DeActive: Scaling Activity Recognition with Active Deep Learning

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Deep learning architectures have been applied increasingly in multi-modal problems which has empowered a large number of application domains needing much less human supervision in the process. As unlabeled data are abundant in most of the application domains, deep architectures are getting increasingly popular to extract meaningful information out of these large volume of data. One of the major caveat of these architectures is that the training phase demands both computational time and system resources much higher than shallow learning algorithms and it is posing a difficult challenge for the researchers to implement the architectures in low-power resource constrained devices. In this paper, we propose a deep and active learning enabled activity recognition model, *DeActive*, which is optimized according to our problem domain and reduce the resource requirements. We incorporate active learning in the process to minimize the human supervision along with the effort needed for compiling ground truth. The *DeActive* model has been validated using real data traces from a retirement community center (IRB #HP-00064387) and 4 public datasets. Our experimental results show that our model can contribute better accuracy while ensuring less amount of resource usages in reduced time compared to other traditional deep learning approaches in activity recognition.

CCS Concepts: • **Computing methodologies** → **Active learning settings**; • **Human-centered computing** → **Ubiquitous and mobile computing theory, concepts and paradigms**; • **Information systems** → *Mobile information processing systems*;

Additional Key Words and Phrases: Active learning, Activity recognition, Deep learning, Smart home

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1 INTRODUCTION

Human activity recognition is becoming an ubiquitous need for many emerging smart environment applications such as remote heath monitoring, participatory sensing, interactive gaming, and green building energy management. Thriving development of low-cost ambient, mobile and wearable devices in recent years has intensified the effectiveness of inferring Activities of Daily Livings (ADLs) in ubiquitous settings [14]. These ubiquitous devices are equipped with diverse sensors like accelerometer, gyroscope, GPS, magnetometer etc. The emergence of Internet of Things (IoT) has delivered multitude of smart infrastructure sensors and connected devices which has also complemented the evolution of smart environment. By exploiting these pervasive and mobile technologies researchers are proposing new methodologies to capture the activity, mobility and behavioral pattern of our daily life. Many algorithmic techniques in activity recognition (AR) literature such as sparse coding [9], transfer

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learning [32], active learning [23], deep learning [48] have been investigated recently for versatile AR application development and deployment. While each approach has its own advantages and disadvantages in terms of scalability, adaptability, and transferability of activity learning, recognition and discovery models, in this work, we particularly focus on leveraging the simplicity of those techniques and exploiting that to fulfill the emergent requirements of large scale activity recognition in heterogeneous settings. Fundamentally we investigate how the underlying inference pipeline of the activity recognition process in deep architecture can be simplified. Such a simplified architecture can then be exploited in various constrained (resource deprived smart devices) and unconstrained environments (heterogeneous smart environments and multiple users population) where the requirements of the applications may vary significantly. This help ramify the performance of deep activity models, and reduce resource footprints in terms of memory, CPU usage and computational time without compromising the inherent power of the core methodologies. Incorporating resource efficiency and cost-effective intelligent labeling techniques with the deep activity models help scale the activity recognition models in diverse environments and showcase the effectiveness of deep activity learning methodology when augmented with other simplistic popular machine learning approaches.

One of the underpinning challenges in scaling these activity recognition models outside any constrained environments is efficient feature representation from unlabeled noisy source of data and accumulating significant amount of labeled training data. Conventional shallow learning approaches heavily relies on the handcrafted features extracted by human interventions. Therefore, the efficiency of the trained model largely depends on the expertise and domain knowledge of the feature engineer. The human designer needs to filter appropriate features to reduce the dimensionality of the feature space as well which is laborious. Also the statistical features can help in learning low-level activities like *walking, sitting, standing* only but these shallow features fail to summarize and generalize complex activties like *cooking, doing laundry, cleaning etc.* which consist combinations of low-level activities. Deep learning based approaches can help us to learn discriminative features without any human interventions. However a major bottleneck for deep learning based approaches is that the model itself is like a black box and the huge number of generated parameters are intractable. As a consequence it becomes increasingly difficult to manage and integrate changes in the model over time.

Deep learning based unsupervised machine learning techniques have been investigated to handle the scarcity of activity labels. While deep learning based techniques have shown significant improvements for large scale activity recognition problems [28], fitting the activity models in presence of unlabeled activity samples and mitigating the biasness of overfitting distributions are still challenging research problems [29]. The unsupervised training and fine tuning phase of deep nets also warrant substantial computational resources and labeled data sources, respectively [30]. While shallow and supervised learning [46] suffer from representing well the large scale activity learning model, the hierarchical deep learning [47] model helps capture the finer details of the activity model. It incrementally helps mitigate the need for handcrafted features in layer by layer but at the cost of more resource-hungry computational operations involving calculations of weight and biasness parameters of the model [20]. The main objective of this work is not to depreciate the intrinsic advantage of deep nets or appreciate the inherent advantages of clustering with neural networks, but to showcase the viability of various combination of these approaches for simplified and effective activity recognition at scale.

Trading the balance between this system-level resource need and application-level performance improvement is a non-trivial research problem, and have been investigated in recent activity recognition application domain [47]. Scaling the deep learning model for small footprint devices such as smartphone and smart wristwatches have also been investigated by exploiting different inference phases of deep model [60]. While the recent approaches investigated the runtime layer compression and deep architecture decomposition by crunching deep learning computational complexity, we propose to investigate simple K-means clustering and active learning approach to curtail the complexity of feature extraction and the burden of ground truth data collection, respectively. While auto encoder is the approach to learn the features in the deep activity models, we investigate a simple

K-means clustering strategy to learn and represent the features of the hidden nodes by exploiting the quantization capability of k-means. This help to percolate the simplicity behind the feature extraction, representation, and learning in a deep activity model and its performance in terms of system resource, computational time and performance improvement.

Existing deep learning models assume that activity labels are available and if not human annotator can be passively employed. In particular, stable supply of structured and labeled data is substantial for an effective deep learning algorithm. Despite the existence of plethora of data in pervasive computing, these collections do not provide much information due to poorly or partially labeled. In order to improve the model incrementally, Active Learning (AL) has been employed to select the most informative data instances and subsequently acquire labels of these data instances. This reduces the burden of labeling data manually and accelerates the training time. If infused together with deep learning, AL framework can help to improve the efficiency of deep model. However AL frameworks only filter out most informative instances from a pool of instances which are relatively small in number. As a result, most of the instances with low uncertainty gets ignored. A handful of labeled instances may not have a significant impact in the training of deep learning. Although most informative instances can play a vital role in learning an important pattern, but instances with low uncertainty can also help to fine tune the parameters of a deep model. In this work, we propose to embed active learning at the training phase of deep learning to query the most informative and cost-effective unlabeled sample points to collect the labels and also utilize the low uncertain instances. The key contributions of this work include:

- We exploit K-means clustering technique to represent and learn the features in the pre-training phase in presence of unlabeled data and fine-tuning phase of output layers in presence of labeled data. Our proposed approach helps to bridge the continuation of generative and discriminative learning of deep activity models while reducing the resource overhead with improved classification performance.
- We propose an active learning technique in the fine tuning phase of the deep learning training process to accumulate the most informative and meaningful labeled samples. Also we label the instances with low uncertainty score by calculating the similarity indices between them and the most informative instances. The density weighted active learning based heuristic augmented with optimized classifier help scale the deep activity models.
- We evaluate our proposed, *DeActive* framework on real activity recognition data traces and a real smart home system, *SenseBox* which we built to validate that simplistic off-the-shelf machine learning algorithms augmented with deep activity models so that we can showcase competitive performance gain and less resource usage.

2 RELATED WORK

Activity Recognition using heterogeneous sensor and data sources has been investigated extensively over the past decade. In this section we contrast our model *DeActive* with other most relevant proposed models.

2.1 Activity Recognition

Inferring Activities of Daily Living (ADL) are approached from two perspective - vision based and sensor modality based. In vision based approach, researchers have exploited microphone and cameras to extract the performed human activity from audio and video or image data [27] [62]. A variety of sensor modalities like accelerometer, ambient sensors, RFID tags, Radar etc [44] [25] have been used in sensor based approach. The major upsurge of mobile and wearable technologies have also accelerated the activity recognition research [22] [54]. Bao and Intille [7] used five biaxial accelerometers which are placed in different parts of the body and detected 20 activities. Hafiz et al. [43] used an array of micro-doppler radars to detect different human body movements. In many of these works, shallow machine learning models like Decision Trees, HMM, SVM etc have been harnessed to find

meaningful relationship between the features learned from the sensor data and the performed activity [44]. The widely used features in activity recognition domain include basis transform coding (e.g.signals with wavelet transform and Fourier transform) [39], statistical parameters extracted from raw sensor signals [19] and symbolic representation [31]. Although these features are widely used in many time series problems, they are heuristic and not task dependent. Activity recognition models also have to address challenges like intraclass variability, interclass similarity, the NULL-class dominance, complexness and diversity of physical activities [19].

2.2 Deep Learning & Activity Recognition

In most of the cases activity recognition models based on shallow classifiers deal with a set of handcrafted features. These features are then fed to the model, but many of these features are not assured to be relevant and eventually this expedites difficulty in inferring complex activities. Some times statistical features fail to capture substantial facets of human body movements. Due to recent advancements in high performance computing and implementation of deep architectures, researchers are now proposing activity recognition models using deep learning [47] [34] [46] [40] [58] [17]. The authors of [24] proposed a hybrid approach using HMM and deep learning to infer activities from triaxial accelerometer data. Francisco et al [21] demonstrated a model based on deep convolution and LSTM recurrent network which is suitable for multimodal wearable sensors. Simple RBM based model can outperform other activity recognition models has been demonstrated in [28]. The authors also prove that resource usage of traditional RBM in smartwatches is manageable. A deep model using an extension of Convolutional Neural Netowrk and recurrent neural network has been proposed in [5]. *DeepEar* [48] a deep learning enabled mobile audio sensing framework addresses the issue of audio data classification. Li et al. [52] [51] proposed an activity recognition system based on convolutional neural network using passive RFID data. By connecting different Convolutional Neural Networks (CNN) through fusion methods, an ensemble model is built to infer the kitchen related activities in [55]. The authors of [56] investigated the effect of transferring kernel in the convolutional layers in mobile activity recognition domain. Their work considered transfer between users, application domains, different sensors and locations. They validated that kernel transfer can reduce the training time by 17%. Guan et al. [33] proposed a Long Short Term LSTM based ensemble model and tackled the problems of having imbalanaced and problematic data for wearable devices. The authors of [69] proposed DEC (Deep Embedded Clustering) to learn feature representations and cluster assignments simultaneously using deep neural networks. DEC reduces the dimension by optimizing the KL-divergence to minimize the withing-cluster distance of each cluster. The proposed feature embedding method works well for clustering but fails to learn the latent data structure.

2.3 Active Learning & Activity Recognition

The use of active learning for attaining ground truth at low cost in activity recognition systems has been addressed in recent years [16] [23] [38]. The authors of [53] [65] used uncertainty based active learning for activity recognition. The authors of [12] used entropy based measure to calculate the informativeness of activity data instances. Legion:AR [49], an activity recognition framework uses active learning and inquires for labels from crowd on demand. AALO [37] uses active learning for labeling overlapped activities. The authors of [4] validates that by using active learning the actual annotation cost can be reduced by 30-75%. [36] employed an entropy based uncertainty measure to select the most informative instances and validated that only 20% of the training data ensures convergence to the same accuracy while using the whole training set. A variety of research where active learning has been augmented with deep learning have also been proposed [67] [70] [64]. Zhu et al. [35] proposed an active learning algorithm GAAL using Generative Adversarial Network (GAN). GAAL generates new uncertain instances and then requests for annotation to the human annotator. These labeled instances are then added back to the training data set. A cost effective active learning algorithm in conjunction with CNN

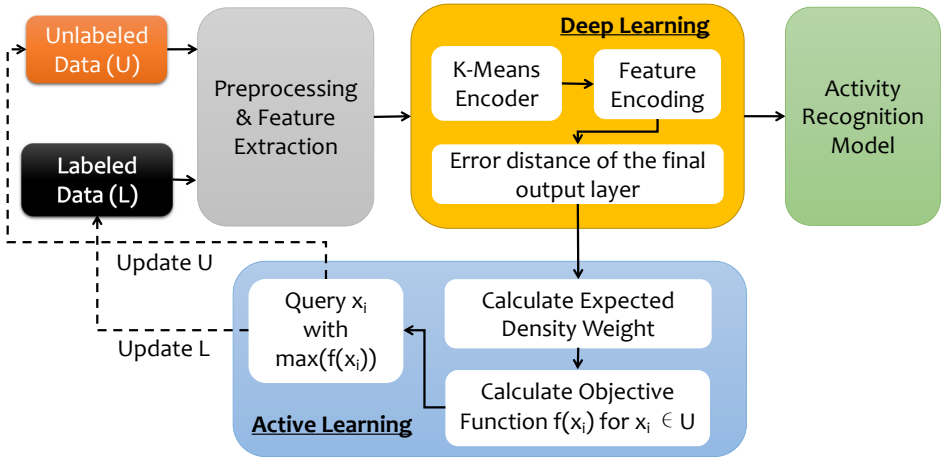


Fig. 1. Overall framework for *DeActive* activity recognition model. Deep Learning phase is composed of k-means encoders. The output of k-means in the final layer is provided to the Active Learning phase which selects the most informative instances from the unlabeled data pool.

(CEAL) to discover the large amount of high confidence samples from the unlabeled set for feature learning has been proposed in [68].

3 OVERALL DESIGN

Our *DeActive* model is designed to work with sensor entities like ambient PIR sensor, accelerometer etc. which are used for activity recognition. As we handle the heterogeneous sensor entities, we need to pre-process the data accordingly due to the variation in data. For example, ambient PIR sensor provides binary values (1=Motion and 0 = No Motion). It is difficult to model an activity recognition classifier using only binary sensor values, so it is necessary to extract some more information using the data. On the other hand, accelerometer sensors provide human movement acceleration which has been an important indicator for activity pattern recognition in recent years. As acceleration does not encounter binary values, the processing of accelerometer data is different compared to PIR sensors. As a result our *pre-processing* step handles different sensor data sources and extracts features. *DeActive* model encompasses two important components - *Deep Architecture* and *Active Learning*.

Real-time human activity and context monitoring using mobile devices or wearables has become an essential constraint. Since deep learning algorithms have high complexity in terms of computation and resource availability [10], researches are currently focusing on accelerating deep learning on mobile devices [28] [8]. Most of the smart home system controllers are embedded systems and have very limited resources. For example the specs of Samsung SmartThings hub V2 is: 1GHz ARM Cortex-A9 CPU, 512MB DDR3 RAM, and 4GB Flash memory. On the other hand these devices do not have any GPUs which can assist executing deep architectures. The authors of [46] proposed a software accelerator *DeepX* for low power mobile devices. *DeepX* is designed to optimize the execution by decomposing the deep architecture and innovative use of resources. In *DeActive*, we try to optimize the parameters of fully connected deep learning model by using k-means as our encoder. The authors of [20] have shown that if properly initialized according to the problem domain, k-means can accelerate the encoding

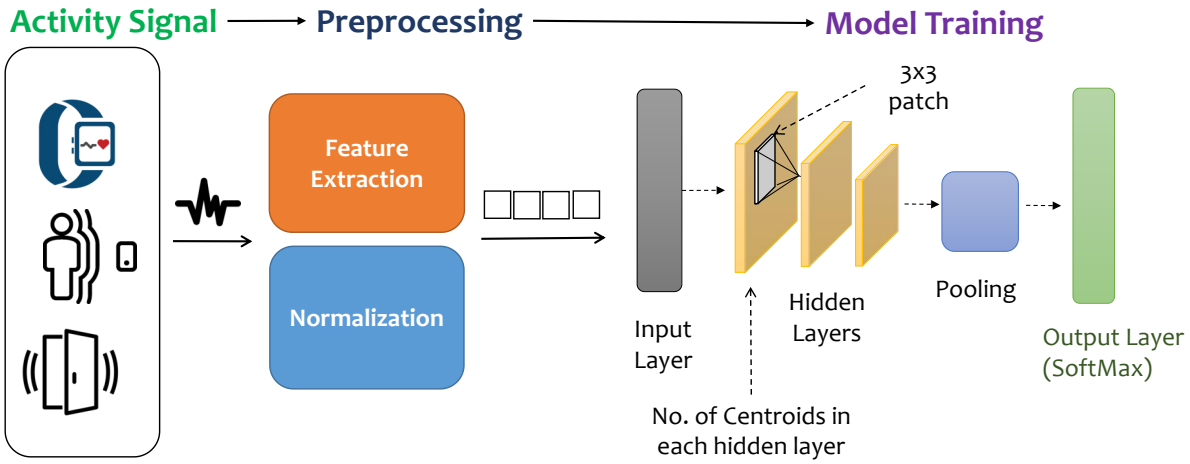


Fig. 2. DeActive pipeline from collecting data to final inference.

process. We just need to tune the parameter k in the hidden layers, as a result of which the calculation of millions of parameters as in stacked RBM autoencoders is minimized.

Active Learning strategies are used to collect ground truth information with minimal human supervision. Simpler active learning strategies like margin sampling, uncertainty sampling and least confidence are easier to implement, however overtime these sampling strategies become biased and overconfident [15]. Other popular query strategies like Query by Committee (QBC) and disagreement based approaches have higher computational complexity as they have to maintain a set candidate hypothesis space which can get intractable overtime. It is possible to initialize a set of hypothesis space with smaller cardinality, however the probability of ignoring the true hypothesis always remains. Cluster based active learning methods may provide a significant advantage over simpler ones in terms of effectiveness [57]. By exploiting the input distribution, we can cluster the most informative instances after each iteration and query the ideal instances of those clusters like the centroids. However cluster based approaches have limitations like querying the outlier cluster. In *DeActive*, we employ a density-weighted heuristic to calculate the most informative data instances. The idea is to query the data instances which lie in the dense region of the cluster so that we can label the neighboring instances as well. We consider the euclidean distance as our similarity measure among the instances while calculating the density. In order to remove the outliers from being queried we take advantage of our k-means clustering and use the *silhouette coefficient* in our final objective function. This coefficient is calculated by the distance measurement between the points in its cluster and other surrounding cluster centers. We also exploit this coefficient to filter out the representative instances of each clusters. If the coefficient value is higher than a predefined threshold, then we consider it and assign its label to all other instances inside the cluster. In Figure 1 we demonstrate our overall *DeActive* framework. We have two different data instance pools - unlabeled and labeled data pools. We then extract both time domain and frequency domain features from the data instances and normalize them. In our *Deep Learning* module, we quantize our feature vectors by using K-means based feature encoding and use the density estimates of the clustering in our *Active Learning* module. In Fig. 2 we demonstrate the pipeline of our *Deep Learning* module. Finally according to the value of our objective function, we then query the selected data instances.

4 UNSUPERVISED FEATURE LEARNING

In recent years a lot of research have been conducted in the area of deep learning for representing data in lower dimension. One of the prominent approach for feature learning in deep architectures is to use layers of non-linear processing units for extraction and embedding of features. These layers are referred as auto encoders. These auto encoders are responsible for assembling lower dimensional representation of the higher dimensional data. Given an input $x \in R^n$, an auto encoder attempts to learn an encoding function $f(x) \in R^k$, $k << n$ by iteratively minimizing the error of reconstructing x through a decoding function $g(f(x)) \cong x \in R^n$. The authors of [20] showed that spherical k-means or spectral clustering can be used as an alternative to encoders using sparse encoding or PCA. One major drawback for using k-means is that the capability of discovering sparse directions in data largely depends on the dataset size and dimension. If the data dimension is higher, we will need a large volume of data to outperform other encoders. However, we consider data is abundant and so our concern is to speed up the process. In this section we discuss how we can exploit the k-means algorithm as our encoder.

4.1 K-Means Clustering

K-means clustering is a partitioning method where a set of observations are partitioned into a specified number of clusters and similar observations reside in the same cluster. Given a set of observations $X = \{x1, .., x_n\}$, the observations are assigned to k clusters by minimizing the error distance between cluster centers $C = \{c_1, c_2, ..., c_k\}$ and X, while assigning $W = \{w1, ..., w_k\}$ class indexes:

$$E(C, W) = \sum_{i=1}^{n} \|x_i - c_{w_i}\| \tag{1}$$

In most of the cases this error distance Eqn. 1 is minimized using heuristics like Lloyd's algorithm, Elkan [18] etc. But these heuristics are unable to adapt in case of large amount of data. As in our case we plan to employ K-means as our hidden encoder layer in deep architecture, so the algorithm needs to process a large volume of data. To address this issue we propose to design our K-means using Stochastic Gradient Descent [11] [66]. The authors of [11] showed that optimizing the k-means cost function using Expectation Maximization (EM) based approach is equivalent to Newton's method. Although second order methods like Newton's method tends to converge faster than gradient descent but optimizing K-means using SGD has been proposed in the literature for addressing large-scale learning tasks, due to its superior performance and low resource footprint [42] [63]. Other clustering models like GMM can also be employed to learn the encoding. GMM have the advantage of doing soft assignment of cluster centroids over hard assignment in k-means. However, k-means is much simpler than GMM in both complexity and model interpretability which motivated us to exploit it and we try to recover the problem of hard assignment by introducing appropriate feature mapping function. Although density based clustering methods like DBSCAN can be also employed but it fails to ensure scalability while handling high dimensional data. Also DBSCAN is unable to capture the underlying data distribution if there are large differences in densities of the clusters. The objective function for k-means is $Q_{kmeans} = \min_k \frac{1}{2}(x - w_k)$. We calculate the gradient $\nabla_{w_k} Q_{kmeans} = -\eta_t \frac{\delta Q(w)}{\delta w}$ by taking the partial derivative of the Objective function. After this we update the learning rate η and weight vector w according to Eqns. 2 and 3. The whole process iterates until the cluster centers are no longer changing.

$$\eta_k = \eta_k + 1 \tag{2}$$

$$w_k = w_k + \frac{1}{\eta_k}(x - w_k) \tag{3}$$

4.2 K-Means as Encoder

The *K-means* clustering algorithm takes two parameters, number of clusters k and a set of observation vectors V. The algorithm returns cluster centers or centroids $C = \{c_1, c_2, ..., c_k\}$ for each of the k clusters. While associating an observation vector v_i to a cluster k_j, the primary goal is to minimize the distance between the vector and cluster center. The result of k-means can be employed to quantize vectors. The goal of vector quantization is to form encoding of vectors which reduces the expected distortion. Eventually k-means algorithm extracts a dictionary $D \in R^{n \times k}$ of k vectors where each vector $x^{(i)} \in R_n, i = 1, ..., m$ is mapped to an encoded vector which reduces the error in reconstruction. The definition of the dictionary is as follows:

$$minimize \sum_i \|D_s^{(i)} - x^{(i)}\|_2^2 \tag{4}$$
$$where \|s^{(i)}\|_0 \leq 1, \forall i \ and \ \|D^{(j)}\|_2 = 1, \forall j$$

In Eqn. 4, $s^{(i)} \in R^n$ is a code vector associated with input data point $x^{(i)}$. $D^{(j)}$ is the jth column of dictionary D. Our goal is to form the dictionary D and extrapolate the code vectors of each data point $x^{(i)}$ in such a way that if given $s^{(i)}$ and D, we can reconstruct the original $x^{(i)}$. Our objective is to reduce the squared difference between $x^{(i)}$ and its analogous reconstruction $D_s^{(i)}$. This is accomplished by two constraints described in Eqn. 4. The first constraint $\|s^{(i)}\|_0 \leq 1$ means that each code vector $s^{(i)}$ is forced to have at most one non-zero entity. The second constraint $\|D^{(j)}\|_2 = 1$ ensures that each column in the dictionary is of unit length. The encoding and reconstruction mechanisms are similar to sparse coding [50]. The difference between K-means and sparse coding is that the latter allows more than one non-zero entity in each code vector $s^{(i)}$ which leads to more precise representation. Although sparse coding can be interchangeable here but the simplicity and scalability of K-means can be useful in scaling our activity recognition system. Also we need to solve a convex optimization problem for every code vector in sparse coding which requires an immense endeavor and conclusively makes it difficult to deploy at large scale. The optimal code vector $s^{(i)}$ used in K-means is:

$$s_j^{(i)} = \begin{cases} D^{(j)T} x^{(i)}, & \text{if } j == \text{argmax}_l \, |D^{(l)T} x^{(i)}| \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Using Eqn. 5 we can form the code vectors rapidly and can train very large dictionaries immediately by alternative optimization of D and s. Also we only have one parameter to tune for K-Means which is the number of centroids for each hidden layer. At the final layer we apply k-means to find the desired k class indexes.

4.3 Initialization

One of the major problems of k-means algorithm is that it may produce empty clusters depending on the initial centroids. Although for static cases this problem is trivial and can be avoided by running the algorithm for couple of times. If empty cluster problem is not handled, it may lead to significant performance reduction. Therefore, it is important to properly initialize the centroids. Random initialization of initial central vectors is one of the simplest approach, but this will not be effective for sensor data. Whether the data are coming from ambient or wearable sensors, the data tend to group too densely in some areas which results in a large number of centroids starting in a dense region. Most of these centroids end up becoming clusters with very few data instances. In order to avoid such scenario, we propose to randomly initialize the centroids from a Normal distribution and then normalize them to unit length in accordance with our constraint. Let $X = \{x_1, ..., x_i\}$ be our data set and $S = \{s_1, .., s_i\}$ is our corresponding code vector matrix. We update the centroids according to Eqn 6. We add the $l2$ norm of the difference between our previous dictionary D_{old} and the new dictionary D with the reconstruction error to make

the update damped. Our goal is to minimize this error and calculate the optimum dictionary. After optimization we get the update rule as Eqn 7. Here SS^T refers to the dot product of code matrix S and its transpose S^T. We update our dictionary D according to Eqn 7 in a loop until convergence.

$$D = \underset{D}{\operatorname{argmin}} ||DS - X||_2^2 + ||D - D_{old}||_2^2 \tag{6}$$

$$= (SS^T + I)^{-1}(XS^T + D_{old}) \approx XS^T + D_{old} \tag{7}$$

4.4 Feature Mapping

K-means returns a set of cluster centers or centroids with k cardinality, which we use to design our feature mapping function. We consider two choices for our feature mapping function: i) We add k binary features to each sample, where each feature j has value one if and only if the jth centroid learned by k-means is the closest to the sample under consideration (Eqn. 8). ii) A non linear mapping, where we calculate the mean distance (μ) between the sample under consideration and other centroids and then a feature has value if and only if the centroid learned by k-means is within the radius of μ (Eqn. 9).

$$f_k^1(x) = \begin{cases} 1 & \text{if } k == \operatorname{argmin}_j ||c^{(j)} - x||_2^2 \\ 0 & \text{Otherwise} \end{cases} \tag{8}$$

$$f_k^2(x) = max\{0, \mu(z) - z_k\} \tag{9}$$

5 ACTIVE LEARNING

Active Learning can help scaling our activity recognition model and reduce the amount of effort needed for manual annotation. While deep learning assumes to have passive labeled data available in per-training phase or select them randomly from a pool of labeled datasets, we propose to investigate how active learning could help to improve the activity recognition performance at scale. Augmenting the training phase of deep activity models with active learning is a crucial step to reduce both computational time and system resource requirements. Therefore, our primary goal here is to help find the most informative data instance which we will query from the user. Here most informative instance is defined as an unlabeled instance which will bring the greatest change in our current training model if label is provided. Let U be the set of unlabeled data instances and L be the set of labeled data instances. The active learning algorithm will select the most informative data instance out of k samples from U in a pool based sampling setting. First we pre-train the deep learning network in an unsupervised way using the unlabeled instance set U. Then we use the labeled data set L to train the final output layer of k-means classifier, followed by fine tuning the network. We consider an active learning strategy using the data density by explicitly considering the structure of the data while selecting queries. If we consider the data instances with high information content, the sampling strategy will get biased and over confident as the time progress. So we also consider the data instances which are representative of the underlying distribution. Here we scrutinize the data instances which lie in the dense region of a cluster. The information density heuristic is calculated by the following equation:

$$f(x) = \underset{x}{\operatorname{argmax}}\, \Phi(x) \times \left(\frac{1}{card(U)} \sum_{x \in U} sim(x, x^*) \right)^{\beta} \tag{10}$$

In our objective function $f(x)$, *card(U)* depicts the cardinality of our unlabeled data instance pool and $\Phi(x)$ represents the utility of x according to expected error reduction of our k means classifier. The $sim(x, x^*)$ measures

the similarity between x and all other data instances. Using equation 1 we get our loss function as following:

$$L(x) = \text{argmin} \sum_{i=1}^{n} \|x - x^*\| \tag{11}$$

Our activity recognition model has no idea about what the error will be when it receives a label from the query. Using the decision theoretic approach instead of reducing error as a known value, we minimize it as an expected value by using the model's posterior distribution as an acceptable approximation. Using this intuition our utility measure $\Phi(x)$ is defined as following:

$$\begin{aligned} \Phi(x) &= \text{argmin}_x E_{y|x}[L(x)] \\ &= \text{argmin}_x \sum_y P(y|x)[\sum_{i=1}^{n} \|x - x^*\|] \end{aligned} \tag{12}$$

The term $\left(\frac{1}{card(U)} \sum_{x \in U} sim(x, x^*)\right)^{\beta}$ in Equation 10 weights the informativeness of x by its average similarity to all other instances. The parameter β controls the relative importance of the density term. Our objective function can be less sensitive to the outliers as it works in a dense region only. However if the dense region is in between the boundary of two clusters it may choose unnecessary data instances and outliers. To ensure that we introduce *silhouette coefficient* s_c^i in our objective function. Let $d(i)$ be the average dissimilarity of x_i with all other data within the same vicinity. This portrays how well x_i is assigned to it's own cluster. $d(i)$ is defined as the average distance from x_i to all other points in its own cluster. We define $e(i)$ to be the lowest average dissimilarity of x_i to any other cluster, of which x_i is not a member. The cluster with lowest $e(i)$ is said to be the *neighboring cluster* of the cluster where x_i resides. Now we define our silhouette coefficient as following:

$$s_c^i = \frac{e(i) - d(i)}{\max\{d(i), e(i)\}} \tag{13}$$

$$s_c^i = \begin{cases} 1 - \frac{d(i)}{e(i)}, & \text{if } d(i) < e(i) \\ 0, & \text{if } d(i) = e(i) \\ \frac{e(i)}{d(i)} - 1, & \text{if } d(i) > e(i) \end{cases} \tag{14}$$

The value of s_c^i ranges between -1 and 1. Smaller $d(i)$ represents x_i to be analogous to its own cluster. On the other hand large $e(i)$ illustrates x_i to be poorly matched to its neighboring cluster. As a result, s_c^i close to 1 depicts appropriately clustered instance and close to 0 means x_i resides on the border of two clusters. So by plugging in the coefficient into our objective function, we ensure that no outliers or unnecessary data instances get queried. The final objective function for our active learning method is

$$f(x) = \text{argmax}_x [s_c^i \, \Phi(x) \times \left(\frac{1}{card(U)} \sum_{x \in U} sim(x, x^*)\right)^{\beta}] \tag{15}$$

The overall active learning strategy of our *DeActive* model is summarized in Algorithm 1.

6 SENSEBOX IMPLEMENTATION

We collected real life data using our *SenseBox* [41] smart home system. The *SenseBox* system is composed of an ARMv5-based hub that is placed in the residences of volunteers, along with several sensors (passive infrared and accelerometer) that communicate back to the sensor hub via AXSEM AX5043 radios operating in the 900 MHz ISM band. The receivers for the AXSEM radios are connected via Ethernet which are inexpensive and provide

ALGORITHM 1: *DeActive* Active Learning

Input: U = A pool of unlabeled instances $\{(x)^u\}_{u=1}^{U}$,
L = A pool of labeled instances $\{(x)^l\}_{l=1}^{L}$,
E_{dist} = Error Distance from K-Means in the final Output layer of the deep architecture
k = Number of Clusters or Activities
Output: Most informative data instances in each cluster.
D = {}
for every $x_i \in U$ **do**
    Calculate the loss using E_{dist} in eqn 11
    Calculate base utility measure $\Phi(x)$ by taking the expected value of the loss give label y.
    Calculate the silhouette coefficient s_c^i for instance x_i
    d Calculate the informativeness $f(x)$ of x_i using eqn 15
    $D = D \cup d$
end for
q = instance with maximum $f(x)$ and query for label l
if $s_c^q > \delta$ **then**
    I = Neighbor instances of q
    Assign label l to instances in I
end if
$L = l \cup I$

adequate reliability for our application. The ARMv5-based hub with 700MHz CPU frequency is built on top of a consumer NAS device, the Cloud Engines PogoPlug. Using the publicly available GPL sources, we rebuilt the kernel to support kernel-level features we required in this application or felt we may require in the future (e.g. Video4Linux, NAT, support for various wireless devices.) As is typical in this scenario, subtle issues with downstream kernel code necessitated fixing several issues before the kernel was able to be successfully built and stable. A high level architecture of our system is demonstrated in Figure 3. As our deep learning algorithm uses torch [3] library, we have built torch for ARM processor.

7 EXPERIMENTAL SETUP

In this section we discuss the experimental setup and datasets we have used to validate our *DeActive*. Apart from using our own data collected using *SenseBox*, we also used four publicly available datasets to justify our framework. We provide descriptions of the datasets in the following:

Opportunity Dataset: The OPPORTUNITY dataset [61] encompasses both ambient motion and accelerometer sensor data from four participants. Each participant performed a session five times and in each of these sessions they performed a set of kitchen activities. Accelerometer sensors are placed on 12 different places of the body. We considered a subset of these data set which included accelerometer data from the upper limbs of the body. About 75% of the data instances do not correspond to any class.

CASAS Dataset: The CASAS dataset [13] contains ambient motion sensor data deployed in the WSU smart apartment. Couple of item sensors are also mounted on some objects to detect their usages. The data represents participants performing five ADL activities in the apartment (Make a phone call, Wash hands, Cook, Eat, Clean).

WISDM Dataset: The WISDM dataset [45] has triaxial accelerometer data from 29 users collected by android smartphone. This dataset has $1,098,207$ data instances of 6 classes - Walking, Jogging, Upstairs, Downstairs, Sitting and Standing.

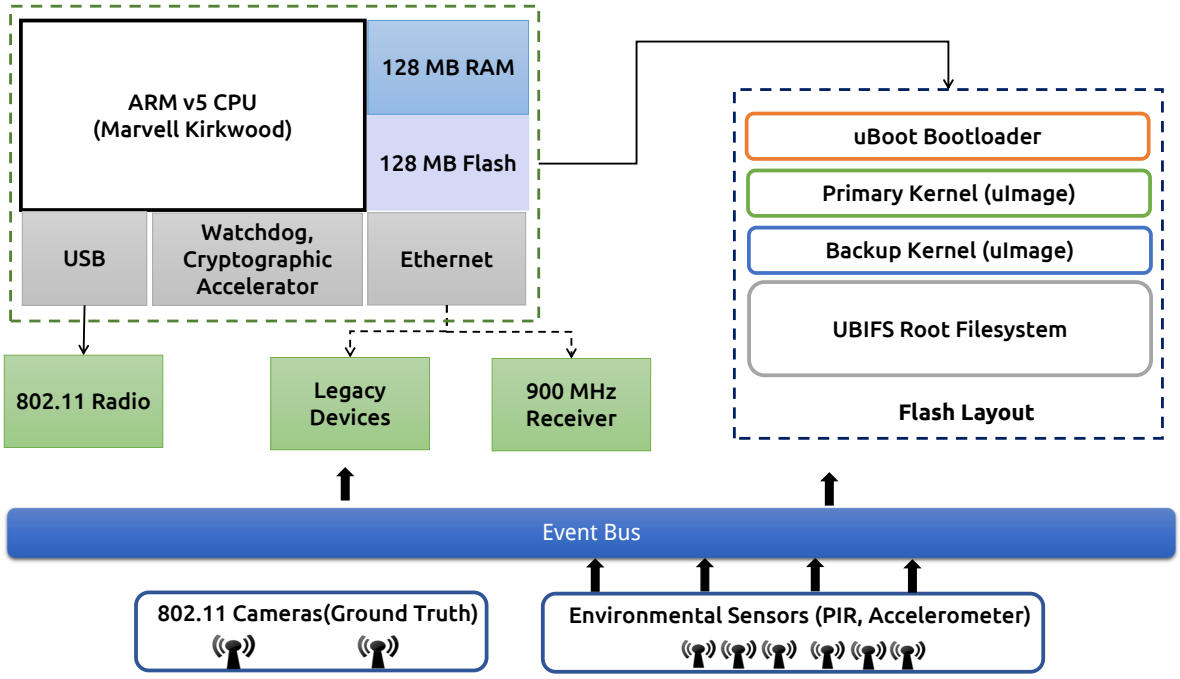


Fig. 3. *SenseBox* architecture which has ARM v5 CPU with 700MHz. Multimodal sensors dump the streaming data in the Event Bus and the system reads the new data from there.

Skoda Daphnet Dataset: The Skoda Daphnet dataset [6] contains the freezing of gait in users with Parkinson's disease. Three acceleration sensors on the hip, thigh and ankle were attached to 10 subjects. The data are classified into three classes - Freeze, No Freeze and No Experiment.

SenseBox Dataset: Using our own smart home system *SenseBox* [41] we collected data from 10 participants [2] (IRB - #HP-00064387) from a retirement community. Three ambient motion sensors and seven object sensors were installed in each participant apartment. We installed three motion sensors in three different rooms (bedroom, living room and kitchen) of each single bedroom apartment. We also placed three door sensors on the main entrance door and two closet doors. Five object sensors were mounted on different appliances (broom, trashcan, laundry basket, dustpan and phone). The users also wore a wearable device, Empatica E4, on their dominant hand which provided 3D acceleration data for each of the activities. We have used motion and object sensors from Wireless Sensor Tags [1] for our experiments. The sensors sent the data to the tag manager which was connected to our SenseBox system. Empatica E4 was not connected to the SenseBox system, it stored the data in its in device memory. We dumped the wearable data each day from the device and uploaded to our server. Our dataset has five activities - Cooking, Cleaning, Brooming, Eating, Sleeping. The ground truth information was collected using video recordings. Each participant were asked to follow a script of activities and we recorded the user movements using an ip camera for two hours. We then labeled the sensor data instances by mapping the timestamps with the video frames. Each participant provided 24 hours of continuous sensor data for 20 days.

7.1 Preprocessing

In order to validate our *DeActive* model, data from two types of sensor modalities are considered - ambient motion sensor and accelerometer sensor from smartphone or wearable. In this section we discuss the preprocessing of data from these sensor modalities.

7.1.1 Ambient Sensor. Ambient motion or infrastructural sensors are embedded in smart environments. Largely these sensors are PIR motion sensors which detect motion in the vicinity. The information received from ambient motion sensors permit to discern the performed activity with more reliability. These motion sensors contribute to identify the presence of a human in a certain part of the home and provide complementary evidence of the performed activity. It provides a value of 1 if a motion is detected otherwise 0. Other type of sensor deployed is door sensors which also provides binary values (OPEN and CLOSE) based on the motion of the door. Each sensor sequence is associated with a timestamp which is discretized to an integer value, day of the week which is also converted to an integer (0-6) where Monday being 0, ID of the previous activity performed and finally the length of the current activity measured in number of sensor events.

7.1.2 Accelermeter Sensor. Deep learning architectures are designed to process and deal noises of sequential sensor data by performing unsupervised feature learning. To extract meaningful information from the data we apply a noise filter and extract statistical features from the data. We apply a simple low pass filter to smooth out the arbitrary noises in the accelerometer data and a high pass filter to remove the effect of gravity. The accelerometer signals are then separated into frames using a fixed width sliding window with 10% overlapping. We used a 3 seconds sliding window and set the sampling frequency at 60Hz. We then extract statistical features which include:

- The mean, standard deviation and variance.
- Signal and differential vector magnitude.
- Signal entropy to differentiate between signals that correspond to different activity patterns but similar energy signals.
- Pairwise correlation of between each pair of dimensions.
- Zero-crossing rate in each dimensions.
- Weighted average of the frequency components to obtain a mean frequency.
- Magnitude and Energy of Fast Fourier Transform (FFT).

7.1.3 Data Normalization. We fuse together the extracted features from multiple sensors of both sensor modalities (ambient and accelerometer) by concatenating them into a single feature vector. After modeling the features for both sensor modalities, our next step is to normalize the data so that the features will be rescaled as we want all features to contribute equally.The normalized data will have the properties of standard normal distribution with zero mean ($\mu = 0$) and unit variance ($\delta = 1$). As we are using stochastic gradient descent for centroid calculation in our k-means encoder, certain weights may update faster than others since the feature values play a role in the weight updates with features being on different scales. Computation of distance measurement in k-means envisages each feature uniformly and so we have to ensure that units of features do not alter the relative approximation of observations. Also If a variance of a feature which is orders of magnitude larger than others, it might influence the classification and make the class estimator unable to learn from other features correctly as expected. So normalizing the features so that they are centered around 0 with a standard deviation of 1 is important. The normalization is done using: $z = \frac{x-\mu}{\delta}$.

8 PIPELINE AND MODEL PARAMETERS

We present the pipeline of *DeActive* in Fig. 2. In the pre-training phase we generate windows with unlabeled data instances.Each window is a two-dimensional (180×3) matrix containing samples of 3 seconds window as the sampling frequency of the accelerometer is 60Hz. We then extract 3×3 patches from the windows and apply k-means clustering on the extracted patches. The generated clusters are normalized to have magnitude 1 and the centroids are used to encode and decode the data instances. We learn the encoding dictionary D in this way. In order to encode the future data instances, we calculate the Euclidean distance for each patch of

the new window to each of the centroids. Based on the calculated distances, individual patches are assigned to centroids/clusters using Eqn. 8 or 9. We used 9 for its effectiveness and speed. We apply such three fully connected layers of encoding. We then apply mean pooling over the final assignment vector. We calculate the reconstruction error by subtracting the original time series from our encoded and then decoded signal and take the mean absolute value (MAV). In Figure 4a and 4b we show the reconstruction error of our encoding model. From Figure 4b, we see that the error does not change much after assigning 150 clusters. So in each hidden layer we set the number of clusters to be 150. In Figure 4a we show a sample reconstruction of 2000 sample time series signal using our encoder. At the final output layer we employed a softmax classifier.

9 EVALUATION METHODOLOGY

We evaluate our model using precision, recall and F1 measures. However these measures also exhibit biasness due to population prevalence and label bias as they inherently ignore handling of negative examples [59]. As a result we also calculate *Informedness* and *Markedness* measures defined in Eqn 16 & 17 to avoid bias by integrating inverse recall and inverse precision respectively.

$$markedness = precision + inversePrecision - 1 \tag{16}$$

$$informedness = recall + inverseRecall - 1 \tag{17}$$

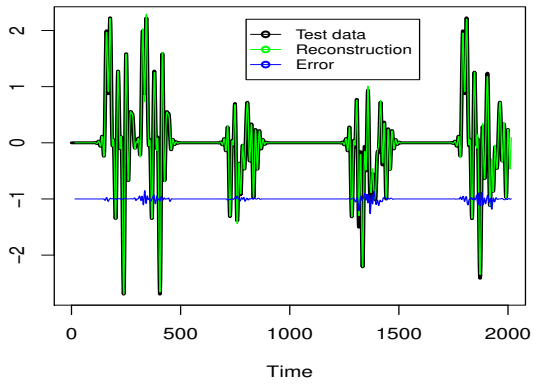
Markedness and Informedness articulate how marked and informed the classifier is respectively with comparison to chance. We evaluated our active learning algorithm by comparing with other simple active learning methodologies - Maximum Entropy sampling, Query By Committee and Random sampling. In order to compare these methods we calculated Normalized Mutual Information (NMI) using the ground truth information. Both the true activity class label and queried label assignment are considered as random variables in NMI. NMI measures the mutual information between these two assignments and normalizes them to zero to one range. If we consider K be the random variable of queried class labels of data instances and C be the true labels then the NMI is computed by equation: $NMI = \frac{2I(C;K)}{H(C)+H(K)}$. Here $I(X;Y) = H(X) - H(X|Y)$ is the mutual information between random variables X and Y. Here H is the entropy function.

9.1 Performance Analysis

In this section, we examine the performance of our *DeActive* model on real world datasets described in the previous section. In our proposed model we use 3 hidden layers. We first normalize the data with zero mean and standard variance. The deep activity recognition models are trained using stochastic gradient decent with mini-batch size of 64. We utilize 10% instances of the datasets to pre-train the models and then 50% instances to fine tune. We leave 20% for validation and rest of the 20% for testing. Due to relatively small number of classes available in our dataset we experienced overfitting problem. We applied “dropout" method which is a widely used technique to tackle the overfitting problem. The dropout probability was set to 0.8. In Table 1 we compare our model with other deep architectures for *SenseBox* dataset. For all of the deep architectures we followed same distribution of splitting to create the tuning, training and testing dataset. All the networks were tuned using back propagation and optimized using gradient descent. It is apparent that our model achieves better accuracy (92.84%) with 3 hidden layers. We experimented with different number of features and empirically we got better results for 500 features for all the deep architectures. We trained our model offline using our lab server.

9.2 Classification Accuracy

We first evaluate accuracy of different datasets with ambient motion sensor data using our model. We show the Precision, Recall, F1, Informedness and Markedness score of individual datasets in Figure 5 and 6 . For *Opportunity* dataset (Fig 5b), we see that preparing coffee achieved lowest accuracy as these activities involved



(a) Reconstruction error using K-Means inspired auto encoder

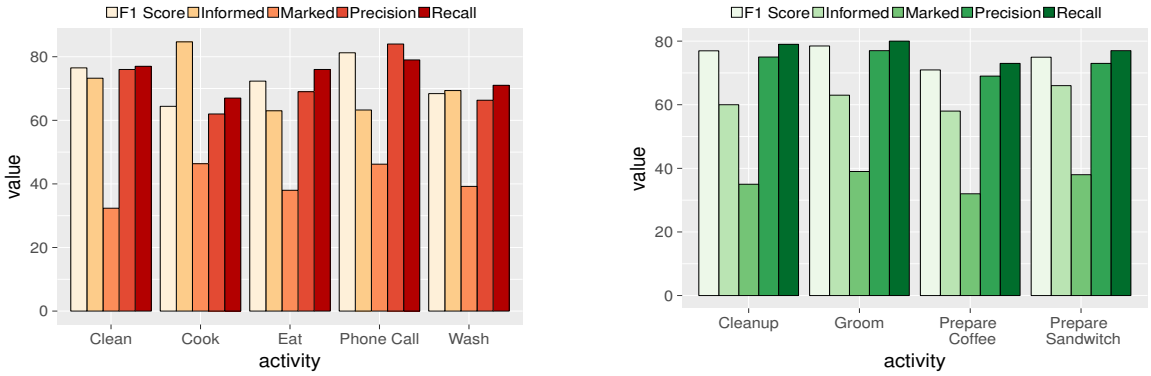
(b) Trend in Mean Absolute Value(MAV) error for increasing number of centroids

Fig. 4. Figure (a) shows the reconstruction error for 2000 data samples of accelerometer. Figure(b) shows the trend in error with varying number of centroids for the hidden layers.

Table 1. Accuracy of different deep architectures on *SenseBox* dataset

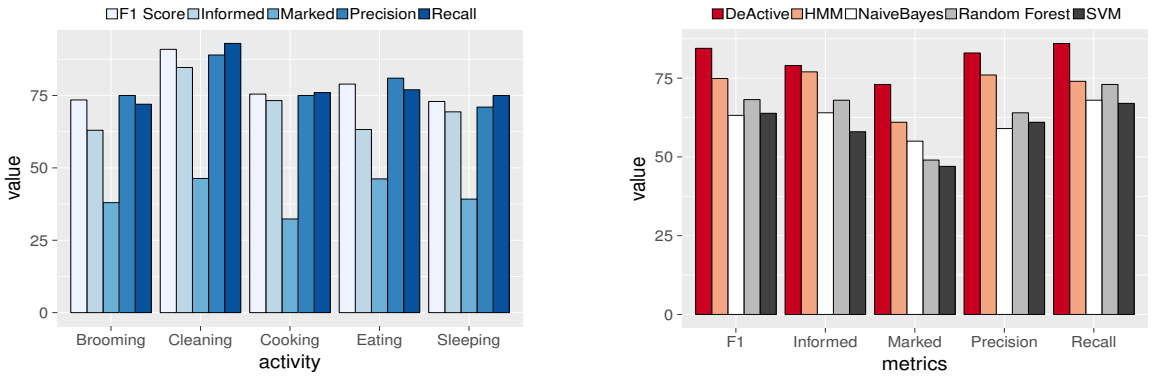
Model	# of layers	# of Nodes	Batch Size	Activation	Output layer	Accuracy(%)
DBN	3	256	64	ReLU	Softmax	85.52
RBM	3	256	64	ReLU	Softmax	89.78
CNN	3 conv, 2 pooling, 2 fully connected	16 (No. of filters in a conv layer)	64	ReLU	Softmax	86.16
Sparse Autoencoder	3	256	64	ReLU	Softmax	84.11
LSTM	2 LSTM 1 fully connected	100 (No. of memory units)	64	tanh	Softmax	88.27
DeActive	1	150	64	Eqn 9	Softmax	87.34
DeActive	2	150	64	Eqn 9	Softmax	89.34
DeActive	3	150	64	Eqn 9	Softmax	92.34

similar movement using kitchen appliances. For *SenseBox* dataset we experience comparatively low accuracy for cooking, eating sleeping and brooming than cleaning. After further investigation we found that *cooking* activity has a lot of false positives. About 38% time our prediction algorithm predicted *cooking* as *eating* and *cleaning*. By reviewing the ground truth information we confirmed that in these cases the participant was in the kitchen but not cooking. The participant sometimes ate in the kitchen and also there are times when he was cleaning the appliances. As a result our model confused these two classes with *cooking* activity. *Eating* activity is also hard to detect using just the ambient motion sensor as the participants ate in different locations at times. We faced similar problem as *cooking* activity in this case and majority of the false positives were labeled as *cooking*. Although we have attached an acceleration sensor with the broom to detect the *Brooming* activity but due to mobility in different rooms while brooming it created false positives. Similarly for *CASAS* dataset we received much higher accuracy for all the activities except *Eat*. The line chart in Figure 12 shows the convergence of accuracy with respect to the percentage of dataset used in the experiment.



(a) CASAS (b) Opportunity

Fig. 5. Precision, recall, F1, informedness and markedness score of each activity in CASAS and Opportunity datasets (ambient motion sensor data).



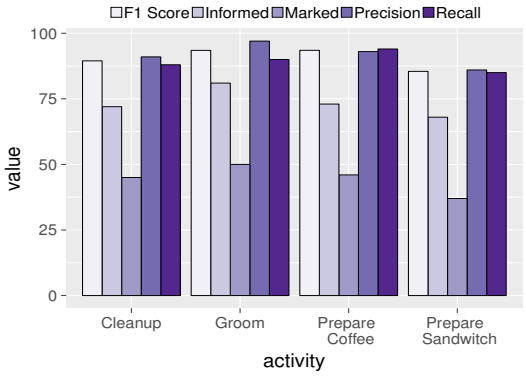
(a) SenseBox (b) Overall

Fig. 6. (a) Precision, recall, F1, informedness and markedness score of each activity in SenseBox dataset (ambient motion sensor data) and (b) illustrates the accuracy of different shallow learning algorithms compared to our *DeActive* framework.

Table 2. Comparison of our DeActive algorithm with other existing approaches for different datasets.

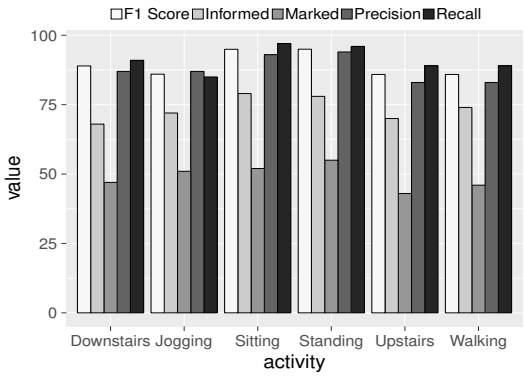
Activity Recognition System	Skoda	Opportunity	WISDM	SenseBox
Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition [21]	95.8	91.20	95.86	88.09
Convolutional Neural Networks for human activity recognition using mobile sensors [26]	88.19	93.17	94.75	84.20
Deep Activity Recognition Models with Triaxial Accelerometers [24]	89.38	86.39	94.46	87.54
Our deep learning framework *DeActive*	97.24	94.06	91.83	92.34

(a) SenseBox

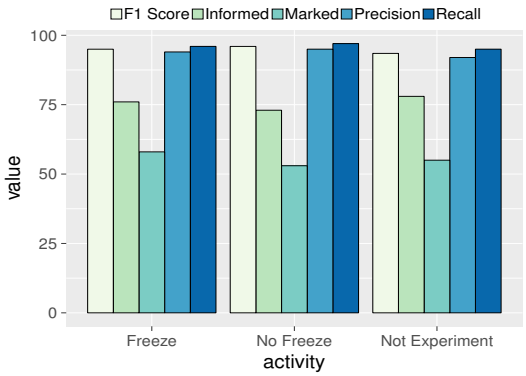


(b) Opportunity

Fig. 7. Precision, recall, F1, informedness and markedness score of SenseBox and Opportunity datasets (3D acceleration data).



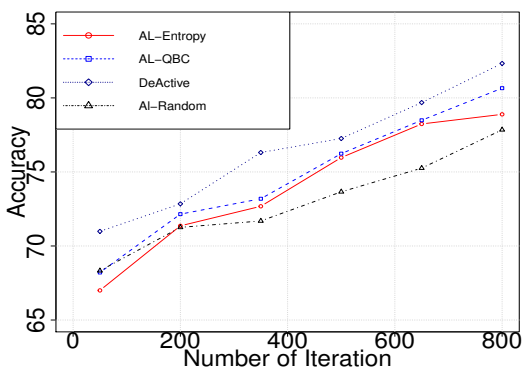
(a) WISDM



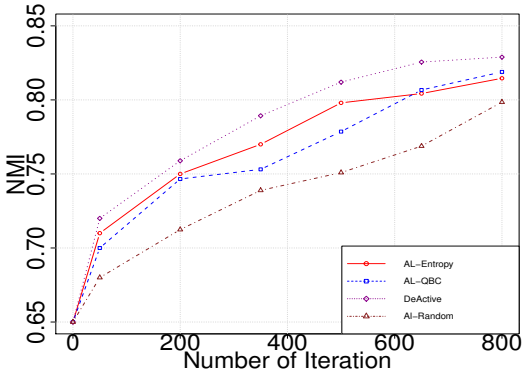
(b) Skoda Daphnet

Fig. 8. Precision, recall, F1, informedness and markedness score of WISDM and Skoda datasets (3D acceleration data).

Now we validate our model with 3D acceleration data. In this case we also show the same metrics used in previous experiment for each activity in each dataset in Figure 8 and 7. Each dataset showed much better accuracy when accelerometers were involved. In both *SenseBox* and *WISDM* a single accelerometer sensor entity is utilized. In our dataset we employed a wearable device placed on the dominant arm of the participant and for *WISDM* a smartphone. *Brooming* (Figure 7a) achieved much better accuracy than using just the ambient sensors as our deep learning architecture was able to find better feature representation from the acceleration data. In *Opportunity* dataset we experience less accuracy for *Prepare Sandwich* and *Cleanup* activity. After further investigation we found that about 31% of *Prepare Sandwich* class was labeled as *Cleanup* and *Prepare Coffee*. These two activities had similar feature representations in our model and as a result the predictor mislabeled them. With *Skoda* data set we have achieved much higher accuracy compared to other datasets as the activities considered had distinct feature representations. In case of *SenseBox* dataset again we achieved low accuracy for *eating* and *cooking* classes. For further validation we looked into our video recordings and found that different participants had different eating behavior. Also the eating pattern largely depends on the cuisine and the type of food you are eating. For

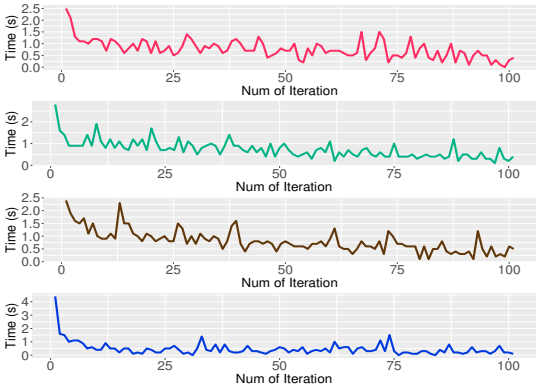


(a) The change in model accuracy after each iteration using different active learning strategies.

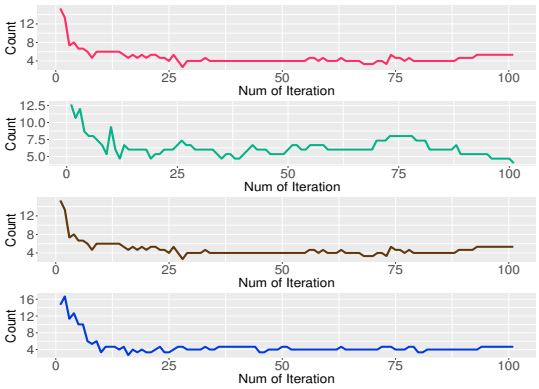


(b) The change in NMI after each iteration using different active learning strategies.

Fig. 9. The figures demonstrate the performance of our active learning algorithm.



(a) Instance selection time of Entropy, QBC, Random and DeActive strategies (up to down) in 100 iterations.



(b) Incorrectly classified instances of Entropy, QBC, Random and DeActive strategies (up to down) in 100 iterations.

Fig. 10. The figures demonstrate the trend of instance selection time and incorrectly classified instances of different active learning algorithm.

example, some foods are eaten using fork and knives (rice, steak vegetables etc.), some using only spoon (soup, stew, chowder etc.) and some using only hand (burger, sandwich etc.). Due to these variations it was difficult to capture distinguishing feature between different eating movements. For *cooking* activity, we experienced similar challenges due to variations in cooking style. Some of the participants were not spending much time in cooking. Also during cooking, we saw that the participants were doing other activities concurrently like talking over the phone, moving stuffs or watch television etc. As a result we achieved low accuracy for *cooking* activity. In Table 3 we show the precision, recall and F1 score of each activity for five random users from our *SenseBox* data set. For each individual in Table 3, we trained our model in leave-one-out fashion. We see that our model was able to infer the *cooking* activity of User 3 and User 4 with higher accuracies than others. Upon further investigation we found that User 3 and User 4 cooked regularly. User 5 experienced lowest accuracy for *cleaning* activity. We noticed that the ground truth labeling of *cleaning* and *brooming* for User 5 were ambiguous. Some of cleaning activity instances involved use of broom which introduced the ambiguity. We encountered similar problem for User 1 in

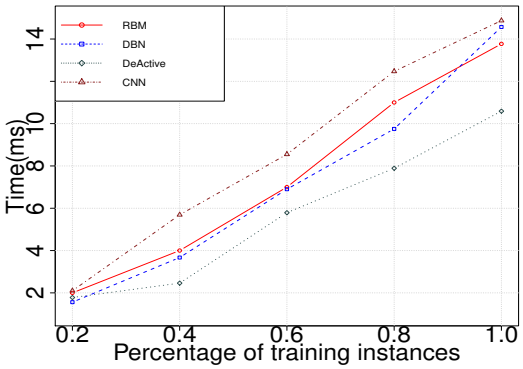


Fig. 11. The execution time of *DeActive* in *SenseBox* architecture.

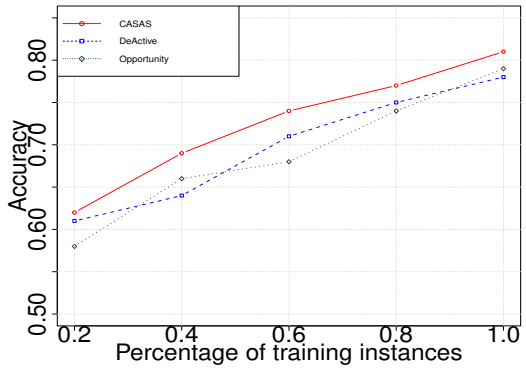


Fig. 12. Convergence of Accuracy with respect to percentage of data instances.

Table 3. Precision (Pr), Recall (Re), and F1 score of leave-one-out evaluation for five random users from SenseBox dataset.

User	Cooking			Cleaning			Brooming			Eating			Sleeping		
	Pr	Re	F1	Pr	Re	F1	Pr	Re	F1	Pr	Re	F1	Pr	Re	F1
User 1	88	89	88	84	81	82	86	89	87	88	90	88	93	88	90
User 2	94	94	94	90	92	90	93	91	91	89	91	89	90	91	90
User 3	96	91	93	92	91	91	92	92	92	89	88	88	89	88	88
User 4	95	90	92	93	88	90	93	92	92	87	92	89	91	93	91
User 5	85	84	84	85	88	86	82	87	84	88	90	88	91	91	91

brooming activity as well. For *WISDM* dataset, the overall accuracy was much higher (≈ 92%) than other datasets as the activities considered have distinct signature pattern in the accelerometer data. In Table 2 we compare our *DeActive* model with some recent existing activity recognition works which use 3D acceleration data from wearable and mobile devices. Although these state-of-the-art models experimented on different datasets, still we have achieved similar or better accuracy. These models also take more training time and require more resources than our model.

9.3 Effect of Active Learning

We applied our active learning algorithm in a 10-fold cross validation manner. We started our active learning experiment with 20,000 unlabeled data instances and randomly selected 1000 labeled instances to train our model. Initial accuracy of our model with 1000 labeled instances is ≈ 65%. We adopt pool based sampling in our experiment where we gather the incoming data instances in a pool and select the informative data instances from this instance pool. After analyzing the results of silhouette coefficient, we empirically define 0.73 as our threshold. In Figure 9a we exhibit the change in model accuracy over 800 iterations. In each iteration we query the most informative 5 data instances and after receiving the label we add it to our training dataset. The instances which are within our predefined threshold (0.73), we also annotate them in accordance with their associated most informative instance. We compare our algorithm with other popular active learning strategies like maximum entropy, Query by Committee(QBC) and random sampling. It is evident from the figure that after acquiring labels of only 4000 instances we achieved accuracy close to 85% whereas utilizing all of the labeled instances (70,000)

we achieved 92.34% average accuracy. So by labeling less than 10% of the dataset we achieved fairly close to optimal accuracy. In figure 12 we showed the convergence of accuracy with respect to percentage of labeled data instances. We see that without active learning, we could only achieve average accuracy of only 70% by utilizing almost 20% of the labeled instances. Therefore, DeActive can provide better accuracy with much fewer labeled instances which also ensures lower annotation effort. Also our active learning strategy outperforms other popular strategies and converges faster. Our model achieves better performance with respect to recognition accuracy after acquiring same percentage of labeled examples.

In Figure 9b we show the effect in NMI for our model. From the figure we see that our model is converging to optimal accuracy faster. The higher NMI represents that the assigned label by our classifier and the label from the annotator is getting closer. We also look at how many instances were incorrectly classified in 100 iterations using our active learning algorithm in figure 10b. It is noticeable from the figure that our active learning algorithm is more stable in correctly classifying instances compared to other strategies which indicates that only vital instances are being selected for querying. Another important parameter for evaluating active learning algorithm is to monitor the speed or the time it takes to select instances in each iteration. Average instance selection times for *entropy, QBC, random sampling* and *DeActive* are - 0.76s, 0.73s, 0.80s, 0.468s. *DeActive* is almost 40% faster than other strategies while selecting instances. In figure 10a we show the progression of instance selection time for the first 100 iterations for all active learning strategies.

9.4 Device Performance

We investigate the performance of our *DeActive* model in *SenseBox* architecture. In Figure 11 we see that our algorithm executes much faster than other algorithms. In [28], the execution time is reported as 20.78 msec with 50 hidden layers and 3,289,600 parameters. In our case the execution time is close to 10 msec with 3 hidden layers. However [28] used Snapdragon 400 quad core CPU whereas we used single core CPU.

10 FUTURE WORKS & DISCUSSIONS

We have demonstrated that active learning can help us to mitigate the manual effort needed for compiling ground truth information and reduce training time. However, active learning is built on a naive assumption that a *single* annotator will *always* provide *correct* label information. In real world scenario, multiple annotators will be involved instead of single annotator model as the single annotator might get exhausted and stop providing labels. Also it is impractical to assume that the annotators are going to provide correct labels all the time. So it is necessary to pose the query to appropriate annotator or else it will be meaningless. In future, we want to investigate an active learning setting with multiple imperfect annotators and pose the query according to their ranks and availability. We understand that the configuration of our *SenseBox* system and [28] are completely different. We plan to deploy our model with a similar setup like [28] and compare the performance of our architecture in future. Our experimental evaluation showed that active learning can help to achieve optimum accuracy in reduced time but not improve it as we have put more emphasis on the efficiency of the system. In order to make smart home systems cheaper, researchers are looking into embedded devices and most of these IoT devices do not have high computational capability. On the other hand deep models require significant computational resources which is a major bottleneck while harnessing the power of deep models in embedded devices. As a result, there is a growing need for more optimized deep architectures and hardware designs which will boost the smart home technologies. By applying k-means based encoder we have mitigated the problem of resource constraint but at the cost of losing accuracy. Alternative methods like sparse coding, GMM, DBSCAN etc. can provide higher accuracy but they are not appropriate for low-powered resource constrained devices. In future, we envision to close this gap between accuracy and efficiency by investigating more appropriate encoding method.

11 CONCLUSION

Scaffolding the activity recognition to many emerging smart environment applications is a pressing societal need. While advanced machine learning approaches albeit help achieve that objective, in this paper, we envision that simple algorithms can be considered as viable and sometime competitive alternatives along that pathway. Motivated by this, we presented an activity recognition model using a simple K-means clustering assisted deep architecture which help to scale activity recognition in large. Our proposed model also consolidated active learning to mitigate the amount of human effort needed for collecting ground truth information. We compared our activity model with other deep and active learning algorithms and validated that our model can outperform them. We built a custom-made smart home system, *Sensebox* and demonstrated that the competence and viability of our model through real deployment in retirement community center. We believe our work is the first step towards enabling the vision that *Simplicity is the Scalability*.

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