor values and redeploying the activity model from one domain to another. Traditionally, it is required to feed the activity model with a huge set of labeled data using a supervised machine learning algorithm so that it can learn the hidden patterns during the training phase. Nevertheless, labeling the ground truth for a sensor data is cumbersome and always not feasible (Hossain et al., 2016). One of the ways to tackle this challenge is to use active learning, where the model can actively query the user for labels (Settles, 2010). Moreover, processing huge datasets incurs high computational costs and increases the training time of the model (Cook et al., 2013). To resolve this issue, researcher started investigating transfer learning, which allows transferring the knowledge learned from one model to another. In effect, transferring knowledge from one model to another allows the new model to train with less amount of training samples, and hence reduces the computational costs as well.

In this paper, we provide a comprehensive review of recent machine learning algorithms in activity recognition such as deep learning, transfer learning, and active learning. We discuss the state-of-the-art techniques and investigate the gaps that can help guide the future research directions. This paper is organized as follows. Section 2 discusses about Transfer Learning in AR, followed by Active Learning in AR in Section 3. Section 4 discusses about the advances in Deep Leaning in AR, Section 5 discusses about semantics-based techniques in AR, section 6 compares the above techniques followed by future research directions and conclusion in Section 7 and 8, respectively.

2 Transfer Learning in AR

Transfer learning can be defined as the ability to extend what has been learned in one context to new contexts (Byrnes, 2001). Woodworth and Thorndike (1901) first explored how individuals transfer learned concepts between different contexts that share common features. Barnett and Ceci (2002) provided a taxonomy of features that influences transfer learning in humans. In the field of machine learning, transfer learning is interchangeably used with different names like learning to learn, life-long learning, knowledge transfer, inductive transfer, context-sensitive learning, and meta-learning (Cook et al., 2013).

Transfer learning lets us transfer knowledge from one domain to another assuming that there exists some relationship between the source and target areas which allows for the successful transfer of knowledge from the source to the target. Figure 1 illustrates three different scenarios where transfer learning can be applied. In scenario-1, the activity is cycling, however, the gender of the person performing the activity is different. The data acquired for the same activity is different when performed by different persons. In scenario-2, the device that is used to capture the activity data is different, i.e., smart phone and smart watch. In Scenario-3, the ambiance where the activity is performed is different, indoors and outdoors. The information extracted by a model in the source domain can help train the model in the target domain with less amount of annotated data. Figure 2 represents the effect of transfer learning, where a reduced amount of data points might be required to train the model in target domain because of using information from the previously trained model. This dramatically reduces the computational costs and the annotating efforts. The various scenarios where transfer learning can be applied is explained comprehensively by Cook et al. (2013). The authors have elaborated on the different modalities, data labeling process and the taxonomy of type of knowledge transferred in transfer learning based AR. Khan and Roy (2017) have investigated transferring knowledge among the models having different probability distributions. The authors have evaluated their AR models using random forest, decision tree and transfer boost algorithms and have used accuracy as an evaluation metric to assess the performance of the model. The authors tested this methodology on HAR (Anguita et al., 2013), Daily And Sports (Barshan and Yüksek, 2013), MHealth (Banos et al., 2014) datasets and have proved that a HAR model can be trained using a reduced number of instances. The probability distribution of the accelerometer data varies heavily among different users, and the performance of a model will degrade if the model is trained for a person and tested on another. In an attempt to address this problem, Deng et al. (2014) have proposed a cross-person activity recognition model that integrates transfer learning and Reduced Kernel Extreme Learning Machine (RKELM). RKELM is popular and is effective when the dataset is extremely huge. It randomly selects a subset of the dataset and analytically computes the weights of the classifier, therefore reduces the computational time and also provides a good approximation of the AR model to that generated from actual data. The methodology was assessed on Activities of Daily Living (ADL) dataset. The authors, Wang et al. (2017b), have introduced a new framework to transfer the labeled activity data from source domain to target domain. The model, *Stratified Transfer Learning* transforms source and target domain into the same subspace where the data distribution is comparable followed by cross-domain activity recognition and assessed on OPPORTUNITY (Roggen et al., 2009), PAMAP2 (Reiss and Stricker, 2012), and Daily And Sports (Barshan and Yüksek, 2013) datasets.

A scenario where the deployment context may be different from the learning context is inevitable. An illustration of such scenario could be when the jogging activity is performed on a treadmill and the same on the streets. The former is performed in a controlled setting where the speed is adjusted to a constant speed, and there may not be any obstructions, however, the latter could suffer from many obstructions and variable speed as they cannot be controlled by us. Diethe et al. (2016) have proposed a hierarchical Bayesian transfer learning model and have also addressed the problem of accurately labeling the data using active learning. The authors have evaluated the model using HAR using smart phone dataset (Anguita et al., 2013) as their source and USC-HAD dataset (Zhang and Sawchuk, 2012) as target. Ying et al. (2015) have proposed a transfer learning model on high variety data (data from different sources) which is validated using statistical hypothesis Kolmogorov-Smirnov and $Ç^2$ goodness of fit test, and evaluated on Walk8, HAR (Anguita et al., 2013), and DaSA (Altun et al., 2010) datasets. Rokni and Ghasemzadeh (2017) have proposed an approach for autonomous retraining of machine learning algorithms without any new labeled training data. The new data considered in this study is from another sensor that is added to the system, and the machine learning algorithms used in this study are Decision Trees, k-Nearest Neighborhood, and SVM. The model was evaluated on OPPORTUNITY (Roggen et al., 2009) dataset and DaSA (Altun et al., 2010) dataset.

AR is highly dependent on numerous factors such as the type of sensor used, the environmental setting, the experimental settings and so on. If a model is trained using one combination of the above settings, that model can be evaluated for a different combination of settings using transfer learning. Transfer learning is still an emerging topic, and researchers are still exploiting the field to discover the applicability of using it for large scale cross-domain human activity recognition.

3 Active Learning in AR

Active learning in AR is a recently emerging field. The active learning algorithms aim at mitigating the learning complexity and cost. It helps to select an optimal number of informative unlabeled data samples and query the annotator for the labels. It minimizes labeling effort and elevates the prediction accuracy (Hossain et al., 2016). Figure 3 shows an illustration of an active learning enabled model. Active learning has been popular in other fields, however in AR; only a few researchers have been working on active learning. Alemdar et al. (2017) has investigated three different techniques (least confidence method, margin sampling, and entropy-based) to find the most informative unlabeled data samples and have proved that the annotation effort has been reduced by a factor of 2-4 times. Hossain et al. (2016) have proposed a dynamic k-means clustering algorithm based active learning approach, and have used uncertainty sampling to find the most informative unlabeled data samples, and validated the proposed approach using real-life data traces. The authors have also proposed a data representation technique for crowd-sourcing the labeling, and they have discussed its repercussion on active learning. Bannach et al. (2017) have investigated the self-adaptability of AR model when a new sensor is introduced to the system and have evaluated their model using a bicycle repair (Ogris et al., 2005), a car maintenance (Stiefmeier et al., 2008) and OPPORTUNITY (Roggen et al., 2009) datasets. Abdallah et al. (2015) have proposed a personalized and adaptive framework for AR that incrementally helps learn the activity model from high speed, multi-dimensional streaming data. It recognized personalized user's activities using active learning, employed ensemble classifier to train the model and evaluated the model using OPPORTUNITY (Roggen et al., 2009), WISDM (Kwapisz et al., 2011), and smartphone accelerometer datasets (Do et al., 2012). Bagaveyev and Cook (2014) have investigated two different approaches to select unlabeled data for annotations using Expected Entropy and Query by Committee for active learning, used random forest based classifier for activity inference, and validated the results on an in house dataset, *Kyoto1*. Active learning in AR is still emerging field and has plenty of scope in the future.

4 Deep Learning in AR

In HAR systems designed using shallow learning, the frequently used feature heuristics are dependent on the domain knowledge of the researcher and the performance of the machine learning techniques is highly dependent on the data representation (Bengio, 2013). The commonly used features are time domain features (mean, variance, time sequences) (Bulling et al., 2014), frequency domain features (Fourier transform, entropy) and other transformations (wavelet transform) (Huynh and Schiele, 2005). However, in deep learning, the features are learned from the raw data hierarchically by performing some nonlinear transformation. The nonlinear transformation determines the type of deep learning network. Deep learning has been popular in the last few years, and numerous work has been done using deep learning in AR. The popular deep learning techniques in AR include Deep Neural Network (DNN), Convolutional Neural Networks(CNN), Recurrent Neural Networks(RNN), Long- Short-Term Memory (LSTM) RNN networks. Wang et al. (2017a) has comprehensively described the deep learning techniques and the effect of applying deep learning to time series activity signals. Hammerla et al. (2016) have explored DNN, CNN, and RNN for activity dataset and concluded that the RNN performed better than the state-of-the-art results for OPPORTUNITY (Roggen et al., 2009), PAMAP2 (Reiss and Stricker, 2012) and Daphnet Gait (Bachlin et al., 2009) dataset. The authors also found that the RNN outperformed CNN for activities which are of short duration. Ordóñez and Roggen (2016) have proposed a novel deep network comprising of convolutional and LSTM layers. The authors optimized the hyper-parameters of their network and fused the various sensor modalities like accelerometer, gyroscope, magnetometer in different combinations and compared the results by evaluating them on OPPORTUNITY (Roggen et al., 2009) and Skoda (Zappi et al., 2008) datasets. Ronao and Cho (2016) have proposed multilayer CNN model with alternating convolutional and pooling layers and showed that their proposed model outperforms the state-of-the-art accuracy for ADLs which were recorded by the authors from 30 different users. Ravi et al. (2016) have used Short Term Fourier Transform of the accelerometer data as an input to the proposed CNN network and have achieved accuracy close to the state-of-the-art results. Bhattacharya and Lane (2016) have designed and developed a Restricted Boltzmann Machine (RBM) based activity recognition model for smart watches and have proved that the model does not have any hardware constraints. The authors have also validated their accuracy with real-life data sets such as OPPORTUNITY (Roggen et al., 2009), Transportation & Physical (Bhattacharya and Lane, 2016), Indoor/Outdoor (Radu et al., 2014) datasets with different state-of-the-art classifiers for each of the activities.

The most recent contributions towards deep learning (Panwar et al., 2017) postulated a novel technique of using ensembles of deep LSTM networks using wearable sensing data. This is the only work using an ensemble of deep learning techniques so it has scope of further research in this direction. Sani et al. (2017) have evaluated the hand-crafted features and the

CNN derived features using kNN using activities of daily living sensor data collected from the wrist and the waist. Studying further about the features derived from a deep learning network and comparing them with the heuristic features will help the researcher to understand the deep learning networks better. San et al. (2017) have proposed a multichannel CNN architecture for multiple sensor data. The authors have evaluated their results with Decision Tree, kNN, and Naive Bayes classifiers and have seen drastic improvements in terms of activity recognition accuracy. Ensemble deep learning models, LSTM, and RNN have not been well investigated for multichannel multi-modal sensor data and therefore, this would be a future direction for research.

5 Semantics in AR

Sensor-based activity recognition approaches can be classified as data-driven and knowledge-driven approaches. A data-driven approach involves data collection, followed by extracting knowledge from the data by performing techniques like basic statistical techniques or other data mining techniques. On the other hand, knowledge-driven approaches use prior domain knowledge followed by the application specific knowledge on the sensory data. One such commonly used model is Ontology modeling (Liu et al., 2016). One of the applications of knowledge-driven activity recognition is in smart home settings. In a home, any person tends to perform a lot of activities pertaining to time, location, context and so on. For example, a person brushes the teeth in the morning, and at night in the bathroom, a person cooks food in the kitchen. The domain knowledge in these cases is the location and the timing of the activity performed. This domain knowledge allows the AR system to correctly detect the activities. (Riboni et al., 2016) has proposed a unsupervised approach to recognize complex activities by exploiting the semantic relationship between activities and smart-home environment, context data and sensing devices. The authors tested the model on CASAS (Singla et al., 2009) and SmartFaber (Riboni et al., 2016) datasets, and achieved an accuracy that is comparable to the supervised state-of-the-art algorithm. (Gayathri et al., 2017) leveraged the strengths of ontological modeling through Markov Logic Network and its probabilistic reasoning and tested the model on CASAS (Singla et al., 2009) dataset. (Villalonga et al., 2017) investigated ontology-based sensor selection for real world AR that can be used to select the best sensor to capture the activity better. (Woznowski et al., 2016) have presented a hierarchical ontological modeling for annotating activity data and further discussed the labeling strategies and the best practices. Ye et al. (2015) have proposed an algorithm that constructs domain ontologies profiles and, extract the semantic features form sensor events into spatial, temporal and thematic aspects. The activities are then recognized by matching segmented sensor sequences to ontological profiles. The authors have evaluated using the Interleaved ADL Activities (IAA) dataset (Cook and Schmitter-Edgecombe, 2009) which is described in Table 1. The authors Liu et al. (2016) have presented an algorithm to identify the complex high-level activities from simple low-level actions in the sensor domain. The algorithm computes the support after adding the subsequent patterns iteratively to build a feature space that can be fed to a SVM classifier. The proposed technique has been evaluated on OPPORTUNITY (Roggen et al., 2009) dataset. In another study, the authors combined the data-driven and knowledge-driven approaches which posit unsupervised techniques to discover sequential activity patterns based on the learned ontological model. Cheng et al. (2013) proposed a zero-shot learning framework based on semantic sequences of data that considers both hierarchical and sequential nature of the activity to detect unseen activities. The model was evaluated on their own Exercise Activity Dataset, and Daily-Life Activities dataset. De et al. (2015) have proposed a conditional random field classifier for activity prediction which captures temporal relationships in activity time series that helps to capture complex activities. The technique was evaluated using an in-house dataset comprising of 19 activities listed in Table 1. Since knowledge-driven approaches combine information from various sources to build the domain knowledge, it can be used for multi-inhabitant activity recognition.

One of the major challenges in multi-inhabitant activity recognition in a smart home environment is that the ambient sensors are susceptible to recording data pertaining to non-subjects. Despite the disadvantages, there has been some research on the same. The authors Roy et al. (2013) have combined the ambient sensors along with the body-worn sensors to extract person-independent context and person-specific context of activity and used Hidden Markov Model to detect the activities. The ambient sensors detect the movements of the subject, however, in addition, it also captures the movements of others who live in its range in a multi-inhabitant environment. Alam et al. (2016b) proposed a probabilistic Hierarchical Dynamic Bayesian Network (HDBN) to combine the postural and gestural micro-activities, and further extended to a multi-inhabitant framework using coupled - HDBN. The authors further discovered the spatiotemporal constraints for activities of users in the multi-inhabitant environment and evaluated their model with a dataset collected from real-life scenarios. The multi-inhabitant activity recognition for smart home environment is relatively a new field, and further work based on ambient and wearable sensors is required to build a robust knowledge-driven system. Building semantic knowledge requires domain knowledge, and it has to be well represented in such a way that the data mining techniques can understand the semantics which is still a challenging problem and requires further studies.

6 Comparative Discussion

All the techniques discussed so far for human activity recognition have its own merits and demerits. Transfer learning allows transferring knowledge, which addresses the problems of class imbalance, insufficient annotated data, domain adaptation, scalable model construction etc. However, for transfer learning to be effective, the quality of the source data is crucial. The activity event start and end time mismatch with the annotations, motion artifacts caused by wearable sensors, intra-class variability are few major concerns that hinders the performance of transfer learning in AR. Active learning helps ease the annotation efforts by querying the labels of informative samples only and therefore reduce the annotation efforts. However, active learning requires a high quality data similar to transfer learning. In addition, selection of an appropriate criteria for selection of informative data points is challenging. The error in re-annotating informative data points leads to propagation of error to the model that tries to learn the activity. Active learning poses another challenge of selection of annotators. Different annotators may label the sequence of data differently depending on their expertise therefore there is a need for annotator selection model (Hossain et al., 2016).

Another most recent trend in AR is deep learning. It is noted that deep learning has been outperforming traditional machine learning methods as deep learning is able to extract the features from the raw data in contrast to expensive feature engineering in traditional techniques. Feature engineering requires domain knowledge, which leads to approximations of the features and makes them sensitive to the challenges related to AR as discussed in Section 1 in comparison to deep learning where the features are hierarchically learned directly from the raw data. Despite the advantages, deep learning methods has high computational requirements. Deep learning for mobile and low powered devices is an emerging field and it is also a potential area for future research. In all of the above techniques, the objective was to learn/classify/detect the activities. However, the context and the intention of doing the activity was not discussed. Semantic based techniques utilize the prior knowledge and integrate with the sensory data to infer the context and the intention of performing the activity. This knowledge-driven approach allows HAR systems to be used in a variety of applications as discussed in Section 1. Nevertheless, these approaches are sensitive to the prior knowledge as the context is derived from it.

7 Future Directions

The nature of the activity data is such that they are self-similar fractal patterns and they repeat over time. The authors of Gupta and Dallas (2014) have used detrended fluctuation analysis coefficients as features in learning their classifier and Sekine et al. (2002) have used the fractal dimensions of wavelet coefficients to differentiate three different walking styles, age groups, and patients suffering from Parkinson disease. As fractal analysis has been explored and proven successful in analyzing physiological data like heart rate variability, and have shown promising results in Gupta and Dallas (2014); Sekine et al. (2002), it is a direction that needs further investigation for activity recognition.

Another future direction in activity recognition could be synthetic data generation. In most cases, for the data mining technique to learn the model effectively, it is essential to train the model with a huge dataset. In addition, as discussed in Section 1, the data could suffer from challenges like intra-class variability and class imbalance. This occurs due to the fact that some activities take a longer time when compared to the others. In a real scenario, a person may walk for a longer duration when compared to jogging. The duration varies drastically for activities like sweeping, cleaning the house, cooking, bathing, jogging, walking upstairs and downstairs, and so on. Generating synthetic data could help solve some of the above problems. Few researcher have already worked on generating synthetic data for activity recognition. Mendez-Vazquez et al. (2009) have used Markov chains to generate the patterns of activities and Poisson processes to generate the time stamps. This study is extensive and considers activities such as walking, reading, sleep, sitting, housework, and exercise. Activity data shows subtle variations, even among the data collected from the same subject for the same activity at a different time, for which generating data synthetically might be a challenging problem. Alzantot et al. (2017) have proposed a synthetic data generation model using deep learning for ADLs using smartphones. The authors have presented a LSTM and Mixture Density Network based generator model to generate the synthetic data and a LSTM based discriminative model that distinguishes between true and the synthesized data. Synthetic data generation requires further investigation to enumerate data patterns that give a better representation of the raw signals for a variety of activity signals so that the AR models can extract maximum information from the data.

Another possible area for HAR could be in processing and fusing data from heterogeneous devices. In recent times, there are a huge number of off-the-shelf devices are available such as Actigraph (ActiGraph, 2018), Microsoft Band (Microsoft Band, 2018), Empatica E4 (Empatica E4, 2018), Fitbit (Fitbit, 2018), Google Home (Google Home, 2018), Amazon Echo (Amazon Echo, 2018). Often it is the case that a model that is developed using the data collected using one device does not perform well with the other devices. This occurs due to the heterogeneities among the devices. The heterogeneities among various mobile devices, smart watches have been discussed in detail by Stisen et al. (2015). The authors have investigated a large number of devices to study device heterogeneities and have proposed techniques to mitigate them. The heterogeneities they address include sampling rate heterogeneity, sampling rate instability and sensor biases. Investigating cross-domain transfer and deep learning to accommodate heterogeneity in the learned models are potential future directions in activity recognition (Khan and Roy, 2018; Khan et al., 2018).

8 Conclusion

Mining the activity data to detect and understand the activity is of utmost importance as activity recognition finds its application in various fields such as personal healthcare like fitness tracking, fall detection of elderly people, monitoring functional and behavioral health using wearables. In this paper, we articulate the recent trends in AR towards addressing the limitations of the traditional machine learning algorithms and mitigating few system design challenges. We note that deep learning architectures have been used largely due to its advantage of hierarchically self-derived features, which help represent the data better compared to the handcrafted features. Therefore, it is highly important to design and develop robust data mining techniques to extract the knowledge and machine learning techniques to infer and validate that knowledge from data which will allow the AR system to make intelligent decisions. This study presents the recent trends and developments in machine learning techniques, to address the next-generation activity recognition challenges across many devices, systems, persons and environments.

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Figure 1 Transfer Learning Illustration

Figure 2 Effect of Transfer learning

Figure 3 Active Learning Cycle

Table 1 Activitles, applications and associated literature/datasets

Dataset/Literature	**Activities**	**Applications**
USC-HAD (Zhang and Sawchuk,	Walking (forward, left, right,	Smart home activity recognition

2012)	upstairs, downstairs), running forward, jumping, sitting, standing, sleeping, elevator up, elevator down	
MHealth (Banos et al., 2014)	Standing still, sitting and relaxing, lying down, walking, climbing stairs, waist bends forward, frontal elevation of arms, knees bending (crouching), cycling, jogging, running, jump front & back	Smart home activity recognition
OPPORTUNITY (Roggen et al., 2009)	Lying on the deckchair, get up, groom, relax, prepare coffee, drink coffee, prepare sandwich, eat sandwich, cleanup, lie on the deckchair	Smart home activity recognition, functional and behavioral health assessment
PAMAP2 (Reiss and Stricker, 2012)	Lying, sitting, standing, walking, running, cycling, nordic walking, watching TV, computer work, car driving, ascending stairs, descending stairs, vacuum cleaning, ironing, folding laundry, house cleaning, playing soccer, rope jumping	Smart home activity recognition
Daily And Sports (Barshan and Yüksek, 2013)	Sitting, standing, lying on back and on right side, ascending and descending stairs, standing in an elevator still, moving around in an elevator, walking in a parking lot, walking on a treadmill with a speed of 4 km/h (in flat and 15 deg inclined positions), running on a treadmill with a speed of 8 km/h, exercising on a stepper, exercising on a cross trainer, cycling on an exercise bike in horizontal and vertical positions, rowing, jumping, playing basketball	Sports analytics
HAR (Anguita et al., 2013)	Walking (straight, upstairs, downstairs), sitting, standing, lying	Smart home activity recognition
Bicycle repair (Ogris et al., 2005)	Pumping wheel, screw/unscrew, turn pedals,	Maintenance activity tracking, billing automation,

	turn pedals and apply break, assembling/disassembling wheel/seat, test bell, test light generator, turn wheel, take/place item from/on carrier	maintenance record documentation
Car maintenance (Stiefmeier et al., 2008)	Open/close trunk, engine hood, check fuel filter cap, and other car maintenance procedures	Maintenance activity tracking, billing automation, maintenance record documentation
WISDM (Kwapisz et al., 2011)	Walking (Front, Upstairs, Downstairs), jogging, sitting, standing	Smart home activity recognition
Smart phone accelerometer (Do et al., 2012)	Walking, running, driving, stay still	Smart activity detection for home automation, fitness tracking
Kyoto1 (Bagaveyev and Cook, 2014)	Make a phone call, Wash hands, Cook, Eat, Clean	Smart home activity recognition, functional and behavioral health assessment
Daphnet Gait (Bachlin et al., 2009)	ADLs	Smart home activity recognition
Skoda (Zappi et al., 2008)	10 manipulative gestures performed in a car maintenance scenario	Maintenance activity tracking, billing automation, maintenance record documentation
Transportation & Physical (Bhattacharya and Lane, 2016)	Walking, running, standing) and a transportation mode (motorized)	Smart home activity recognition, smart home automation
Indoor/Outdoor (Radu et al., 2014)	Daily activities indoors and outdoors	Smart home automation, smart home activity recognition
Exercise Activity (Cheng et al., 2013)	Bench dips, squat upright row, Dumbbells (DB) side raises, DB shoulder press, DB curl, triceps extension, chest press, push up, DB fly, bent-over row	Fitness tracking, Food suggestion based on exercise
Daily-Life Activities (Huynh et al., 2008; Stikic et al., 2011)	Sitting, standing, walking, posture upright, posture kneeling, hands on table, hand above chest, wrist movement, arm pendulum swing, translation motion , cyclic motion, intense motion, washing related, meal related	Smart home activity recognition
HappyFeet (Faridee et al., 2018)	10 different dance micro steps involving subtle movements of limbs	Activity monitoring and tracking in teaching environments

De et al. (2015)	Walk indoor, run indoor, use refrigerator, clean utensil, cooking, sit and eat, use bathroom sink, indoor to outdoor, outdoor to indoor, walk (upstairs, downstairs), just stand, lying on bed, Sit on bed, lying on floor, sit on floor, lying on sofa, sit on sofa, sit on toilet	Remote monitoring of patients (Alzheimer's disease, bulimia, or anorexia)
Dernbach et al. (2012)	Cleaning, cooking, medication, sweeping, washing hands, watering plants	Smart home activity recognition
Pham and Olivier (2009)	Chopping, peeling, slicing, dicing, coring, spreading, eating, stirring, scooping, scraping and shaving	Smart home activity recognition, kitchen activity recognition
CASAS (Singla et al., 2009)	Fill medication dispenser, watch DVD, water plants, converse on phone, write birthday card, prepare meal, sweep and dust, select an outfit	Smart home activity recognition, functional and behavioral health assessment
SmartFaber (Riboni et al., 2016)	Taking medicines, cooking, eating	Smart home activity recognition, Cognitive assessment