Tennessee TECH

Cognitive Health Prediction on the Elderly Using Sensor Data in Smart Homes

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Agendas

- Introduction/Motivation
- Background Research
- Data
- Methodology
- Results & Discussion
- Future Works

INTRODUCTION

WHAT DOES THE STATISTIC SAYS?

- 13% of the U.S. population in 2013 was of the age 65 and over and is estimated to rise to more than 20% by the year 2030 [2].
- 5.2 million people above the age of 65 have cognitive disabilities like Alzheimer and Dementia [1].

PROBLEM?

- Cognitive disabilities can limit their ability to perform day-to-day activities, requiring them to be dependent on caregivers.
- In 2016, the total annual costs associated with the care of patients with Alzheimer’s was estimated at $236 billion [1].
- And is estimated to increase to over $1 trillion in 2050 [1].
- So how do we provide better care and reduce the cost?

INTRODUCTION

- Smart home sensor systems can provide aid to elderly residents and their caregivers.
- The daily activities and behavioral patterns of residents can be monitored through sensors embedded within various areas in the home.
- Smart homes can reduce the cost by alleviating some responsibilities on care providers and reducing medical emergencies.

HYPOTHESIS

Through the application of various machine learning approaches, we can analyze data from the sensors installed in smart homes in order to detect anomalous behavior that might be predictive of cognitive impairment.

RELATED WORK

Research towards analyzing behavior of residents within sensor-based environments

RELATED WORK

Research Paper	Tool Used	Short Description
Lotfi et al. 2012	Neural Networks (Echo State Network)	Inform caregiver of any anomalous behavior that can be expected in future for dementia resident. But only works only for resident with routine activities.
Jakkula & Cook 2011	One Class SVM	Improve detecting anomalous behavior in a smart home data.
Novák, Binˇas, & Jakab 2012	Self-organizing maps	Added artificial anomalous behavior & could detect 75% of it.
Helal, Cook, &Schmalz 2009	Markov model	Use sensor data and video to analyze diabetic patient behavior.
Zhu, Sheng, and Liu 2015	Semi-supervised	Anomaly detection on wearable sensors in mock environment.
Dawadi, Cook, and Schmitter-Edgecombe 2016	Clinical Assessment using Activity Behavior (CAAB)	Created a Clinical Assessment using Activity Behavior (CAAB) approach to predict clinical assessment scores of the smart home resident but most the participants were healthy.
Cook, Schmitter-Edgecombe, and Dawadi 2015	Various machine learning algorithms	Use smart home and wearable sensors to collect data from older adults while they performed complex activities of daily living and automatically recognize a difference in behavior between healthy, older adults versus adults with Parkinson's disease.

DATA [10]

- Made available by Washington State University's CASAS program.
- Real-time data from sensors to analyze and monitor residents' health and behavior.
- Ten elderly residents between the ages of 80 and 91 living in single resident smart homes.
- Five out of the ten residents are diagnosed with MCI, while the other five are considered cognitively healthy.

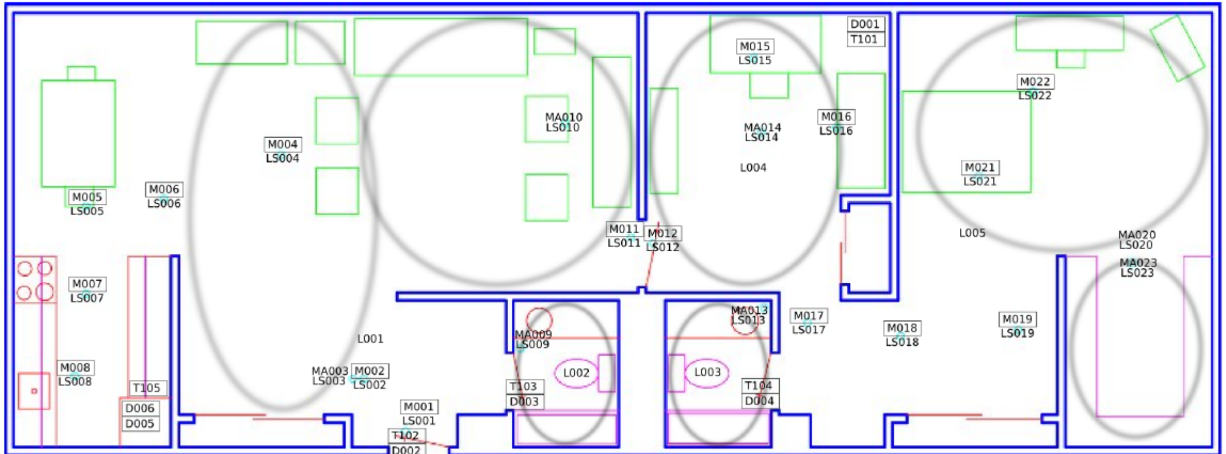

fig. Smart Home Floorplan Layout with Sensor [8]

DATA

```
2011-06-15   00:06:32.834414 M021     ON   Sleep="begin"
2011-06-15   00:06:33.988964 M021     OFF
2011-06-15   00:12:32.670631 BATV012  9540
2011-06-15   00:15:01.957718 LS013    6
2011-06-15   00:25:01.892474 LS013    7
2011-06-15   01:05:01.622637 BATV013  9460
2011-06-15   01:10:17.369388 BATV001  9500
2011-06-15   01:25:47.117808 BATV105  3100
2011-06-15   01:36:27.665051 BATV021  9520
2011-06-15   01:37:01.761435 BATV102  3160
2011-06-15   01:58:18.094543 BATV022  9480
```

→

```
2011-06-15,00:06:00,"Sleep"
2011-06-15,00:12:00,"Sleep"
2011-06-15,00:15:00,"Sleep"
2011-06-15,00:25:00,"Sleep"
2011-06-15,01:05:00,"Sleep"
2011-06-15,01:10:00,"Sleep"
2011-06-15,01:25:00,"Sleep"
2011-06-15,01:36:00,"Sleep"
2011-06-15,01:37:00,"Sleep"
2011-06-15,01:58:00,"Sleep"
```

fig. Sensor Data Snippet, annotated (left) cleaned (right) [8]

Class	Dataset 1	Dataset 2
Healthy	33,252 (5 residents)	10,004 (4 residents)
MCI	9,093(5 residents)	9093 (5 residents)
Total	**42,345 (10 residents)**	**19,097 (9 residents)**

Table 1: Dataset detail

Features	Description
Month	Month of the year
Activity	Resident activity
Precede by	Activity performed before current activity
followed by	Activity performed after current activity
Activity start time	Time at which resident starts the activity
Activity end time	Time at which resident ends the activity
Duration	Time required to do the activity
Time to Next Activity	Time taken to start next activity
Hour of day	Hour of day
Start time of day	Activity start part of the day
End time of day	Activity ending part of the day
Day of week	Day of a week
Is weekend	Flag for weekday or weekend
Motion sensor count	Number of motion sensor activated
Light sensor count	Number of light sensor activated
Light on count	Number of light turned on
Light off count	Number of light turned off

Table 2: Feature Used

METHODOLOGY

- Comprehensive analysis of traditional machine learning techniques for predicting mental cognitive impairments among elderly people in a smart home environment.
- All of our experiments are done in python using the sci-kit learning tool's.
- Label encoding is used to encode the categorical values.
- The label encoded data is then passed through data scaling.
- The algorithm is run on the scaled data using 10 fold cross validation

- Logistic Regression
- Linear Discriminant analysis (LDA)
- Decision Tree
- Support Vector Machine (SVM)
- K-Nearest Neighbor (KNN)
- Random Forest
- Ada Boosting
- One-Class SVM

RESULTS & DISCUSSION

RESULTS ON DATASET 1

Algorithm	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	**.77**	.69	.77	**.79**	.51
LDA	**.77**	.70	.77	.71	.52
KNN	**.77**	**.75**	**.78**	.76	.60
Random Forest	.74	.74	.75	.74	**.66**
Decision Tree	.70	**.75**	.71	.72	.63
Ada Boost	.70	.71	.71	.71	.57
SVM	.76	.72	.76	.73	.56
One-Class SVM	.52	.55	.53	.53	.54

Table: Performance of all algorithms on Dataset 1

Algorithm	Precision	Recall	F1-Score
Healthy	.83	.91	.86
MCI	.47	.30	.37
Average	.75	.78	.76

Table: KNN Performance on Dataset 1

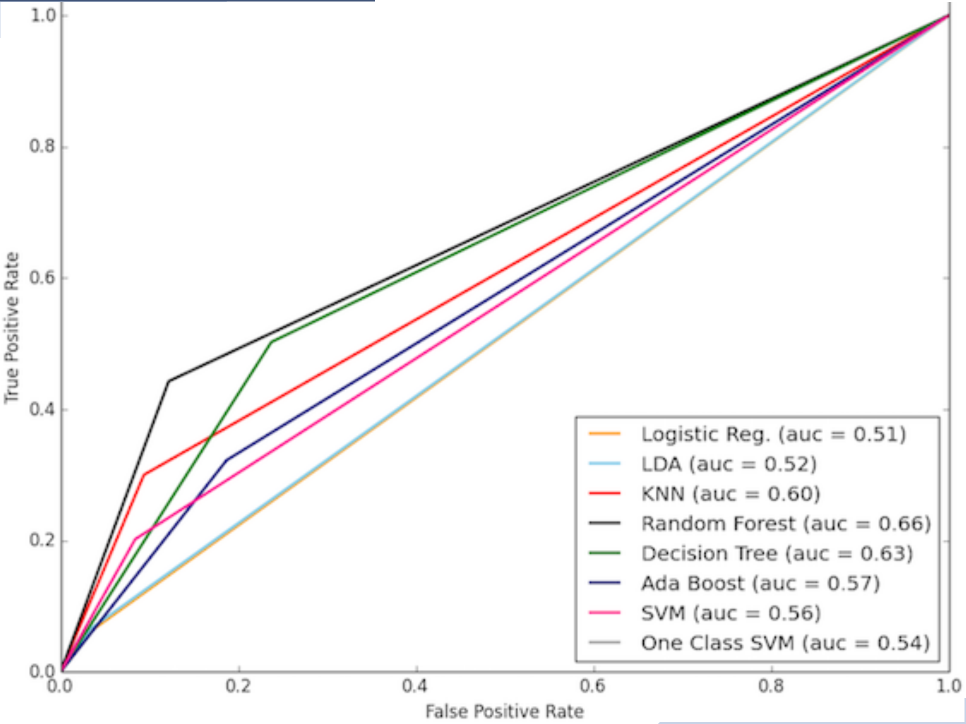

Fig: AUC of all algorithms on Dataset 1

RESULTS ON DATASET 2

Algorithm	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	.64	.65	.65	.65	.65
LDA	.64	.65	.65	.65	.65
KNN	.67	.68	.67	.67	.66
Random Forest	**.73**	**.74**	**.73**	**.73**	**.72**
Decision Tree	.68	.68	.68	.68	.68
Ada Boost	.65	.66	.66	.66	.66
SVM	.71	.71	.71	.71	.71

Table: Performance of all algorithms on Dataset 2

Algorithm	Precision	Recall	F1-Score
Healthy	.70	.84	.77
MCI	.78	.61	.68
Average	.74	.73	.73

Table: Random Forest Performance on Dataset 2

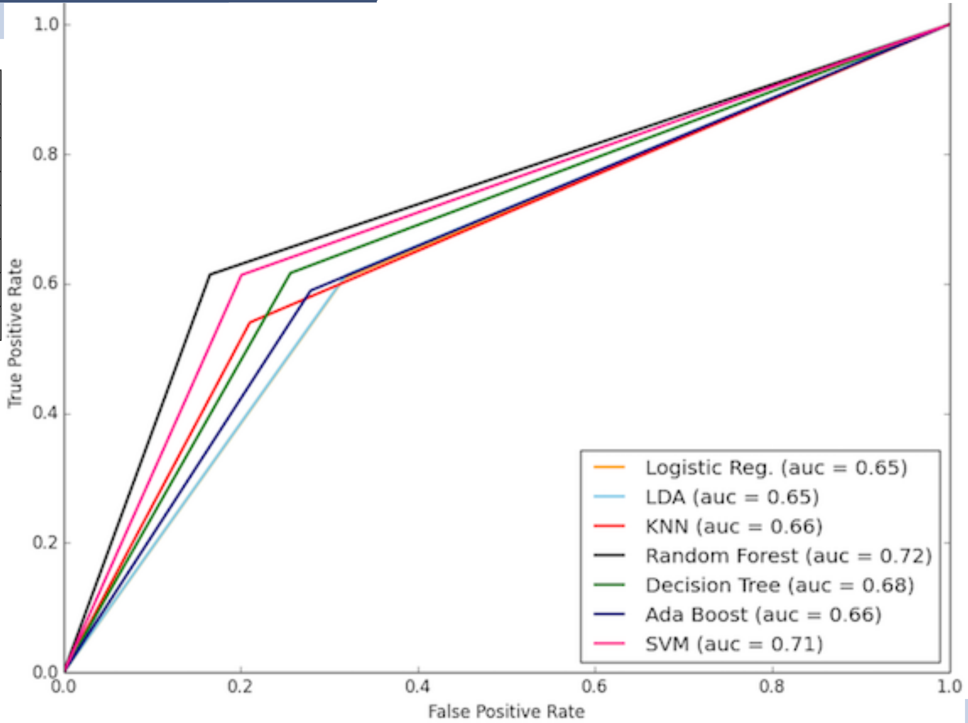

Fig: AUC of all algorithms on Dataset 2

DISCUSSION

- KNN shows the best performance to all other algorithms in dataset 1. However, dataset 1 has low recall for MCI class because of data being more biased toward healthy class.
- The low recall can be increased by making dataset more balanced.
- Random forest in dataset 2 which is a balanced dataset has the best performance with recall of 61% for MCI class and recall of 84% for healthy class.
- We are using segments of sensor values of each residents as one data point. This can introduce bias while using 10 fold cross validation because training and testing data will have data point from the same resident.
- Using leave-one-subject-out (training on 9 residents and testing on the 10th) cross validation might be able to deal with such bias.

CONCLUSION

- Smart home environments aim to not interfere with the normal activities of the residents and hope to reduce the cost of health care associated with caring for the resident.
- Our objective was to see if we can use automated machine learning techniques in smart home data to predict the cognitive health of resident and help clinician better allocate the resource and reduce the cost of elderly care.
- We formulated the problem as both a supervised and unsupervised learning problem.
- Analyzing the resident behavior using smart sensor data we have shown that machine learning can provide a physician and health care worker with valuable insights on resident mental health.

FUTURE WORK

- Since it is not easy to get a labeled dataset, we would like to focus more on improving the performance of our unsupervised approach.
- We also plan to investigate unsupervised graph- based approaches in order to discover anomalous activities and movements that can be used to report unusual, out-of- the-norm, behavior by a resident - a possible sign of the onset of dementia.
- In addition, we hope to involve a clinician as a domain expert so that we can validate our results.

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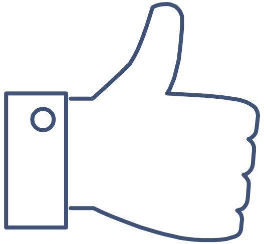

THANKS!

Any questions?