

# Human Activity Recognition using Skeleton Data from RGBD Sensors

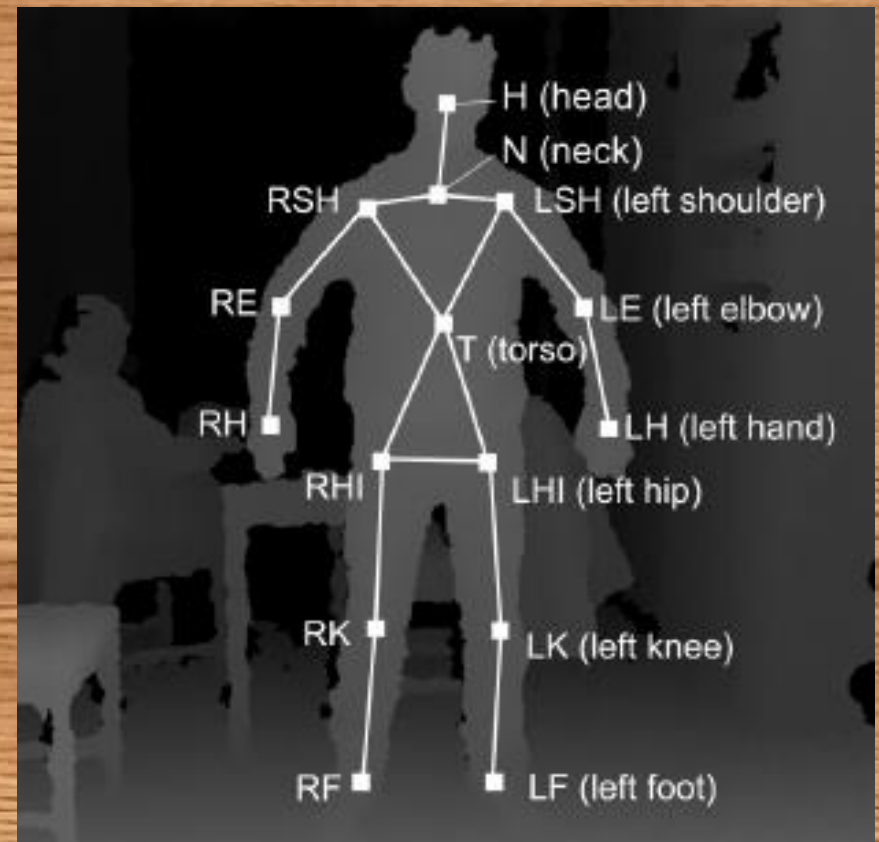
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**-Presented By: Dhanesh Pradhan**

# Overview: Problem Statement

## Overview

Develop Human Activity Recognition Algorithm exploiting skeleton data extracted by RGBD sensors

## System Architecture

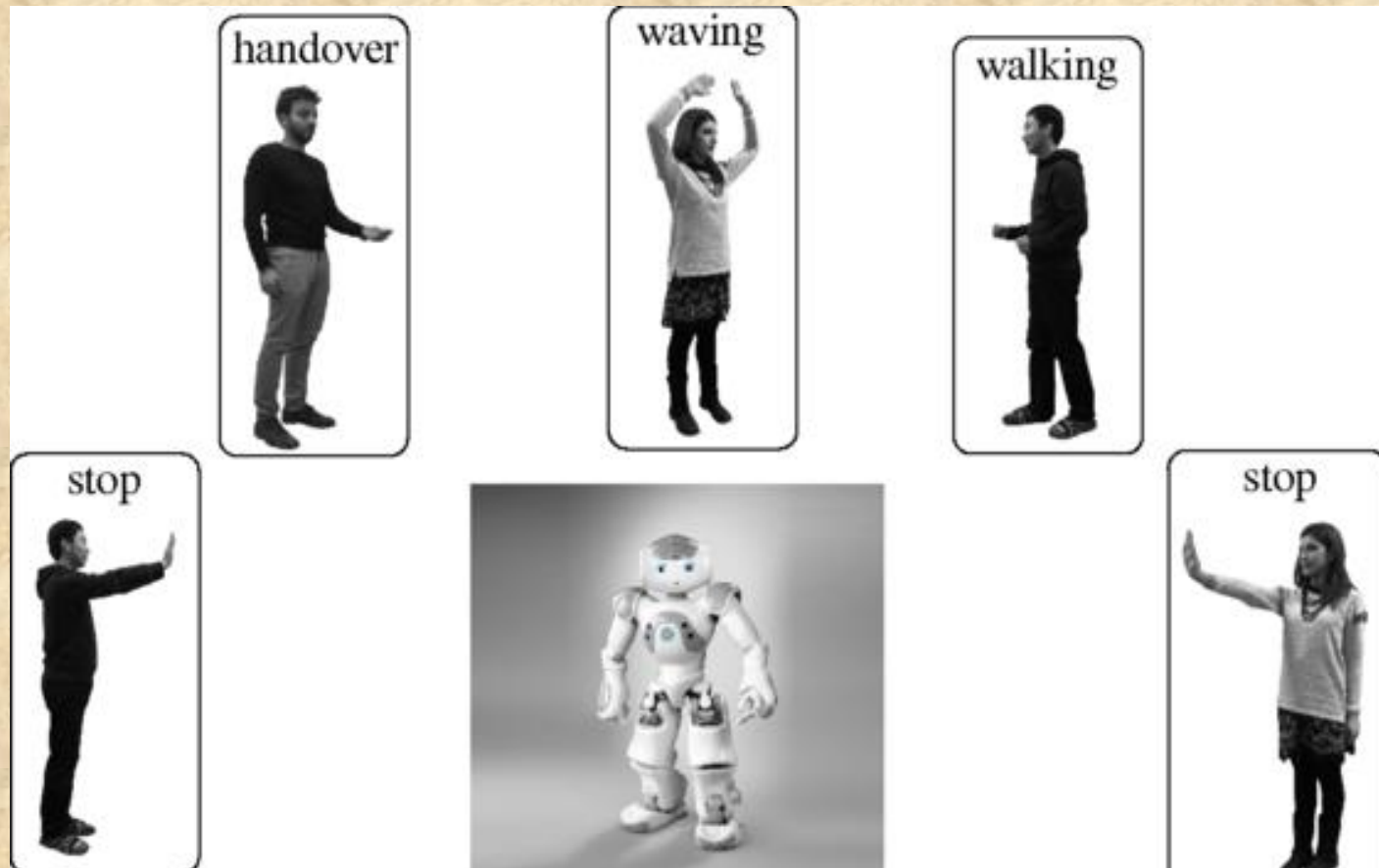
Result 1

Result 2

Result 3

Result 4

Conclusion



# Overview: CAD-60 Dataset

## Overview

### System Architecture

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## Description:

- 60 RGB-D videos
- 4 subjects
- 5 different environments
- 12 activities

## Issues:

3 Right handed  
person

1 Left handed  
person

## Data pre-processing

### HDC classifier architecture for human activity recognition

x,y,z axes

Kinect gives 14 joints + torso

Initialize Axis Item Memory to 3 hypervectors

Initialize Joints Item Memory to 14 hypervectors

Skeleton Joints Data

$$d_i = (J_i - J_0) / \text{norm}(J_2 - J_0)$$

Discretize skeleton data into MAXL levels

Initialize Joints Continuous Item Memory to MAXL hypervectors

MAXL Discrete data levels

Training Hypervectors =  
 $\text{Sum}(iM_{\text{joint}} * iM_{\text{axis}} * CiM(\text{level}))$

Store Training Hypervectors in  
Auto-associative memory

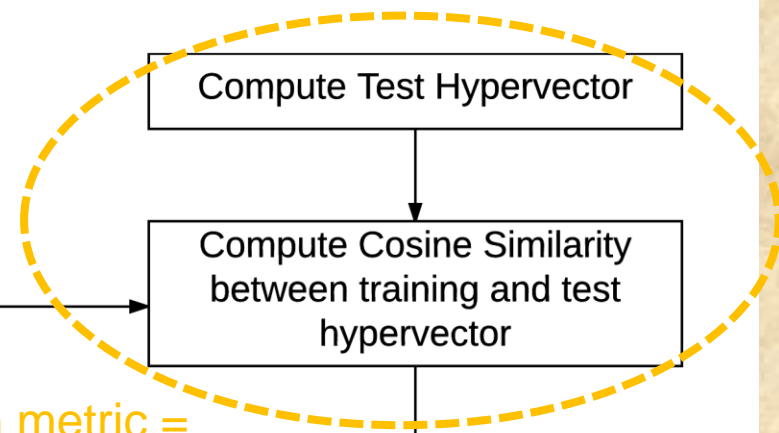
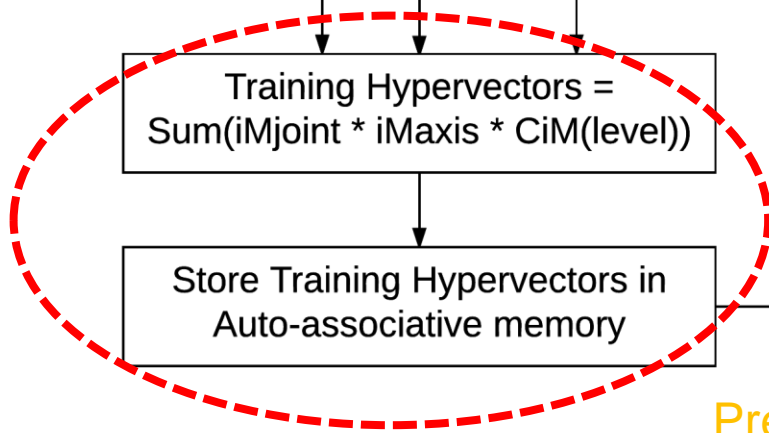
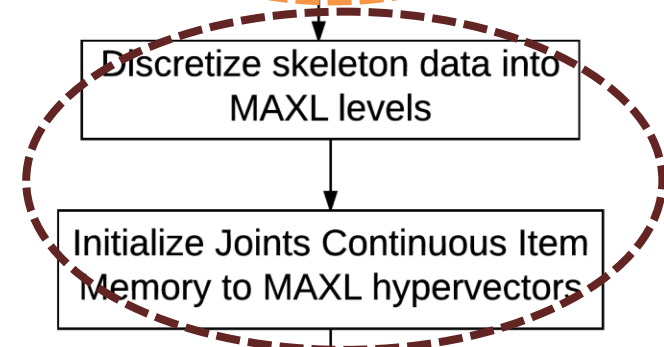
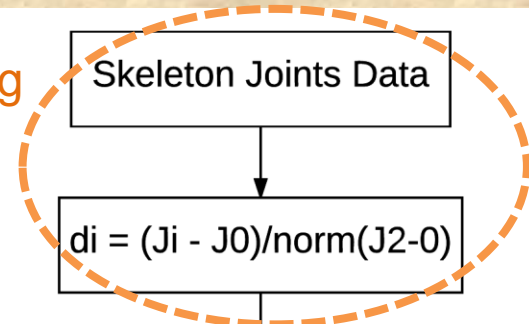
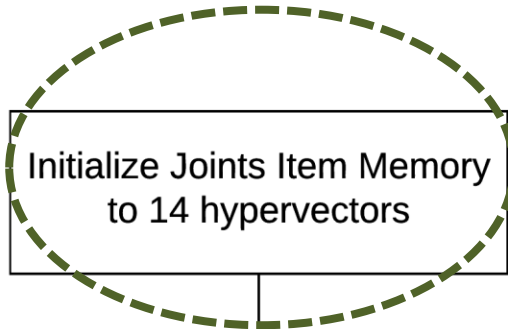
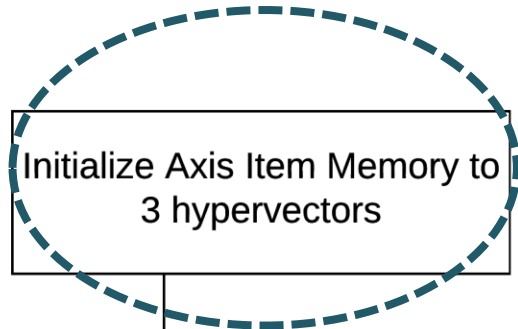
Compute Test Hypervector

Compute Cosine Similarity  
between training and test  
hypervector

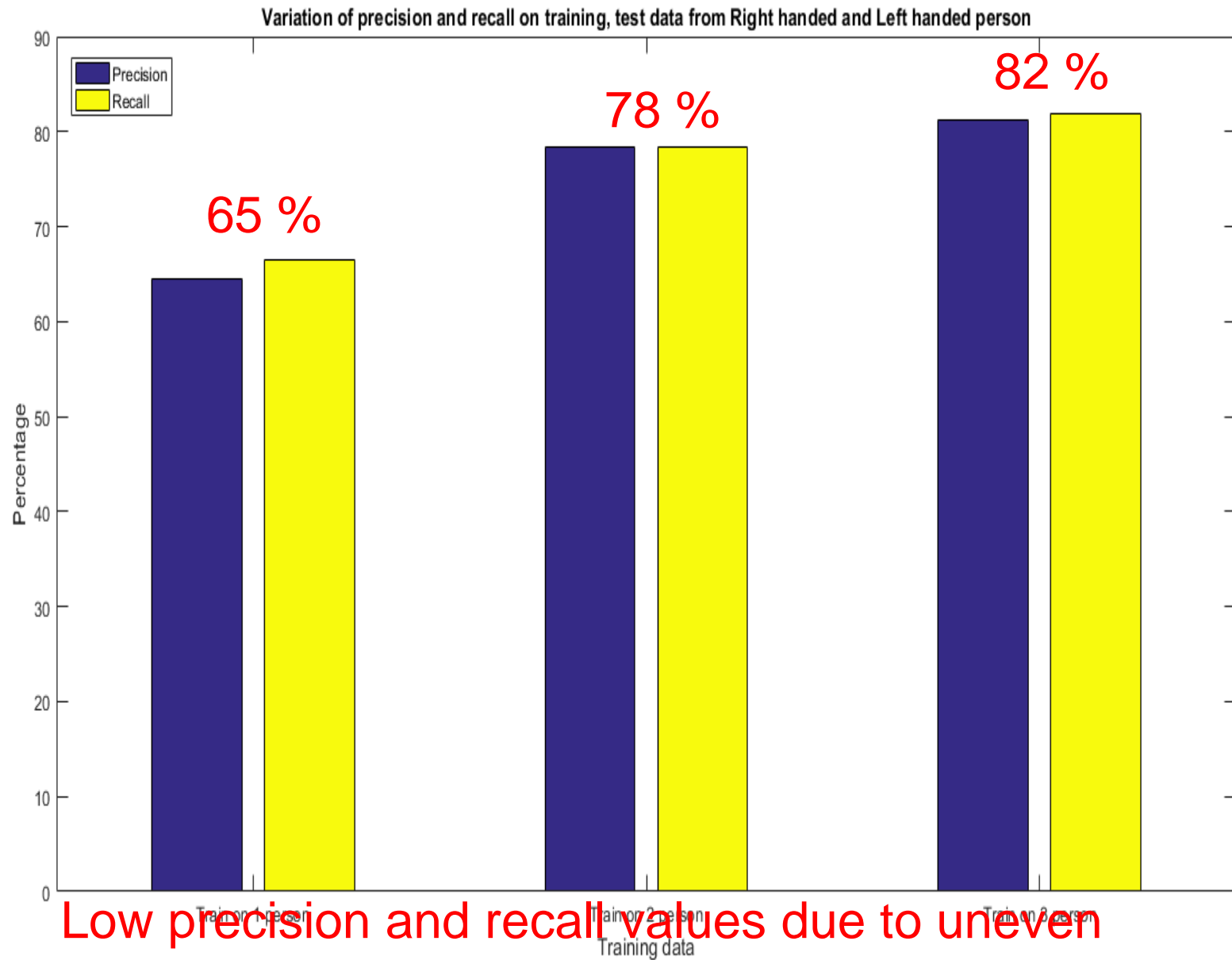
Assign label and calculate  
precision, recall

Compute training hypervector  
and store in memory

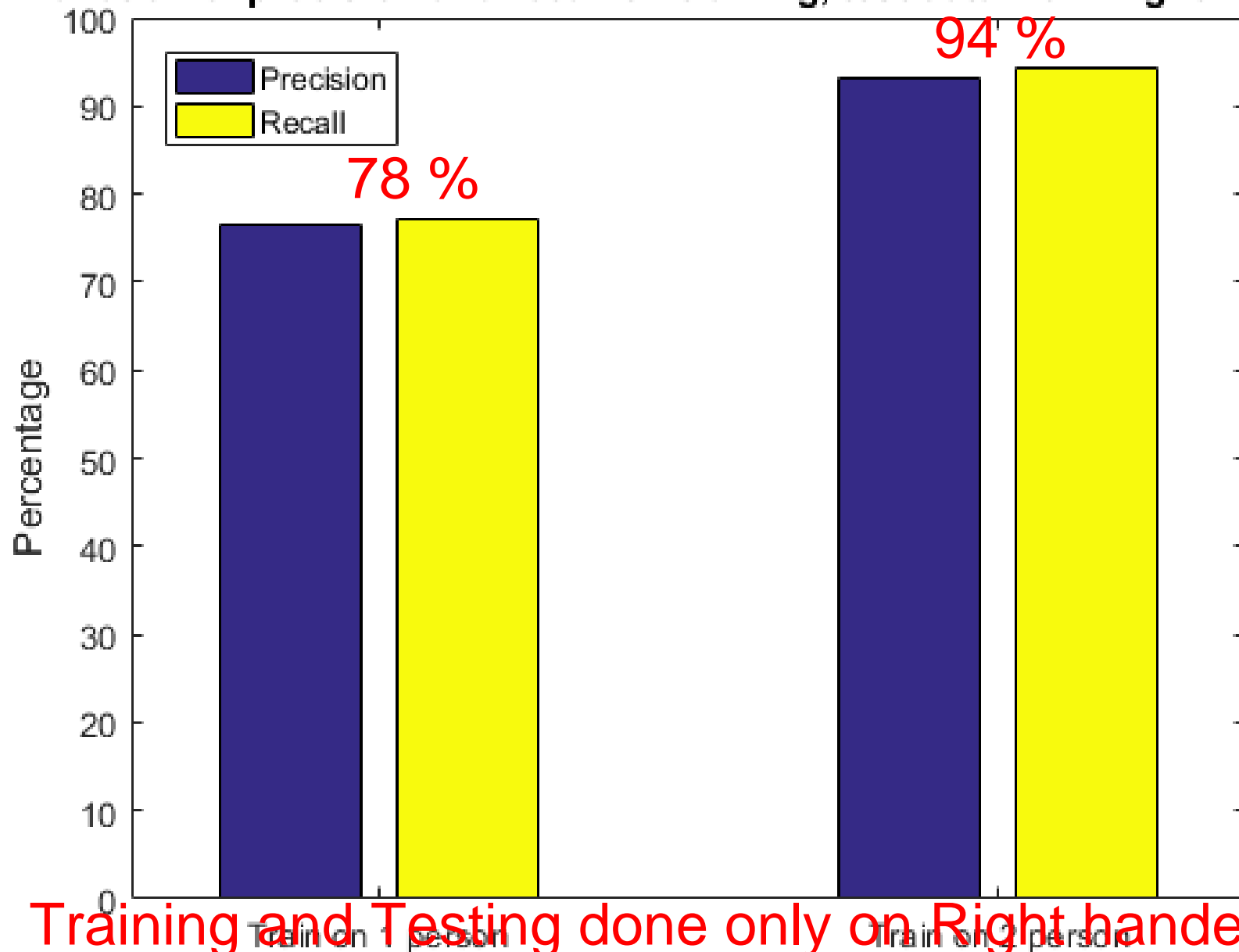
Prediction metric =  
Cosine similarity



# Result: Training on Right and Left



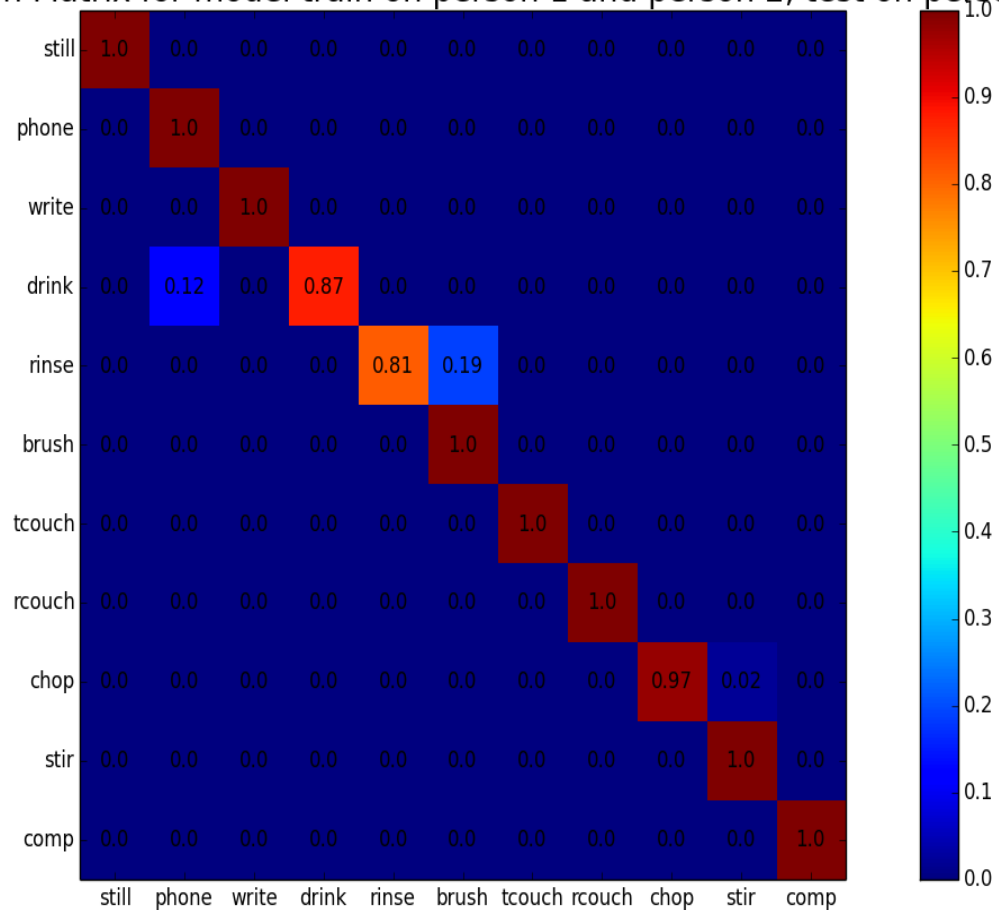
Variation of precision and recall on training, test data from Right handed



Training and Testing done only on Right handed person

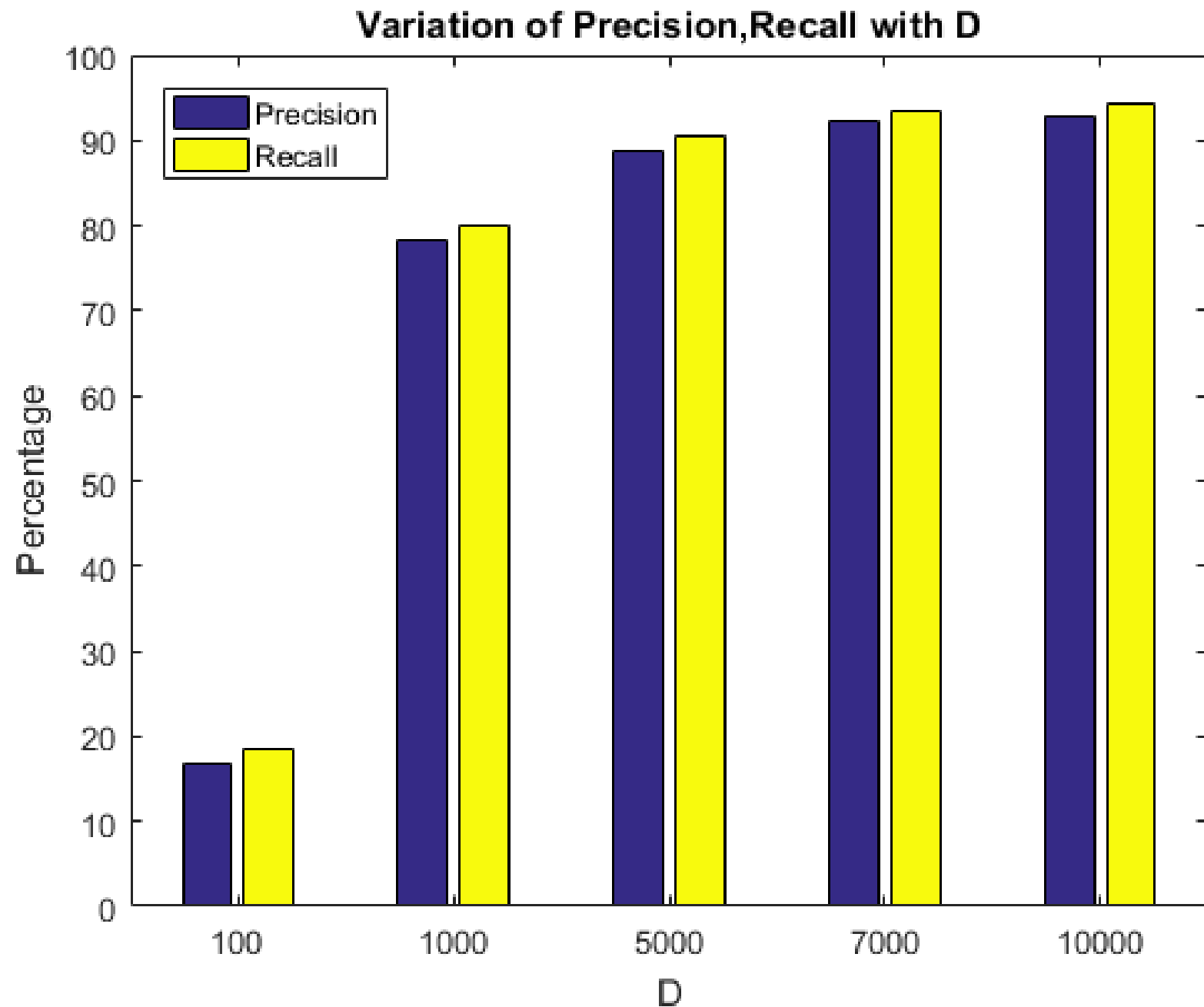
# Result: Confusion Matrix

Confusion Matrix for model train on person 1 and person 2, test on person 4



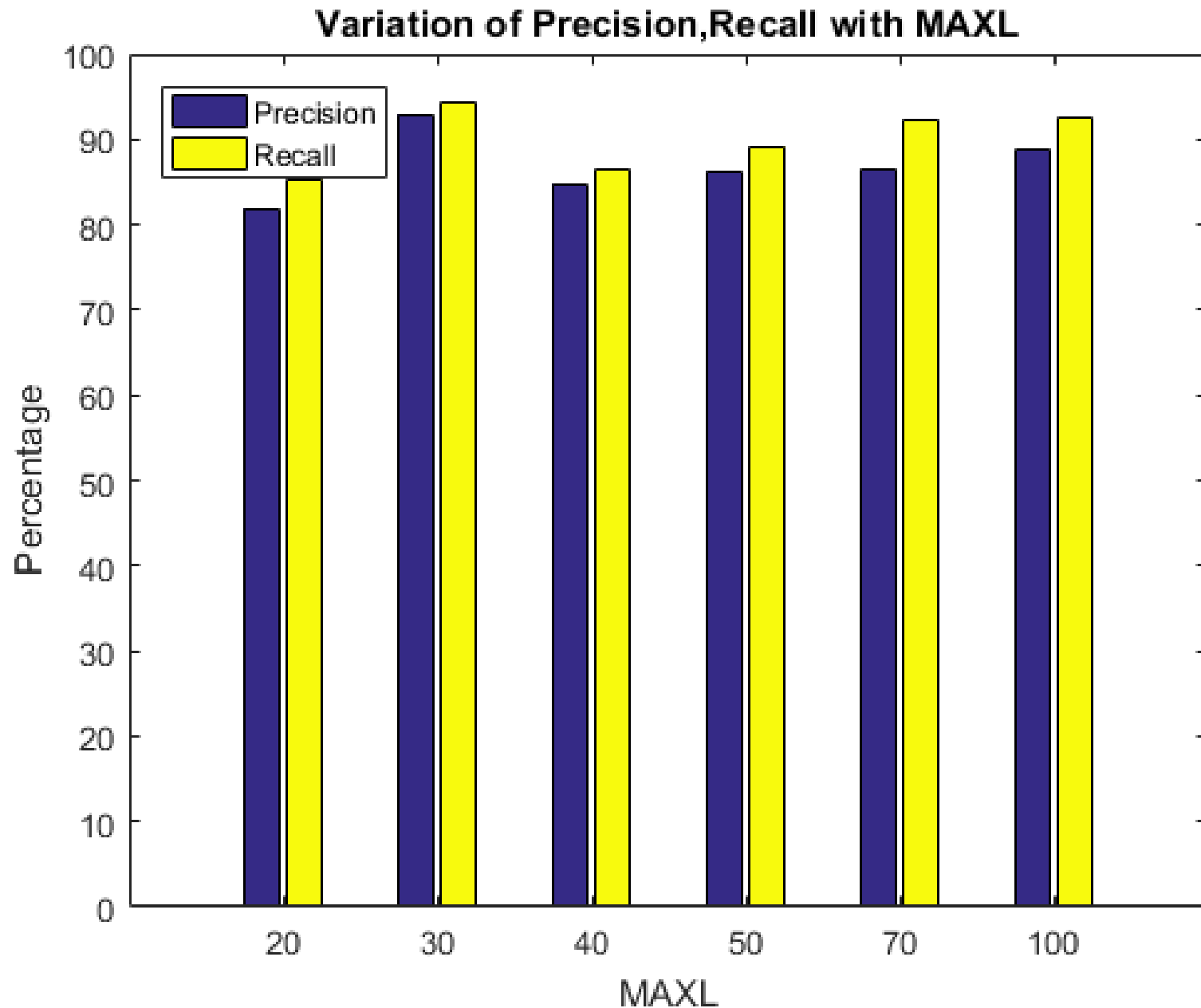
Conclusion

# Result: Variation of precision and





# Result: Variation of precision and



		"New Person"	
Algorithm		Precision (%)	Recall (%)
Overall	Sung et al., AAAI PAIR 2011, ICRA 2012. [1,2]	67.9	55.5
	Koppula, Gupta, Saxena, IJRR 2012. [3]	80.8	71.4
	Zhang, Tian, NWPJ 2012 [4]	86	84
	Ni, Moulin, Yan, ECCV 2012 [5]	Accur: 65.32	-
System Architecture	Yang, Tian, JVCIR 2013 [6]	71.9	66.6
	Piyathilaka, Kodagoda, ICIEA 2013 [7]	70*	78*
	Ni et al., Cybernetics 2013 [8]	75.9	69.5
Recognition	Gupta, Chia, Rajan, MM 2013 [9]	78.1	75.4
	Wang et al., PAMI 2013 [10]	Accur: 74.70	-
	Zhu, Chen, Guo, IVC 2014 [16]	93.2	84.6
Recognition	Faria, Premebida, Nunes, RO-MAN 2014 [17]	91.1	91.9
	Shan, Akella, ARSO 2014 [18]	93.8	94.5
	Gaglio, Lo Re, Morana, HMS 2014 [19]	77.3	76.7
Recognition	Parisi, Weber, Wermter, Front. Neurobot. 2015 [20]	91.9	90.2
	Cippitelli, CIN 2016 [21]	93.9	93.5

Result 4

Conclusion

Pradhan, HDC 2017: Precision (81.18 %) and Recall (81.88 %)  
Or  
Pradhan, HDC 2017: Precision (93.04 %) and Recall (94.27 %)  
(Only right handed person)

# Conclusion

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System  
Architecture

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Conclusion

- Precision and Recall can be improved by getting more training data for left handed person
  - Record video from Kinect
  - Mirror data from right handed person
- Spatial and Temporal Hyperdimensional Computing needs to be applied together to improve results
- Use combination of features:  
skeleton + joint orientation + HOG RGB + HOG depth