SUPPORT VECTOR MACHINE BASED MID LEVEL HUMAN ACTIVITY CLASSIFICATION IN SMART HOME ENVIRONMENTS

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ABSTRACT

With an increase in popularity of wearable technology, people are more inclined to wear trackers on them, in a bid to aid them in monitoring their daily lifestyles. In this paper, we aim to look at how wearable technology can assist us in predicting the different actions of the said wearer. With this modelling technology, it will be extremely beneficial, particularly in the healthcare industry where we can monitor the actions of the patients and elderly. We classify mid-level activities such as opening and closing doors, fridge, drawers etc. using Support Vector Machine, which helps in predicting the actions of a 'known' person doing daily actions to 95% and 'unknown' person to 81%

Keywords *– Human activity recognition, IoT, Support Vector Machines*

1. INTRODUCTION

In the 21st century, there is an increasing trend of consumers donning on wearables and these wearables have the potential to generate out huge amount of personal health data which can assist them in their daily lifestyle. [1][2]
With the rise of IoT, the problems of accessing the data from the sensors and compiling them have been removed and it is easy to consolidate huge amount of data from these sensors to make insights out of them. By amassing these data, we can work on the main objective of the project which is to recognize human activity and user context just from the data obtained through the different sensors attached to the human body. With this result, we can move one step further in the health care sectors. In the field of elderly care, elderlies who are suffering from Alzheimer diseases will have locomotive issues and with these wearables, we are able to perform Gait analysis and therefore predicting anomalies in their daily movements. With this prediction, we can move on to using different mechanism to assist these people in their daily movements.
This report serves as showcasing a model in predicting the movements of a user based on the different sensors attached on the model. The modelling tool used will be SVM and the actions to be predicted in the model will be explain in the dataset below.

2. DATASET

3.1. Data Source

The dataset we have used comes from the Opportunity Challenge Dataset for Activity and Context Recognition with Opportunistic Sensor Configuration. It was a challenge held in 2011 which aimed to predict the different gestures done by the test subject in a daily setting. The different gesture are normal daily actions as shown below.

OPEN FRIDGE	CLOSE FRIDGE	OPEN DRAWER 1	CLOSE DRAWER 1
OPEN DISHWASHER	CLOSE DISHWASHER	OPEN DRAWER 2	CLOSE DRAWER 2
CLEAN TABLE	MOVE CUP	OPEN DRAWER 3	CLOSE DRAWER 3
		OPEN DOOR 1	CLOSE DOOR 1
		OPEN DOOR 2	CLOSE DOOR 2

[Table 1: Different activity gestures]

In this dataset, we have 115 different sensor readings from more than 70 sensors all placed in the experiment room as well as on the test subject itself. Each sensor provides the displacement of the test subject actions in 33 to 34 milli seconds. As such, there are 3 different readings for the same sensor on the test subject. The data collection was taken over 5 days for 4 different test subjects. With this huge amount of data collected for this experiment, we aim to achieve good results in the prediction of the actions done by each test subject.

3. PRE-PROCESSING & EXPLORATORY DATA ANALYSIS

3.1. Preprocessing steps

3.1.1. Filling missing values
Some readings have NaN due to disconnections by the Bluetooth receiver service. We impute the null values by replacing with the same most recent readings of the same target class. E.g. if right arm readings are lost when performing the activity 'open door', the most recent values associated with the right arm when the subject performed the same activity are copied. This granularity in imputation is with the belief that the same activity will most likely create the same/similar set of readings.

3.1.2. Data Scaling
Each column in the data is individually scaled to achieve zero mean and unit variance.

3.2. Exploratory Data Analysis

After cleaning up the data we computed the metrics revolving each activity in terms of duration such as min, max, average and median, as presented below.

Class	Min (secs)	Max (secs)	Mean (secs)	Median (secs)
Null_Activity	0	359.20	16.71	4.16
Open_Door1	1.27	7.6	2.8	2.77
Open_Door2	1.07	6.23	2.53	2.67
Close_Door1	0.767	4.699	1.848	1.7
Close_Door2	1.566	7.03	4.235	4.267
Open_Fridge	3.3	5.933	4.404	4.367
Close_Fridge	0	3.933	1.74	1.7
Open_Dishwasher	0.567	12.433	2.46	2.367
Close_Dishwasher	0.633	3.967	2.142	2.067
Open_Drawer1	1.4	5.633	2.78	2.767
Close_Drawer1	1.2	3.966	2.354	2.3
Open_Drawer2	0.8	3.867	2.10	2.033
Close_Drawer2	1.967	6.43	4.45	4.48
Open_Drawer3	2.7	6.766	4.976	4.934
Close_Drawer3	0.7	3.304	1.934	2.034
Clean_Table	1.367	7.633	2.903	2.634
Drink_Cup	2	64.933	8.42	7.2
Toggle_Switch	0.7	17.067	6.29	5.88

[Table 2: Activity duration]

4. RGTSVM PACKAGE

This section provides special mention about an opensource package 'Rgtsvm' [5] [6] in R which allows implementation of SVM in GPU. The corresponding paper is available in [4] The GPU implementation provides faster training time and the package itself is handy with available methods to train, tune and make predictions using simple commands. The train method also allows to change the kernels, adjust gamma and C values and has an option to scale the readings (zero mean, unit variance) automatically before training.

5. BASELINE APPROACH

5.1. Train – Validation - Test split

The five-day data of subjects S1, S2, S3 are merged together to create ~497K readings (records). Using a stratified sampling approach, we select 5% of the dataset to get 25K records, which is then split in 80-20% ratio as the train and validation sets. The class count for training is tabulated in Table 3.

Class	Record Count
Null_Activity	19784
Open_Door1	178
Open_Door2	154
Close_Door1	90
Close_Door2	191
Open_Fridge	212
Close_Fridge	110
Open_Dishwasher	375
Close_Dishwasher	178
Open_Drawer1	163
Close_Drawer1	159
Open_Drawer2	105
Close_Drawer2	235
Open_Drawer3	254
Close_Drawer3	111
Clean_Table	438
Drink_Cup	1880
Toggle_Switch	199

[Table 3: Class count for training set]

The remaining ~472K records are retained as a new test set – S1-3_oa (Subjects S1to S3_otheractivities)

We also consider subject S4 separately (~14.7k records over five days) as a test set S4. By having two separate test sets, we aim to understand the effect of the classifier in:
- Training and inference on the same subjects but different activity timespan
- Training on a set of subjects and inference on a new subject, to check for generalization.

5.2. Evaluation
The default SVM-C configuration as provided in the package are:
SVM-Type: C-classification
SVM-Kernel: radial
cost: 1

gamma: 0.00840336
Detailed baseline results are provided in table 4.

Activity	precision	recall	f1-score	support
Null_Activity	0.93	0.99	0.96	375882
Open_Door1	0.79	0.56	0.66	3376
Open_Door2	0.60	0.78	0.68	2914
Close_Door1	0.72	0.25	0.37	1696
Close_Door2	0.88	0.63	0.73	3613
Open_Fridge	0.89	0.82	0.85	4016
Close_Fridge	0.70	0.29	0.41	2076
Open_Dishwasher	0.62	0.74	0.68	7120
Close_Dishwasher	0.66	0.68	0.67	3377
Open_Drawer1	0.70	0.54	0.61	3080
Close_Drawer1	0.62	0.80	0.70	3013
Open_Drawer2	0.74	0.27	0.39	1976
Close_Drawer2	0.92	0.59	0.72	4458
Open_Drawer3	0.89	0.86	0.87	4826
Close_Drawer3	0.81	0.11	0.20	2104
Clean_Table	0.99	0.07	0.12	8320
Drink_Cup	0.92	0.69	0.79	35717
Toggle_Switch	0.90	0.85	0.87	3780
avg/total	0.91	0.91	0.90	471344

[Table 4: Per class F1-Score (Top-1) on results of 3 subjects' other activities S1-3_oa]

Activity	precision	recall	f1-score	support
Null_Activity	0.84	0.97	0.90	119452
Open_Door1	0.76	0.05	0.10	877
Open_Door2	0.27	0.08	0.12	654
Close_Door1	0.00	0.00	0.00	556
Close_Door2	0.56	0.26	0.36	1154
Open_Fridge	0.43	0.59	0.50	1007
Close_Fridge	0.20	0.00	0.00	539
Open_Dishwasher	0.47	0.00	0.01	2849
Close_Dishwasher	0.02	0.00	0.01	970
Open_Drawer1	0.00	0.00	0.00	879
Close_Drawer1	0.33	0.33	0.33	698
Open_Drawer2	0.00	0.00	0.00	583
Close_Drawer2	0.79	0.01	0.02	1502
Open_Drawer3	0.00	0.00	0.00	1276
Close_Drawer3	0.00	0.00	0.00	743
Clean_Table	0.00	0.00	0.00	2765
Drink_Cup	0.24	0.11	0.15	7856
Toggle_Switch	0.64	0.58	0.61	2648
avg/total	0.74	0.81	0.76	147008

[Table 5: Per class F1-Score: Top-1 on results of subject S4]

The test set S1-3_oa has an accuracy of 0.9148 while the other test set S4 achieves only 0.7941.

6. PROPOSED APPROACH

6.1. Temporal consideration of human activities

The baseline approach does not consider the temporal factor for activities. In practical scenario, any of the target activities require more than a second to perform. Since each reading occurs every ~34 millisecond, the combined sequence of sensor readings need to be considered.

We consider using Exponential Moving Average (EMA) to study the effect of contribution of previous readings to the current one while retaining highest weight towards most recent reading (as the weights reduce exponentially) The window size was selected for 4 based on the median duration of all the activities combined. (as seen in the EDA section above)
*EMA = alpha * Yt + (1-alpha)*Yt , when t>1; Yt when t=1*, where alpha = 2/(window_size + 1) and Yt denotes the current sensor reading.

6.2. Kernel selection

The following 3 common kernels were chosen for model fitting for the given dataset namely,

- Radial Basis $K(x, x') = \exp\left(-\frac{\|x - x'\|^2}{2\sigma^2}\right)$
- Linear $u^T v$
- Polynomial (fixed at degree 3)
  $K(x, y) = (x^T y + c)^3$

By using this 3 different Kernel Selection, we can identify the best parameter required for this model itself. Through the discussion with the team, we believe that Radial Basis Function will have the best results as the data set is based on the spatial relationship between the different actions on the different parts on the body. As such, there should be a higher dimension relationship within the dataset itself. After which, the second-best result should be the polynomial function followed by the Linear Function.

6.3. Hyper parameter tuning

The hyperparameter tuning was performed using grid search by varying Gamma, C and Kernel for different ranges. Table 6 provides the accuracy for only the top performing configurations and is not the exhaustive list.

S. No.	C	Gamma	Kernel	Accuracy
1	0.8	0.0254	Radial	0.9324
3	1.0	0.0254	Radial	0.9372

4	1.2	0.0254	Radial	0.9405
5	1.2	0.0154	Radial	0.9384
6	1.4	0.0254	Radial	0.9430
7	1.4	0.0154	Radial	0.9412
8	1.6	0.0254	Radial	0.9453
9	1.6	0.0154	Radial	0.9436
10	2.0	0.0254	Radial	0.9487
11	2.4	0.0254	Radial	0.9509
12	2.8	0.0254	Radial	0.9527
13	3.2	0.0254	Radial	0.9548
14	**3.6**	**0.0254**	**Radial**	**0.9556**
15	3.6	0.0254	Linear	0.8816
16	3.2	0.0254	Linear	0.8814
17	**3.6**	**0.0254**	**Polynomial**	**0.9584**
18	3.6	0.0554	Polynomial	0.9573
19	3.8	0.0554	Polynomial	0.9573
20	3.2	0.0254	Polynomial	0.9562

[Table 6: Grid Search results]

The optimal arguments were {C=3.6, gamma=0.0254, kernel=Radial} which gave accuracy = 0.9556 and F1 score=0.9780. This model was selected for the test dataset predictions. Although polynomial kernel results look promising the performance against the test set was not better in comparison to the radial kernel.

6.4. Test data

The test datasets are modified by the same process as the trainset to include the temporal characteristics. Thus S1-3_ova and S4 records are processed by a sliding window of 4. The data is centered and scaled before giving to the chosen model.

7. EXPERIMENTAL RESULTS

7.1. Evaluation

The test results for the two datasets – S1-3_oa and S4 are provided in the table 7.

S. No.	Approach	Top – 1 Accuracy	Top – 2 Accuracy	Top – 3 Accuracy
1	Baseline – S1-3_oa	0.9148	0.9665	0.9823
2	Baseline – S4	0.7941	0.8819	0.9093
3	Proposed – S1-3_oa	**0.9555**	**0.9853**	**0.9925**
4	Proposed – S4	**0.8176**	**0.8985**	**0.9216**

[Table 7: Test results]

The Top-1 f-score results per class of the improved model on the test dataset (S1-3_oa) are available in the table 8and on subject S4 are available in table 9. The Top-1,2,3 accuracy based ROC charts are also presented in Figure 1 and 2 respectively.

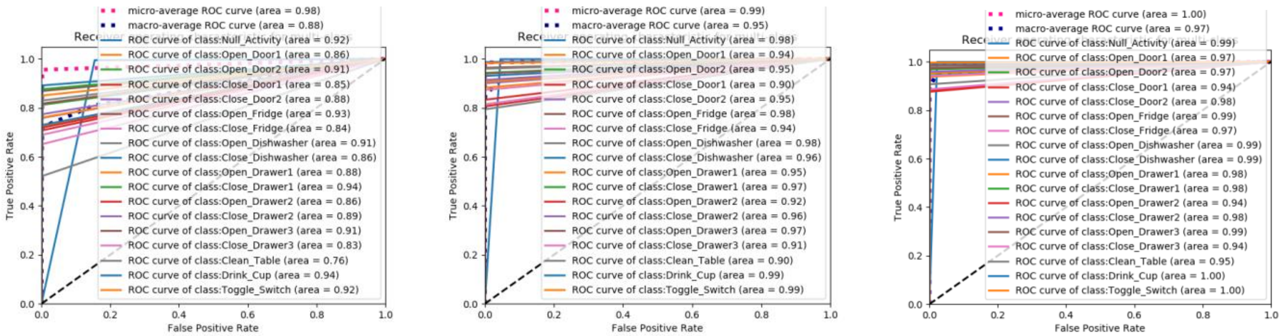
Activity	precision	recall	f1-score	support
Null_Activity	0.96	0.99	0.98	375882
Open_Door1	0.91	0.72	0.81	3376
Open_Door2	0.88	0.81	0.84	2914
Close_Door1	0.85	0.71	0.77	1696
Close_Door2	0.94	0.76	0.84	3613
Open_Fridge	0.95	0.87	0.91	4016
Close_Fridge	0.82	0.69	0.75	2076
Open_Dishwasher	0.83	0.83	0.83	7120
Close_Dishwasher	0.93	0.73	0.82	3377
Open_Drawer1	0.88	0.76	0.82	3080
Close_Drawer1	0.82	0.88	0.85	3013
Open_Drawer2	0.79	0.72	0.75	1976
Close_Drawer2	0.95	0.77	0.85	4458
Open_Drawer3	0.98	0.82	0.89	4826
Close_Drawer3	0.86	0.65	0.74	2104
Clean_Table	0.97	0.52	0.68	8320
Drink_Cup	0.96	0.89	0.92	35717
Toggle_Switch	0.97	0.85	0.91	3780
avg/total	0.96	0.96	0.95	471344

[Table 8: Per class F1-Score (Top-1) on results of 3 subjects' other activities S1-3_oa]

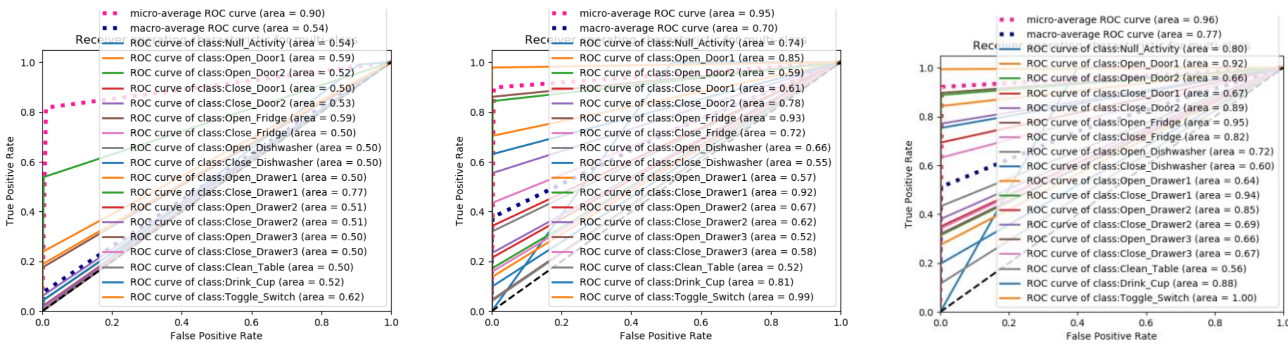
Activity	precision	recall	f1-score	support
Null_Activity	0.83	0.99	0.90	119452
Open_Door1	0.78	0.19	0.30	877
Open_Door2	0.36	0.04	0.07	654
Close_Door1	1.00	0.00	0.01	556
Close_Door2	0.84	0.06	0.11	1154
Open_Fridge	0.59	0.18	0.27	1007
Close_Fridge	0.00	0.00	0.00	539
Open_Dishwasher	0.00	0.00	0.00	2849
Close_Dishwasher	0.00	0.00	0.00	970
Open_Drawer1	0.00	0.00	0.00	879
Close_Drawer1	0.38	0.54	0.44	698
Open_Drawer2	0.37	0.02	0.04	583
Close_Drawer2	0.59	0.02	0.03	1502
Open_Drawer3	0.00	0.00	0.00	1276
Close_Drawer3	0.00	0.00	0.00	743
Clean_Table	0.00	0.00	0.00	2765
Drink_Cup	0.31	0.05	0.08	7856
Toggle_Switch	0.92	0.24	0.38	2648
avg/total	0.73	0.82	0.75	147008

[Table 9: Per class F1-Score: Top-1 on results of subject S4]

7.2. ROC Charts



[Figure 1: ROC plots – Top-3 activity classification results on 3 subjects' other activities S1-3_oa]



[Figure 2: ROC plots – Top-3 activity classification results on subject S4]

8. CONCLUSION

We have managed to achieve decent results by applying SVM on the Opportunity Dataset. By having two separate test sets, we determined that classifiers perform better when they classify for the same subject whose training data are fed versus a different subject whose activity patterns are not known.

Before using RGTSVM package in R, we have difficulties in running the model as the training time required for each model and grid search would take far too long. As such, with this package in R, we can delve deeper into the data set and tune more parameters more robustly to obtain a better result.

We have also understood the relevance in SVM for multi-type classification. By using kernel tricks, we bring the data up to high dimensions and classify the dataset accordingly. However, with a large amount of data, the training time required for SVM is exponentially large which makes it hard to scale without the use of GPU.

9. FUTURE ENHANCEMENT

Further feature engineering techniques are still possible, such as using a neural network (e.g. CNN, RNN) and can be pipelined to the SVM classifier. We can increase the scope of the project to a more natural environment out in public. The current setup of this experiment for is in a controlled room with 4 test subjects. We believe that better insights are possible if we were to increase the number of test subjects and segregate it according to gender. We can also increase the complexity of actions to be predicted such as falling down.

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