Holland Bloorview
Kids Rehabilitation Hospital

A world of possibility

Facial Gesture Recognition for Access Technology for Children with Cerebral Palsy and Complex Communication Needs

Jack Han, Silvia Orlandi, Tom Chau

Undergraduate Thesis Presentation

Department of Mechanical and Industrial Engineering, University of Toronto

April 17, 2019

Bloorview
RESEARCH INSTITUTE

No boundaries

Cerebral Palsy

Children with cerebral palsy (CP) can experience:

- Movement and posture disorders
- Complex communication needs (CNN)
- Speech impairment

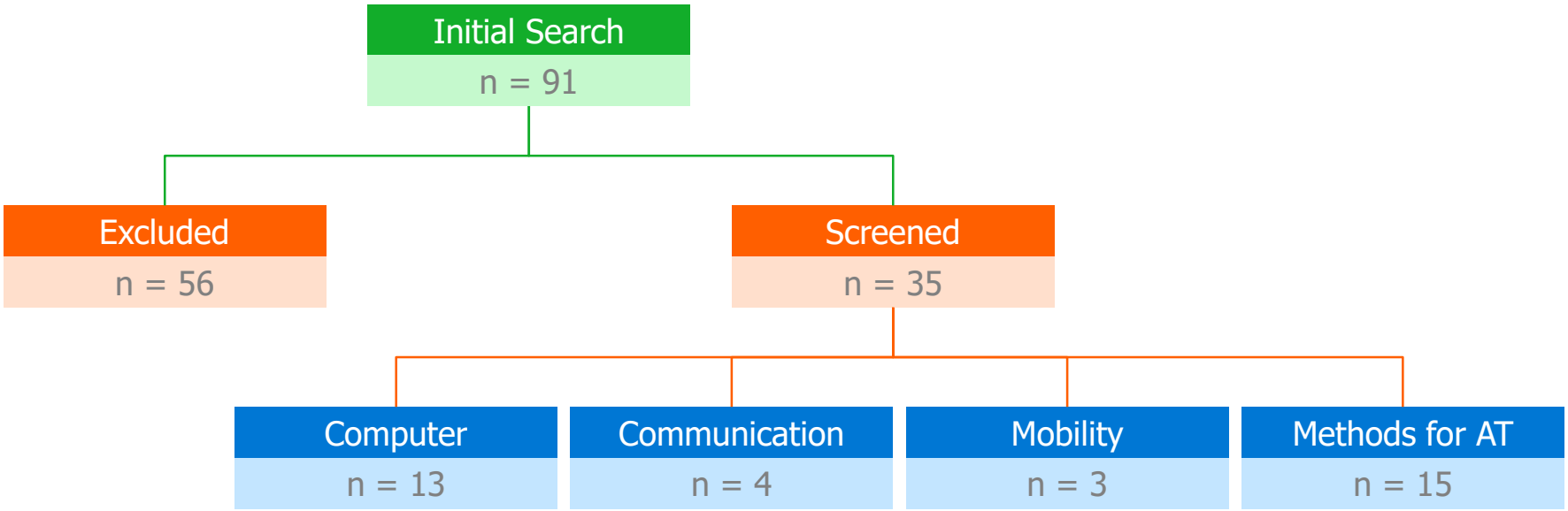
Limited in use of conventional access technology (AT)

Facial gesture recognition represents a promising pathway

www.rogerebert.com

Literature Review

- Initial search conducted on PubMed, Scopus, and Ovid
- To be written as a topical review paper



Literature Review

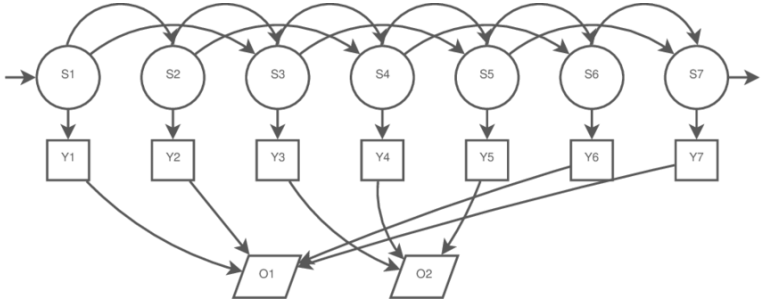
(Shin et al., 2008)

(Palleja et al., 2013)

(Grauman et al., 2003)

- Limited facial features considered for selection
- AT largely not designed for children with CP

Motivation and Aims



Research Questions:

1. Are HMM classifiers able to classify between smiling, mouth opening, and miscellaneous gestures?
2. Can a systematic method of feature selection improve classifier performance?

Extended Cohn-Kanade (CK+) Database

(Lucey et al., 2010)

Smiling

117 samples

Mouth Opening

80 samples

Miscellaneous

385 samples

Feature Extraction

Original Video Sample

Facial Landmarks (IntraFace)

57 Mouth Region Features Extracted

HMM Input

Smiling Mouth Opening Miscellaneous

Number of Features

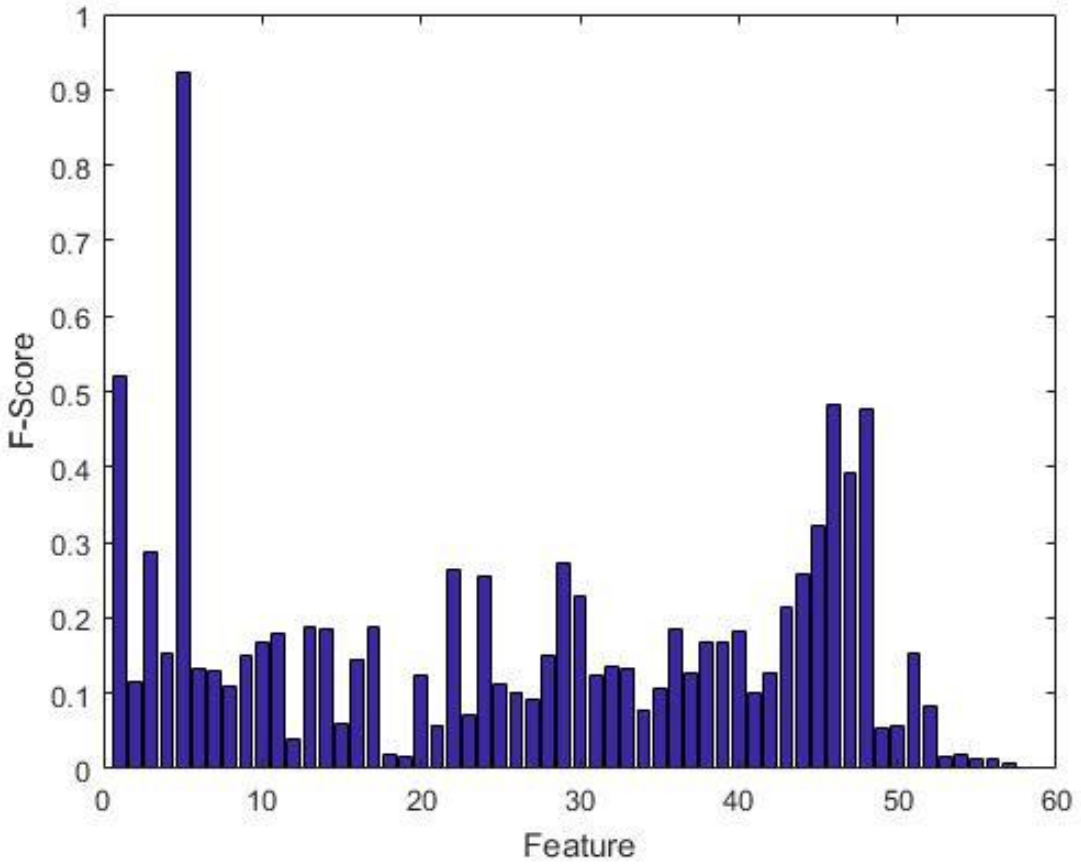
Number of Frames

1.222	0.037	0.390	...
1.239	0.037	0.390	...
1.263	0.038	0.416	...
1.263	0.060	0.416	...
1.300	0.113	0.452	...
1.339	0.132	0.492	...
1.339	0.132	0.492	...
1.352	0.094	0.483	...
1.370	0.113	0.483	...
1.407	0.113	0.464	...
1.425	0.094	0.483	...
1.444	0.094	0.446	...
1.462	0.076	0.427	...
...	...	...	...

Feature Selection

Thresholding

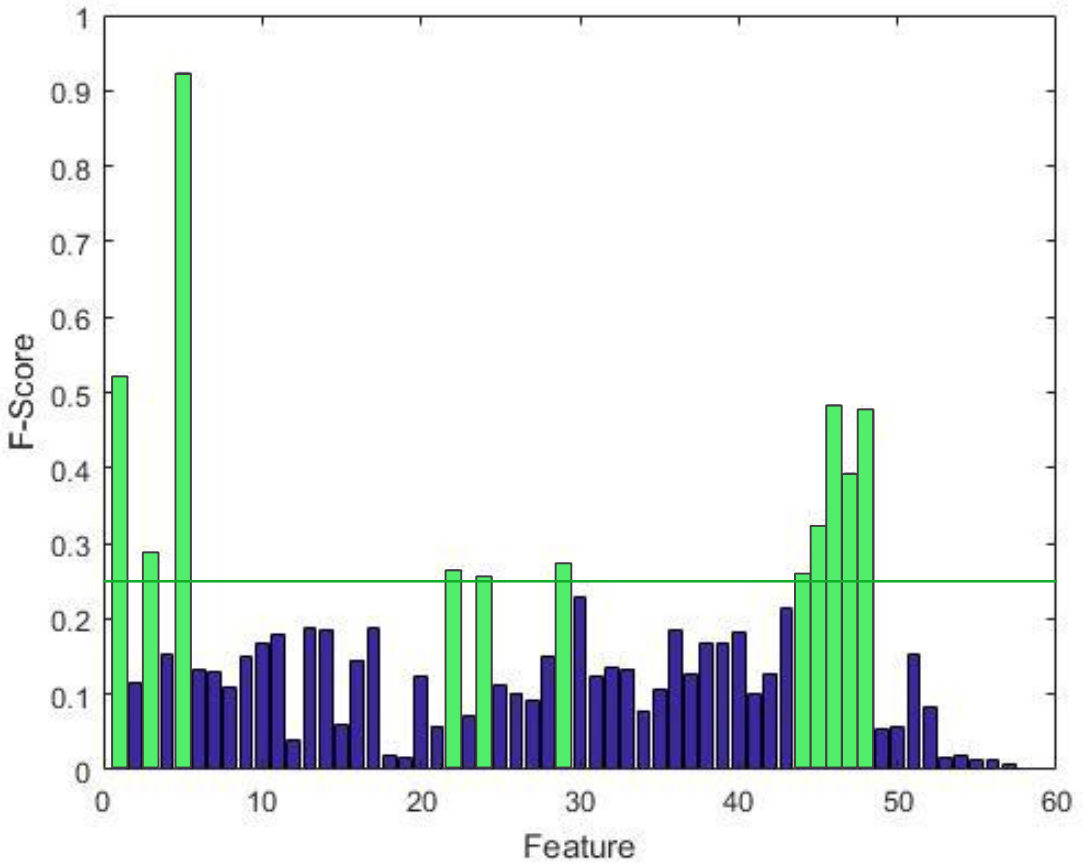
- Select features which differentiate each class well
- Choose a minimum F-score value
- Features that exceed F-score threshold are selected



Feature Selection

Thresholding

- Select features which differentiate each class well
- Choose a minimum F-score value
- Features that exceed F-score threshold are selected



Feature Selection

Eliminating Redundant Features

Feature 32

Feature 33

Feature Selection

Eliminating Redundant Features

- Calculate Spearman's Rank Correlation Coefficient for each pair of features

Feature 32

Feature 33

p = 0.983

Feature Selection

Eliminating Redundant Features

- Calculate Spearman's Rank Correlation Coefficient for each pair of features
- Find correlated pairs and remove lower F-score

Feature 32

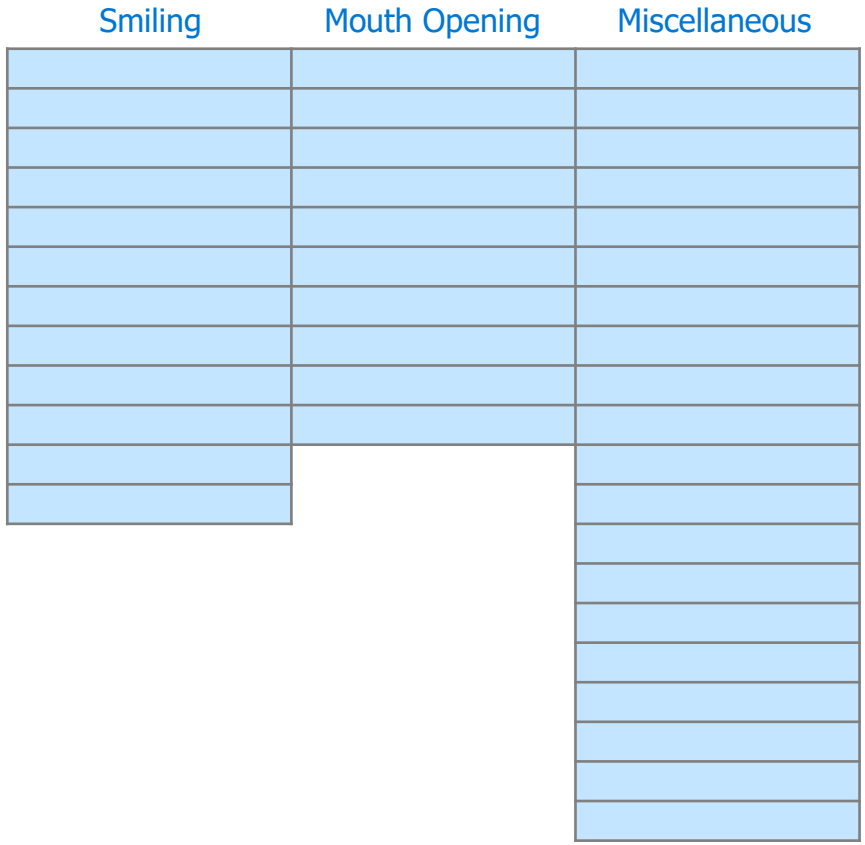
Feature 33

p = 0.983

Feature Selection

Downsampling imbalanced classes

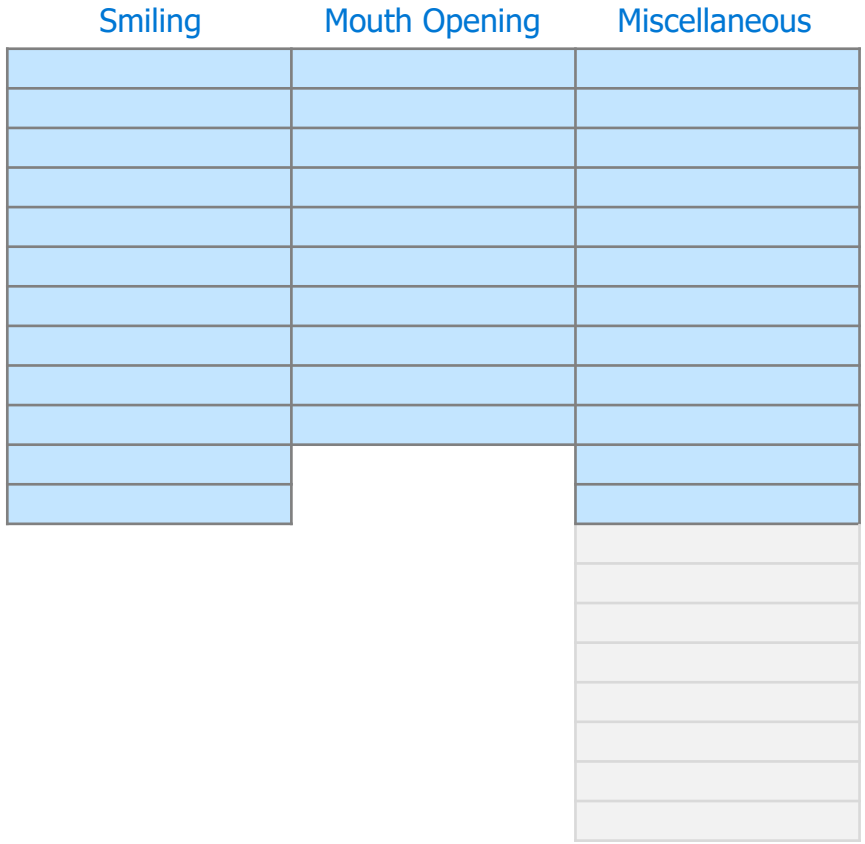
- Randomly remove samples from miscellaneous class
- More balanced classes may improve classifier performance



Feature Selection

Downsampling imbalanced classes

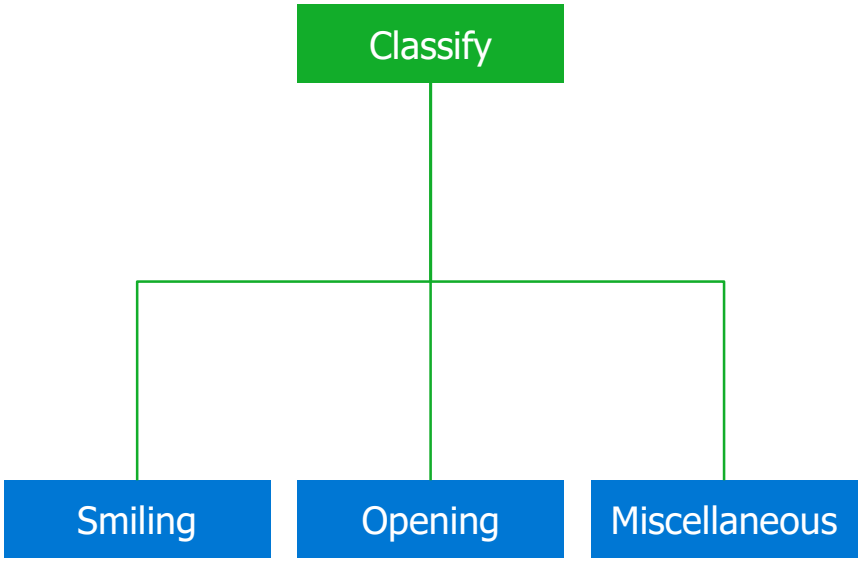
- Randomly remove samples from miscellaneous class
- More balanced classes may improve classifier performance



Classifier Architecture

3-Class

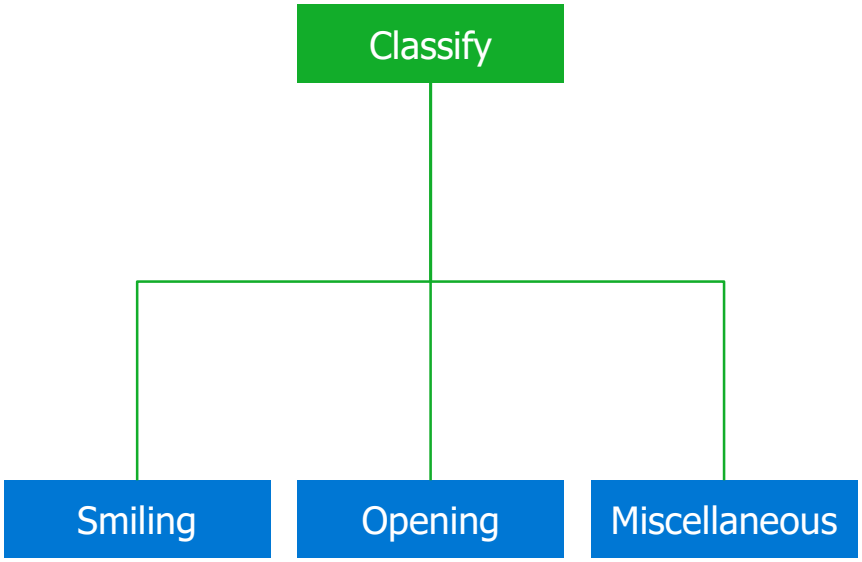
- 1 set of features for 3 classes



Classifier Architecture

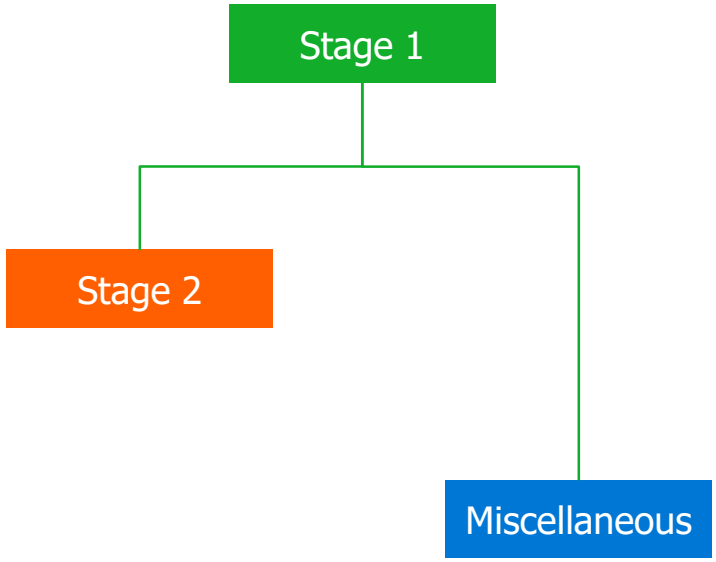
3-Class

- 1 set of features for 3 classes



Cascade

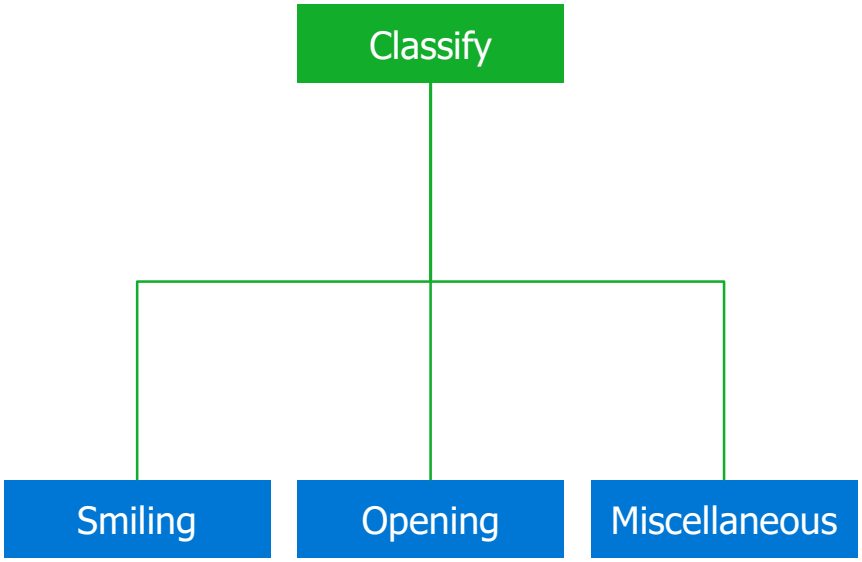
- 2 stages of binary classifiers with different sets of features



Classifier Architecture

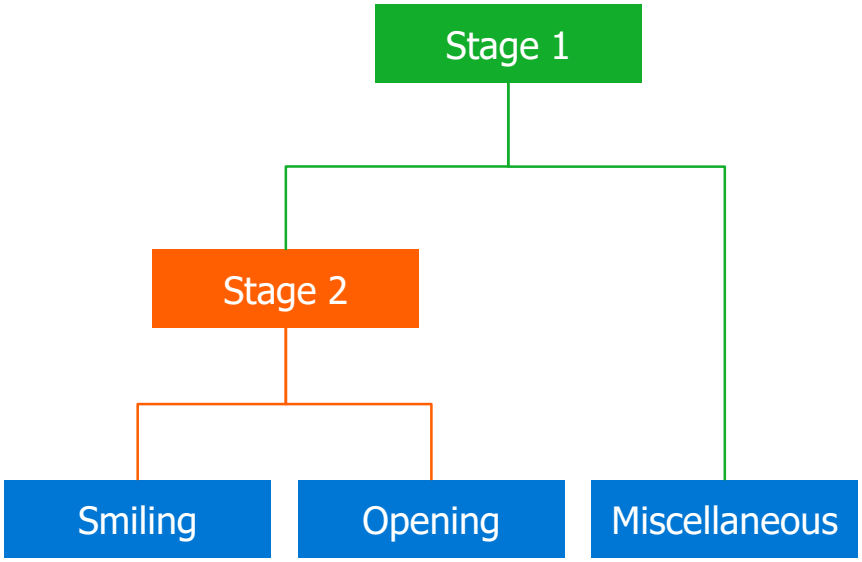
3-Class

- 1 set of features for 3 classes



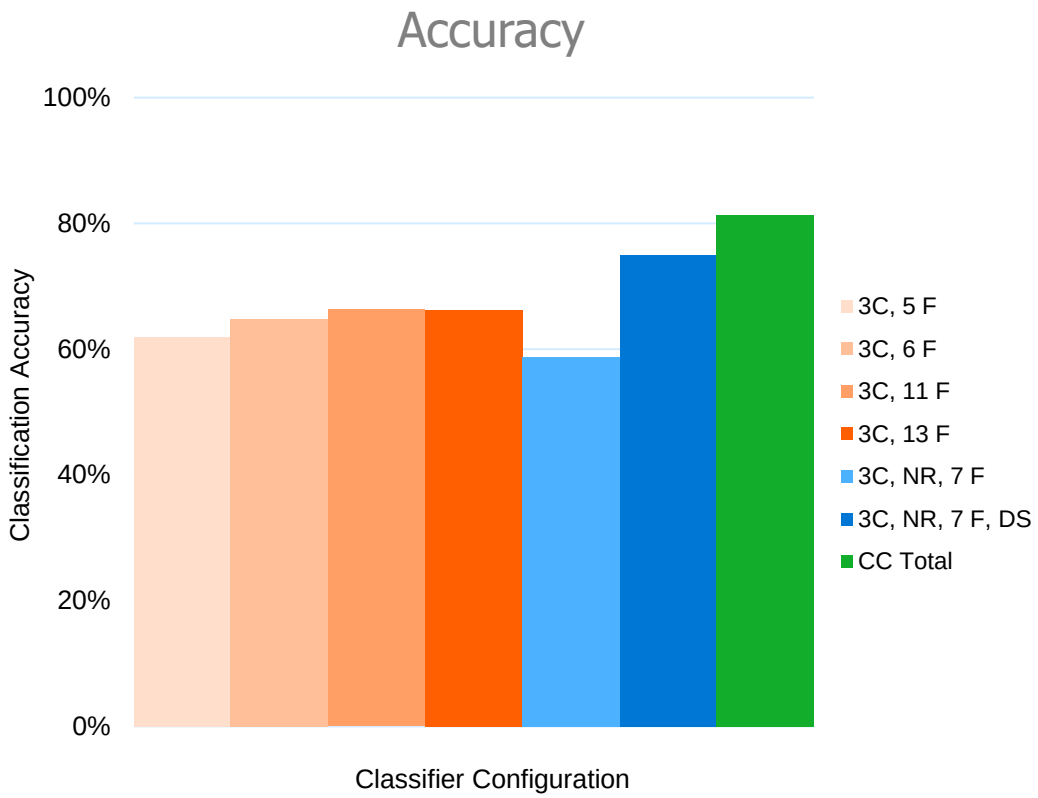
Cascade

- 2 stages of binary classifiers with different sets of features



Evaluation of Feature Selection

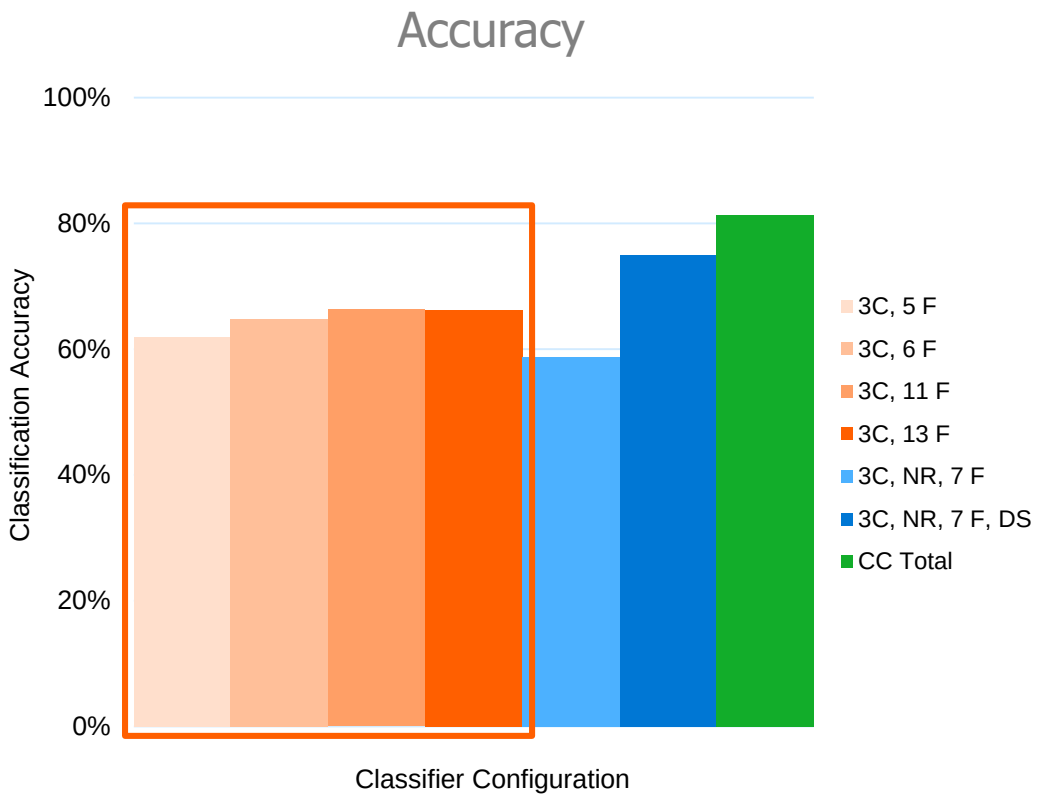
Classifier performance increases with:



Evaluation of Feature Selection

Classifier performance increases with:

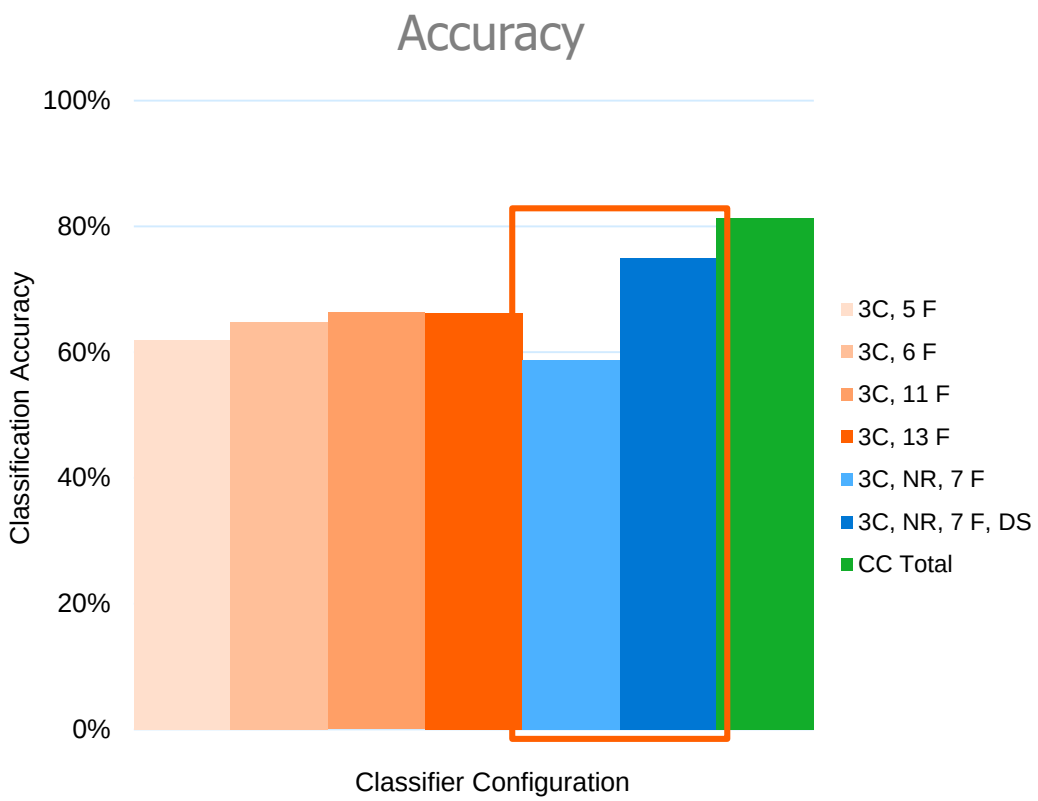
- More features (marginal)



Evaluation of Feature Selection

Classifier performance increases with:

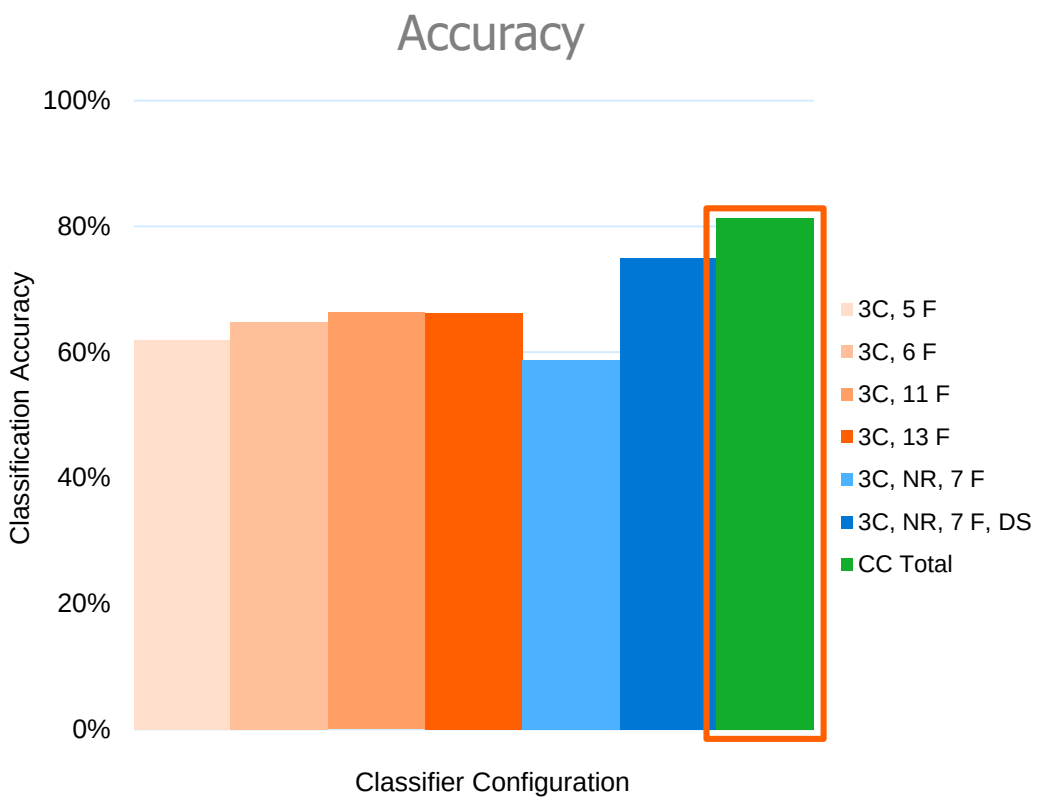
- More features (marginal)
- Removal of redundant features with balanced classes



Evaluation of Feature Selection

Classifier performance increases with:

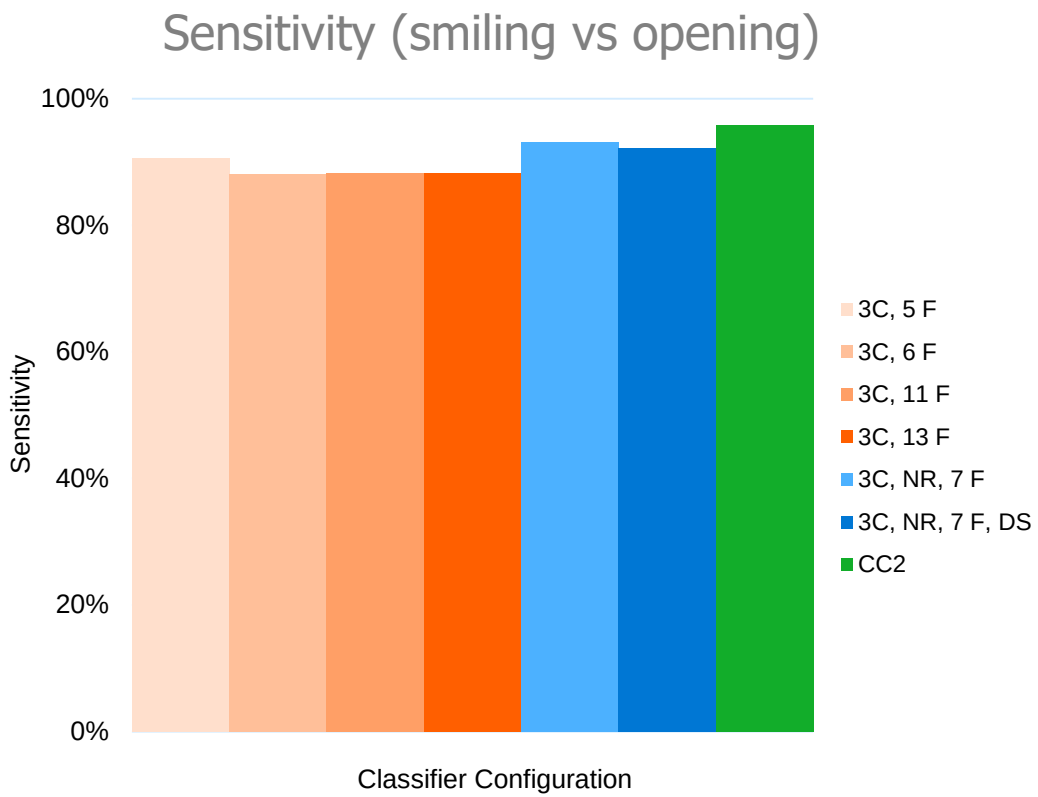
- More features (marginal)
- Removal of redundant features with balanced classes
- Cascade of binary classifiers



Evaluation of Feature Selection

Classifier performance increases with:

- More features (marginal)
- Removal of redundant features with balanced classes
- Cascade of binary classifiers



Evaluation of Feature Selection

Classifier performance increases with:

- More features (marginal)
- Removal of redundant features with balanced classes
- Cascade of binary classifiers

Cascade Classifier Performance

- F1 score reveals no major area of weakness
- Accuracy comparable with facial gesture AT in the literature
- Sensitivity and specificity high for each stage

Cascade classifier F1 scores

Stage 1	
Smiling/Opening	83.56%
Miscellaneous	80.04%
Stage 2	
Smiling	98.35%
Opening	97.82%

Conclusion and Future Work

- HMM classifiers are feasible for facial gesture recognition for AT
- Systematic feature selection
  - Allows more features to be considered
  - Improves classifier performance

Future Work

- Classify between neutral face and facial gestures
- Develop prototype for testing with children with CP

Thank you.

Holland Bloorview
Kids Rehabilitation Hospital Foundation

prism lab

Cerebral Palsy
ALLIANCE

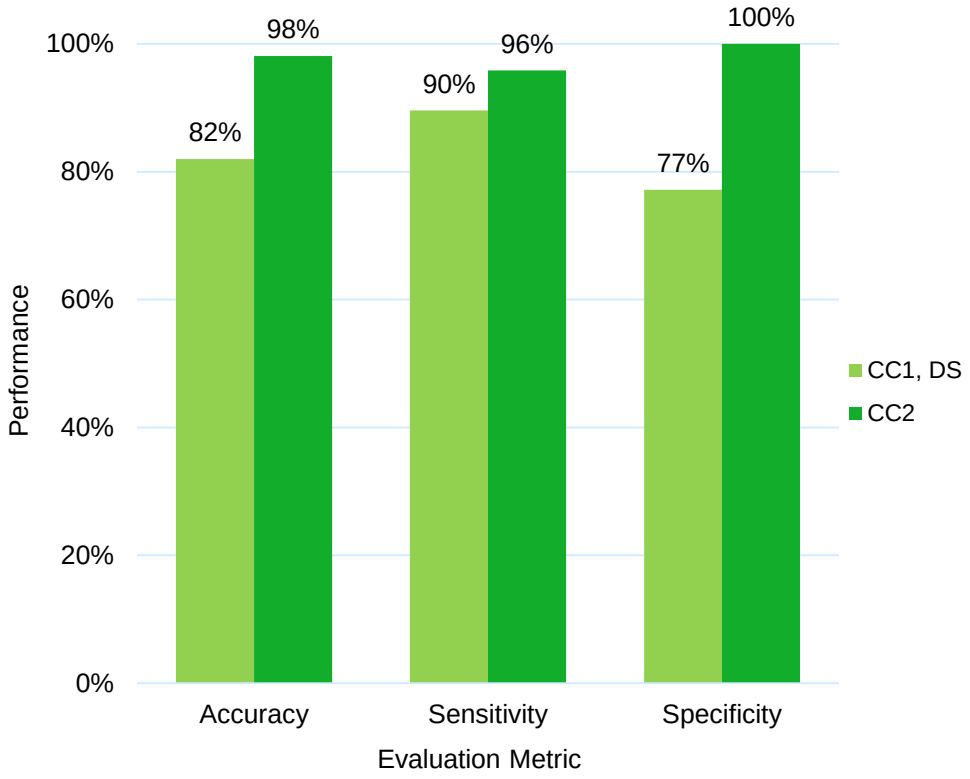
Cascade Classifier Performance

Stage 1 5 features

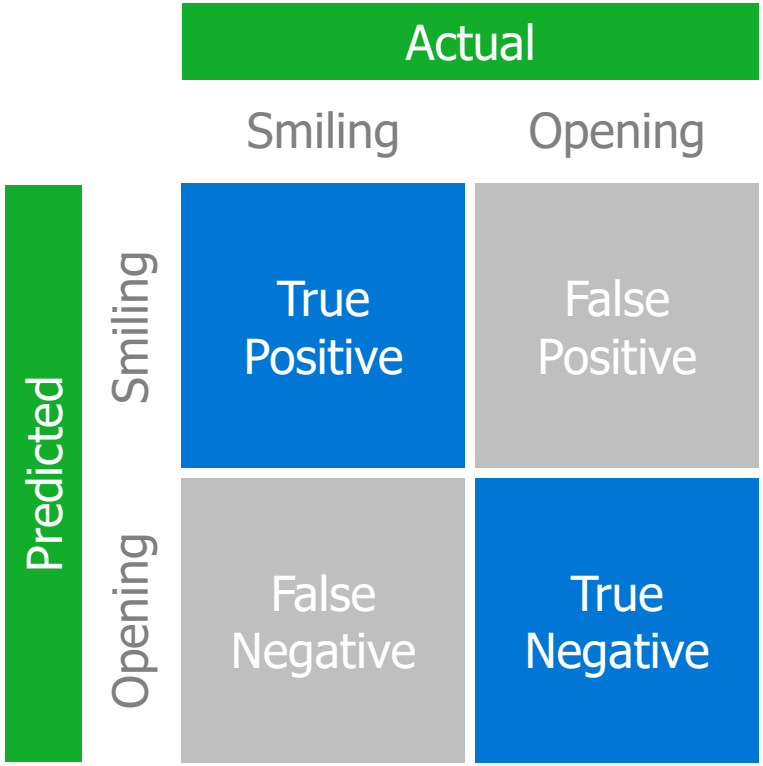
Stage 2 2 features

Total 6 unique features

- High performance for few features
- No major area of weakness



Confusion Matrix



Leave-One-Subject Out Cross Validation