Classifier Ensemble Optimization for Human Activity Recognition in Smart Homes

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ABSTRACT
Recognizing human activities is an active research area due to its applicability in many applications, such as assistive living and healthcare. Currently, the major challenges in activity recognition include the reliability of prediction of each classifier as they differ according to smart homes characteristics. It is not possible that one classifier always performs better than all the other classifiers for every possible situation. Therefore, in this paper, a method for activity recognition is proposed by optimizing the output of multiple classifiers with evolutionary algorithm. We combine the measurement level output of different classifiers in terms of weights for each activity class to make up the ensemble. Classifier ensemble learner generates activity rules by optimizing the prediction accuracy of weighted feature vectors to obtain significant improvement over raw classification. For the evaluation of the proposed method, experiments are performed on two real datasets from CASAS smart home. The results show that our method systematically outperforms single classifier and traditional multiclass models.

Categories and Subject Descriptors
I.2.8 [**ARTIFICIAL INTELLIGENCE**]: Problem Solving, Control Methods, and Search – *Heuristic methods, Plan execution, formation, and generation.*
G.1.6 [**NUMERICAL ANALYSIS**]: Optimization – *Constrained optimization, Stochastic programming.*
G.4 [**MATHEMATICS OF COMPUTING**]: Mathematical Software – *Algorithm design and analysis, Reliability and robustness.*

General Terms
Algorithms, Performance, Design, Human Factors

Keywords
Activity recognition, Classifier ensemble, Weighted classification, Evolutionary algorithm, Smart Homes

1. INTRODUCTION
With the growing healthcare requirements of aging population, smart home technology has attracted a lot of attention. A smart home is an intelligent agent that perceives state of resident and the physical environments using sensors [1]. It is one of the best solutions that allowed the provision of monitoring and health assistance for persons with special needs and the elderly to receive services in their own home environments [1]. In recent years, several smart homes have been developed such as CASAS and MavHome [2] at Washington State University, Aware Home [3] at Georgia Tech University, Adaptive House [4] at University of Colorado, House_n [5] at Massachusetts Institute of Technology (MIT), and House A [6] at Intelligent Systems Laboratory. This fact is supported by a large number of applications developed using activity recognition to provide solutions to a number of real-world problems such as remote health monitoring, life style analysis, interaction monitoring, and behavior mining [7] [8].

Many researchers have designed a variety of models to recognize the activities of daily living and have greatly contributed to improve the smart home technology [7-10]. Despite the great work and diversity in the existing classification methods, the most notable problem is that single classifier cannot always lead to good recognition results. Sometimes, a classifier can outperform other classifiers on a particular problem but in general, it is not always the case when one classifier overrides the others in all possible situations. The process of selecting an appropriate classifier is still a trial and error process that clearly depends on the relationship between the classifier and the smart home characteristics [11]. The predictable factors such as the available amount of training data, the spatial variability of data samples, deployed sensors in smart homes and the total activity occurrences in the dataset influence the performance of classifiers to a significant degree. In most of the practical applications, the reliabilities of predictions vary among the various classes in any classifier.

In order to overcome the problems of single classifiers, classifier combination is proved to be more accurate and robust than an excellent single classifier in many application domains [12-14]. Therefore, in this study, a novel method to recognize daily life activities is proposed by optimizing the measurement level output in terms of weighted feature vectors of classifiers using evolutionary algorithm. This solves the problem in which single classifier learners suffer from statistical, computational and representational problems which may affect the accuracy. Statistical problems arise due to high dimensional variance in the sensors data that excessively increase the size of the search space. Computational problems occur when the training data is computationally complex and can get stuck in local optimum. Our proposed Classifier Ensemble (CE) optimization method combines the complementary performance advantages of classifiers for more accurate results. In the proposed method, the weighted feature vector of a classifier is determined from its training performance for each class, which indicates the possibility that the input sensor values pertains to the class. As a

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result, the weighted feature vectors of all classifiers are ensemble together in Genetic Algorithm (GA), a type of evolutionary algorithm, to learn the optimized activity rules for final decision about activity class label. We integrated the weighted feature vectors of probabilistic and statistical methods such as the Artificial Neural network (ANN) [9], Hidden Markov Model (HMM) [7], Conditional Random Field (CRF) [8], and Support Vector Machines (SVM) [10] as base classifiers. To evaluate and validate the proposed approach, experiments are performed using two real datasets collected in the CASAS smart home [2], a research project at Washington State University (WSU) focused on the creation of an intelligent home environment. The recognition results show the significance of proposed approach in terms of high accuracy as compare to single classifiers and traditional multi model techniques.

The rest of the paper is organized as follows. We briefly describe related work and their limitations in Section 2. In Section 3, we introduce our proposed evolutionary algorithm based classifier ensemble optimization method for activity recognition in smart homes. In Section 4, we analyze and evaluate our experimental results to validate the proposed approach. Finally, conclusion and future work is presented in Section 5.

2. RELATED WORK

In the last decade, a lot of research has been done in the area of classifier ensemble for designing high performance classification systems. A classifier ensemble is used under different names such as combing classifiers, committees of learners, mixtures of experts, classifier fusion, and multiple classifier systems [12-15]. The combine decision has been proven to be more accurate in long run than classification decision of the best single classifier. In this regard, Genetic algorithm (GA) is known the best search algorithm for the optimization of classifiers output [16]. There exist several previous studies on the usage of GA as learning classifiers that may vary in the number of classifiers, using different combing methods for intended application domains.

Matthew et al. [17] proposed an extended version of learning classifier and utilized GA to produce generalizations over the space of all possible condition-class combinations. They improved the learning speed for terabytes of data in their parallel data mining systems. Ekbal et al. [12] applied GA to recognize named entities for Bengali, Hindi, Telugu, and Oriya. To find more accurate results they quantify the amount of votes per classifier for each output class. They used Maximum Entropy (ME), Conditional Random Fields (CRF), and Support Vector Machine (SVM) as base classifiers for GA based ensemble. Kuncheva et al. [16] used a GA to design the classifier fusion system and determined that, as a learner component, GA outperforms other classifier models. They combined Linear Discriminant Classifier (LDC), Quadratic Discriminant Classifier (QDC), and logistic classifier for better accuracy of results. Rongwu et al. [18] proposed classifier ensemble as a learning paradigm where many classifiers are jointly used to solve the prediction problem. They used seven wearable sensors including five accelerometers and two hydrophones. Their used classifiers are Linear Discriminant Classifier (LDC), Quadratic Discriminant Classifier, k-Nearest Neighbor (k-NN) and Classification And Regression Trees (CART). Also, GA has been successfully used as a learner to select optimal genes for analyzing DNA microarrays [19] where classification is treated as two class problem. All theoretical and empirical studies of GA learning show higher accuracy in real world applications such as spam email filters, character recognition, text categorization, face recognition, computer-aided medical diagnosis, pattern recognition and gene expression analysis[17] .

The state-of-the-art and most popular activity recognition techniques are based on probabilistic and statistical models like Hidden Markov Models (HMM) [7], Conditional Random Fields (CRF) [8], Artificial Neural Network (ANN)[9], Support Vector Machine [10], and some other classification methods [20][21]. However, a number of difficulties and limitations remain with these approaches. The learning capability of these models depends on the observation of activity class distribution (the observed state) and the transitions between adjacent activities (transitions between states) according to the characteristics of smart homes. The choice for best classifier is highly dependent upon the problem domain and associated nature of dataset. In practice, no single classifier can achieve an acceptable level of accuracy on all datasets [11]. Every classifier operates well on different aspects of the training or test feature vector

To overcome the limitations of existing work, we proposed an alternative state-of-the-art GA based classifier ensembles optimization for the recognition of daily life activities. The measurement level outputs of individual classifiers are fed into GA ensemble as input for combining the benefits of classification performance for each classifier. As a result, optimization of the output weights of multiple classifiers improves the accuracy of results when compared with single classifier or other combining methods.

3. GA-BASED CLASSIFIER ENSEMBLE OPTIMIZATION

Here, we propose a GA based classifier ensemble optimization method that integrates the measurement level classification results generated by multiple classifiers in terms of weighted feature vector into a final activity label. Let us assume that we have k classifiers and $W_k=\{w_1, w_2,...,w_n\}$ be the weighted feature vector representing the relative significance of k^{th} classifier for all classes. The weight w_i is the degree of importance of k^{th} classifier for class i. This implies the estimation of how important k^{th} classifier is in the classification of the class i compared to the other classifiers. The search space S for classifier ensemble is defined is the set of weighted feature vector of k classifiers and the activity rule space R is the optimized weighted feature vector of k^{th} classifier on a given threshold $\propto$ with "don't care term". The proposed method consists of four major components: (1) Data preprocessing: to represent the sensory data as an observation vector for classifier input, (2) base classifier for AR: to provide details about applied classifiers with preferred parameters settings, (3) A GA based classifier ensemble learner: to optimize the weighted feature vectors of multiple classifiers, and (4) recognition phase: to recognize the performed activities. The details of each component are described in the following sections.

3.1 Data Preprocessing

Data preprocessing is an important step towards accurate training of machine learning techniques [6]. Data collected from ubiquitous sensors based on subject interactions are stored in sensor logs and annotation files with attributes *start time, end time, sensor id*, *sensor value* and *activity label*. In order to recognize the performed activities, recorded dataset is preprocessed into the form of $\{(x_1, y_1), \dots, (x_n, y_n)\}$. The x_i is the vectors whose components are the values of embedded sensors $\{S_1, \dots, S_n\}$ such as stove-sensor, refrigerator-sensor, and doorsensor. The values of "y" are drawn from a discrete set of classes $\{c_1, \ldots, c_m\}$ such as a "Leave Home", "Read", and "Sleep".

3.2 Base Classifiers for Activity Recognition

In this section, we introduce the base classifiers (i.e., ANN, HMM, CRF, and SVM) used for ensemble optimization in the proposed method with preferred settings of our experiments. Brief description of each classifier is given as:

Artificial Neural Networks (ANN): It is an information processing network of artificial neurons connected with each other through weighted links. In activity recognition, the structure of the network, number of hidden layers, number of neuron in each layer with number of deployed sensors and total occurrences of activities in smart homes affects the learning process of different activities. The activation of the neurons in the network depends on the activation function [9]. In the proposed method, multilayer neural network with back propagation learning algorithm is utilized to recognize the human activities [5] and the weights are updated by the following equation:

$$\Delta w_{ki} = -c\left[-2\sum_{j}\{(y_{j(desired)} - y_{j(actual)})f'(act_j)w_{ij}\}f'(act)_i x_k\right] \quad (1)$$

where Δw is the weights adjustment of the network links. In our network, we used one hidden layer with twenty neurons, tangent sigmod function as an activation function given below:

$$\varphi(v) = \tanh\left(\frac{v}{2}\right) = \frac{1 - \exp(-v)}{1 + \exp(-v)} \quad (2)$$

Learning of the network is limited to maximum 1000 epochs. We used the multi-layer neural network can be seen as an intuitive representation of a multi-layer activity recognition system.

Hidden Markov Model (HMM): It is a generative probabilistic graph model that is based on the Markov chains process [7]. The training model is based on the number of states (activity class labels) and their transition weight parameters. Parameters are learned through observation (sensors value) and following parameters are required to train the model:

$$\lambda = \{A, B, \pi\} \quad (3)$$

Where λ is graphical model for activity recognition, A is a transition probability matrix, B represents the output symbol probability matrix, and π is the initial state probability [7]. We used Baum-Welch algorithm to determine the states and transition probabilities during training of HMM. The i^{th} classification weight of an activity is given as:

$$\lambda_i = \{A_i, B_i, \pi_i\}, \qquad i = 1, \ldots, N \quad (4)$$

Conditional Random Fields (CRF): It is a discriminative probabilistic graph model for labeling the sequences. The structure of the CRF is similar to HMM but learning mechanism is different due to absence of the hidden states [8]. In CRF model, the conditional probabilities of activity labels with respect to sensor observations are calculated as follows:

$$p(y_{1:T}|x_{1:T}) = \frac{1}{Z(x_{1:T}, w)} exp\left\{\sum_{j=1}^{N_f} w_j F_j(x_{1:T}, Y_{1:T})\right\} \quad (5)$$

In equation 5, Z denotes normalized factor and $F_j(x_{1:T}, Y_{1:T})$ is a feature function. To make the inference in the model, we compute the most likely activity sequence weights as follows:

$$y^*_{1:T} = \mathrm{argmax}_{y'_{1:T}}\, p(y'_{1:T}|x_{1:T}, w) \quad (6)$$

Support Vector Machine (SVM): SVM is statistical learning method to classify the data through determination of a set of support vectors and minimization of the average error [10]. It can provide a good generalization performance due to rich theoretical bases and transferring the problem to a high dimensional feature space. For a given training set of sensors value and activity pairs, the binary linear classification problem require the following maximum optimization model using the Lagrangrian multiplier techniques and Kernel functions as:

$$\text{Maximize (w.r.t } \alpha) \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=0}^{n}\sum_{j=1}^{n} \alpha_i\, y_i \alpha_j y_j K(x_i, x_j) \quad (7)$$

$$\text{Subject to:} \sum_{i=1}^{n} \alpha_i y_i = 0, \quad 0 \le \alpha_i \le C \quad (8)$$

Where K is the kernel function that satisfies $K(x_i, x_j) = \Phi^T(x_i)\Phi(x_j)$. In our case, we used radial basis function (RBF) for recognizing the activities.

$$K(x_i, x_j) = \exp\left(\frac{-\|x_i - x_j\|^2}{(2\sigma^2)}\right) \quad (9)$$

We use the SVM by simply substituting every dot product of activities weights in dual form with RBF kernel function. SVM can handle its non-linear nature. The activity recognition is multi-class problem so "one-versus-one" method is adopted to classify the weights of different activities

3.3 A GA-based Classifier Ensemble Learner

In this section, a GA-based classifier ensemble learner is designed from the output of base classifiers in terms of weighted feature vectors that optimizes the measurement level classification results into a final decision about activity class label.

Algorithm 1. GA-based Classifier Ensemble Learner

Input: λ - crossover rate
n - number of generations
μ - mutation rate
s - population size
t - training classifier data
$\propto$ - fitness threshold
Output: R - optimized activity rules
Begin
pop = randInitial(s)
while *(!max(n)||convg(n))*
fitness = compEvoultionFitness(pop, t, $\propto$*)*
if *!(fitness)*
pop = fCrossover(pop, λ*)*
pop = fMutation(pop, μ*)*
end
end
R = ranked (pop)
End

The weighted features vectors are fed into GA through chromosomes that reflect the relative importance of each classifier for a particular activity class. The pseudo code of ensemble learner is presented in Algorithm 1. We model the population initialization, evolution fitness, and stochastic operators of the GA as follows:

3.4 Population Initialization

In GA population, weights of classifiers are combined into a string of real values as chromosome. Here, the problem to be solved is the optimization of weighted feature vectors in order to combine different measurement values given by k classifiers and determine the final decision. The well-known Michigan approach [22] is used to maintain a population consisting of candidate weighted feature vectors as a set of genes in chromosome that represents a single activity rule. Each activity rule of length β consists of two portions, the antecedent portion (1 to β-1) is the logical combination of weights of k classifiers and the subsequent portion (last bit) represents the activity class c_i. The size of the activity rule $\beta = cl*k$ is fixed depending on the number of k classifiers and cl class labels in a smart home. The representation of weights is divide into k parts for k classifier system: $W_1,...,W_k$. W denotes the weight vector for k^{th} classifier, w_{ik} is the i^{th} weight of W_k, and represent the relative importance of the k^{th} classifier for class i. It is a positive number between 0.0 and 1.0. For example, when cl =3 and k= 4, a possible chromosome encoding is shown in Figure 1.

Sample Values	0.59	0.12	0.29	0.33	0.25	0.42	0.35	0.49	0.16	0.15	0.24	0.61	4
Classifier weights	w_{11}	w_{12}	w_{13}	w_{21}	w_{22}	w_{23}	w_{31}	w_{32}	w_{33}	w_{41}	w_{42}	w_{43}	c_i
	$\longleftarrow k_1 \longrightarrow$			$\longleftarrow k_2 \longrightarrow$			$\longleftarrow k_3 \longrightarrow$			$\longleftarrow k_4 \longrightarrow$			Activity Class

Figure 1. Activity Rule Encoding

The initial population is generated by setting the weights in each chromosome randomly. Once initial population is generated, the GA stochastic operations iteratively update the population according to the evolution fitness to assign the activity class.

3.5 Evolution Fitness

In the each iteration, an objective function called evolution fitness is used to qualify each activity rule and score it according to its performance in the classification optimization process. The evolution fitness function "*EF*" evaluates the candidate weighted vectors wv of classifiers measurement level output in search space against optimized activity rules R for a class label c on the following basis

$$EF = \frac{\sum_{i=1}^{n} F_i(wv, R_i)}{n} \tag{10}$$

Where n is the total number of optimized activity rules and

$$F_i(\mathrm{wv}, \mathrm{R}_i) = \begin{cases} 1 & \sqrt{\sum_{j=1}^{m} \left(wv_j - R_{ij}\right)^2} \leq \propto \\ 0 & otherwise. \end{cases}$$

Here, $\sqrt{\sum_{j=1}^{m} \left(wv_j - R_{ij}\right)^2}$ is the measure to calculate the difference between search space and activity rule space based on activity class differences where $\propto$ is the constant to control the influence of success on overall learning process. Chromosomes are then ranked according to these scores called fitness values.

3.6 GA Stochastic Operations

In the each iteration of GA, a new population is generated by probabilistically selecting the fittest chromosomes from the previous population. Some of the chromosomes are transferred intact into the next generation. The others are used as a basis for creating new offspring by applying genetic operators, such as selection, crossover, and mutation.

3.6.1 Selection

In the proposed solution, selection of the fittest chromosome is based on its ranking according to evolution fitness. The whole population is sorted in descending order of fitness values, and a pair of parent selection for crossover operator incorporated the low fitness chromosome with the best fit chromosome. After ranking of population, in order to guarantee exploration of whole search space, one parent is randomly selected from top 50% of highly ranked population, while the other is selected from the other half of the population.

3.6.2 Crossover

Crossover is performed on the selected parents to create the new offspring. A dynamic two point crossover is applied as a reproduction operator. Two uniform cut points are selected at random from the integer range [1, β-1] and two new state strings $Ofsp_1$ and $Ofsp_2$ are created by swapping the values between cut points. For example, if the value of cut points $c_1=3$, and $c_2=9$ are selected randomly as crossover points, we exchange the bits around that point as shown in Figure 2. In the each iteration of GA, the fittest replacement mechanism is applied so the entire generation is replaced with the new generation by keeping the best fit from last generation.

				c_1						c_2		
Par_1	0.23	0.56	0.21	0.32	0.15	0.53	0.68	0.21	0.11	0.74	0.15	0.11
Par_2	0.26	0.59	0.15	0.31	.052	0.35	0.65	0.07	0.28	0.32	0.23	0.45
$Ofsp_1$	0.23	0.56	0.21	0.31	.052	0.35	0.65	0.07	0.28	0.74	0.15	0.11
$Ofsp_2$	0.26	0.59	0.15	0.32	0.15	0.53	0.68	0.21	0.11	0.32	0.23	0.45

Figure 2. An example of two-point crossover on 12-bit chromosome

3.6.3 Mutation

In the proposed approach mutation as a background operator inaugurates the diversity in current population to increase the fitness of chromosomes. The mutation operator adds a random value on randomly selected genes of a chromosome according to the mutation rate. This operation confirms the diversity in the weighted ensemble of classifiers and avoids the stagnation of search space during the optimization process.

Algorithm 2. Recognizing the activities

Input: *R(1…m)* – optimized activity rules
wv – base classifiers weighted features
$\propto$ - fitness threshold
Output: *Al*– Activity label
Begin
for *j = 1: size(R)*
  if *(evaluate (wv, R(1…m)) <* $\propto$*)*
    voteList[]= vote+1
  end
  Al = max (voteList)
end
End

The stopping criterion for classifiers ensemble learner is either a fixed number of generations or all training instances passed correctly. Later in the results and evaluation section, we discuss the optimal values for the number of generations, the size of the population, the crossover rate and the mutation rate.

3.7 Recognition Phase

This phase recognizes the activity class label based on the classifier weighted features and optimized activity rules. For a particular set of classifiers weighted features, optimized activity rules are fired after considering the fitness threshold to recognize activity class labels. If more than one activity rules are fired then conflicting class labels are resolved by majority voting. The pseudo code for the recognition phase is given in Algorithm 2.

4. RESULTS AND EVALUATION

In this section, we present the results to evaluate and validate the feasibility of classifier ensemble optimization in the activity recognition domain. The proposed method has been implemented in MATLAB 7.6. The configuration of the computer is an Intel Pentium(R) Dual-Core 2.5 GHz with 3 GB of memory and Microsoft Window 7. We split the dataset using the 'leave one day out' approach; therefore, the sensor readings of one day are used for testing and the remaining days for training. The optimal values for the number of generations, the size of the population, the crossover rate and the mutation rate are evaluated. For population size, we analyzed its range from 25 to 60 and found an optimal point at 45. Similarly, different generation sizes are estimated for the convergence of the proposed method and a stable point is observed after 400 generations, there is no significant improvements are found after this point. We also analyzed the optimal point for crossover and mutation rate with different values and discovered optimal points at 0.7 and 0.04 Furthermore; we set the value of $\propto = 0.25$ to control the influence of success during the recognition phase. The results of our experiments are shown in $n \times n$ confusion matrices. For *Tulum2009,* the results are presented in Table 1, the activities 'Group Meeting', 'Watch TV', and 'Leave Home' are recognized with high accuracy. The most confusion takes place during the 'Cook Breakfast', 'Cook Lunch' and 'R1 Snack' activities. These were recognized correctly most of the times but mixed with five to six other cooking and eating activities.

The confusion matrix for *TwoSummer2009* shows that 'Grooming' and 'R1 Shower' are recognized with the highest accuracy as they only confused 4 to 5 times with other activities. While, all other activities are recognized with the acceptable accuracy, confusion among activities does not exceed more than 13 times that is insignificant in comparison to the total occurrences of the activities. The most confusion takes place in the recognition of 'R1 Work' and 'R2 Work' activities as shown in Table 2. The above confusion matrices show that our proposed method not only recognize dissociated activities, such as 'Sleeping and 'Watch TV' with significant accuracy but its outperforms all other techniques for the recognition of activities that are highly correlated, such as 'Cook Breakfast', 'Cook Lunch' and 'Snack Activity'. This validates the significance of the proposed method for recognizing the daily life activities.

Table 1. The confusion matrix of recognized activities in the *Tulum2009*

Activities	Cook Breakfast	Cook Lunch	Enter Home	Group Meeting	Leave Home	R1 Eat Breakfast	R1 Snack	R2 Eat Breakfast	Wash Dishes	Watch TV	Total Activity Occurrence
Cook Breakfast	**74**	1	-	2	-	1	-	1	1	-	80
Cook Lunch	3	**48**	-	1	-	-	10	5	2	2	71
Enter Home	-	-	**69**	2	2	-	-	-	-	-	73
Group Meeting	1	-	-	**10**	-	-	-	-	-	-	11
Leave Home	-	-	3	-	**72**	-	-	-	-	-	75
R1 Eat Breakfast	2	-	-	-	-	**56**	8	-	-	-	66
R1 snack	1	1	-	-	-	1	**484**	1	1	2	491
R2 Eat Breakfast	2	2	-	-	-	-	-	**42**	1	-	47
Wash Dishes	1	-	-	-	-	-	7	2	**59**	2	71
Watch TV	-	-	-	-	-	-	3	-	-	**525**	528

Table 2. The confusion matrix of recognized activities in the *TwoSummer2009*

Activities	Cleaning	Meal Preparation	Grooming	R1 Shower	R1 Sleeping	R1 Wake up	R1 Work	R2 Shower	R2 Sleeping	R2 Wake up	R2 Work	Total Activity Occurrence
Cleaning	**22**	2	-	1	1	-	1	-	-	1	-	28
Meal Prep.	2	**190**	-	-	-	2	3	-	-	2	-	199
Grooming	-	-	**43**	2	-	-	2	-	-	-	-	47
R1 Shower	-	-	-	**36**	1	1	2	-	1	-	-	41
R1 Sleeping	-	-	-	4	**41**	-	2	2	-	3	-	52
R1 Wakeup	-	2	-	-	4	**39**	-	-	2	1	-	48
R1 Work	-	3	6	2	7	-	**405**	3	7	-	10	443
R2 Shower	-	2	-	3	-	-	1	**20**	-	-	2	28
R2 Sleeping	-	-	-	3	3	-	-	1	**18**	-	1	26
R2 Wakeup	-	3	-	-	-	2	1	-	-	**19**	-	25
R2 Work	-	13	4	1	2	-	11	-	1	-	**320**	352

We compare our proposed method Classifier Ensemble (CE) with the results of base classifiers and Majority Voting (MV) [23] as a combination method. The MV method goes with the decision when there is a consensus for it or at least more than half of the classifiers agree on it. We kept all the data settings unchanged and reported the results in Figures 3 and 4. A remarkable improvement in terms of accuracy has been achieved compared to the previous work. As can be seen from Figure 3, our proposed model achieves significant improvement in all recognized activities in *Tulum2009* except 'Wash Dishes', in comparison to ANN and 'R1 Snack' and 'Cook Breakfast' in comparison to CRF. The most noticeable improvements are achieved for the recognition of 'Cook Lunch', 'Enter Home, 'Leave Home' and 'R2 Eat Breakfast' activities.

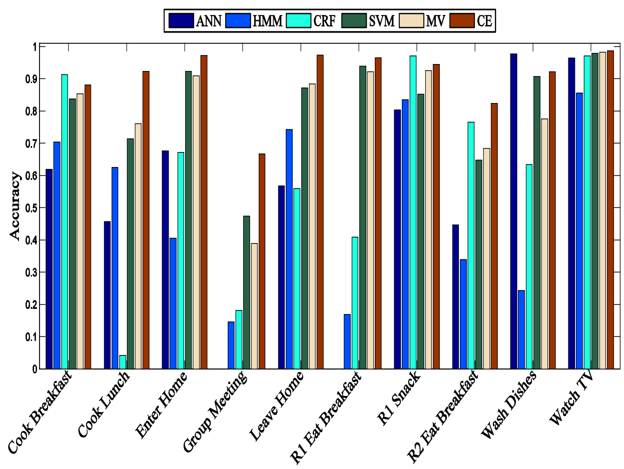

Figure 3. The *Tulum2009* activity recognition results

For TwoSummer2009, significant improvements in accuracy are achieved except 'R2 Sleeping in Bed' and 'R2 Wakeup' in comparison of ANN. The most noticeable improvements are in case of 'R1 Shower', 'R1 Sleeping in Bed' and 'R1 Wakeup' as shown in Figure 4. Class level comparison of accuracies shows the variations in performance of all classifiers and validates the better performance of the proposed approach in most of the cases.

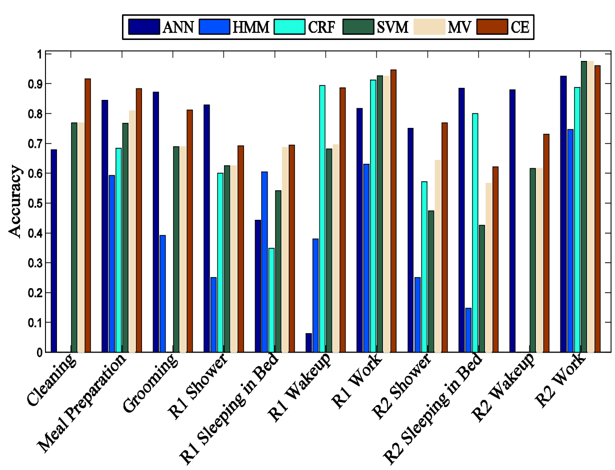

Figure 4. The *TwoSummer2009* activity recognition results

It can be seen from Figure 5, our proposed model shows stable results in comparison of avg., max., and min. accuracy of all techniques. In case of min. accuracy some of the base classifiers show zero results that means they fail to classify even a single occurrence of at least one activity class label. The maximum accuracy is either high or similar, while the minimum and average accuracy is always high in all classes. The above results and statistics clearly show that dataset characteristics highly affect the classifiers' individual class level assignments and thus their overall performances. Our proposed CE method shows overall better performance in case of both datasets.

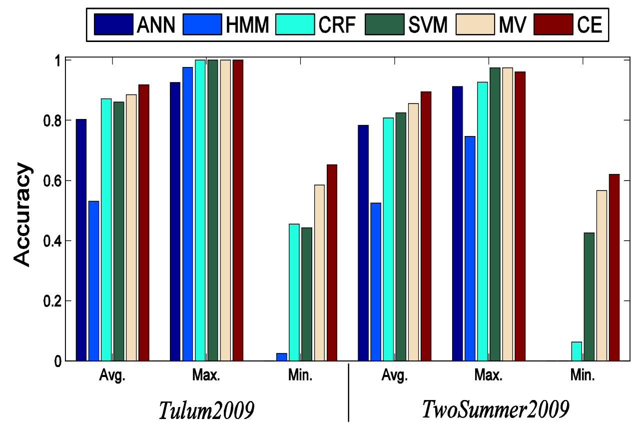

Figure 5. Accuracy comparisons (Avg., Max., and Min.)

5. CONCLUSION

In this paper, we proposed a novel technique of classifier ensemble optimization for activity recognition in smart homes. Our main idea is based on the fact that usually classifiers perform complementary to each other for the recognition of activities to be identified. The advantage of the proposed approach is to combine the measurement level decisions of base classifiers by considering their relative competence in the context of assigned weights to each activity class. We have used ANN, HMM, CRF, and SVM as base classifiers for activity recognition. The proposed design of GA, optimized the weighted feature factors for different output classes in each classifier for final activity class label. In the proposed method the weights are encoded in a chromosome as a string of real values. Hence, a GA based ensemble of multiple classifiers leads to a significant accurate results for recognizing the daily life activities. We evaluated our proposed technique on three publically available smart home datasets and experiments show the effectiveness of our proposed approach with the promising results in comparison to the state-of-the-art single classifiers and multi model techniques.

In this study, daily life activities are recognized independently with high accuracy but in reality the activities performed by human users are highly complex and interdependent on each other. This limits the applicability of this model at present; however, the generic nature of training and implementation will lead to the success of proposed method for conceivable complex situations. In our future research, we will extend our proposed method to recognize the interleaved, consecutive and parallel activities with comparable accurate results.

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