

ASL Complete Alphabet Recognition

Group #6

Dima Al Dulaijan

Faisal Mushayt

Myles Cork

BOSTON
UNIVERSITY



Related Work



Paper 1: Real-time American Sign Language Recognition with Convolutional Neural Networks

- Interpret alphabet signs excluding j and z
- Model
 - GoogLeNet
 - Loss: Log Loss
 - Optimizer: Not Mentioned, although most likely SGD
 - Pre-trained, but reinitialized last 2-3 layers with Xavier initialization
 - Re-trained on 2 datasets

Paper 1: Real-time American Sign Language Recognition with Convolutional Neural Networks

- Results
 - 72% accuracy on a-y excluding j and z
- Conclusion
 - Produced a somewhat robust model for a-e, but would need more data for whole alphabet
- Future Work
 - Other models
 - More image preprocessing
 - Language model

Paper 2: Using Deep Convolutional Networks for Gesture Recognition in American Sign Language

- Interpret alphabet + digits
- Model
 - Custom deep CNN
 - Loss: categorical cross entropy
 - Optimizer: Not mentioned
 - 1 Dataset
- Tested classifying two sets, a-z and 0-9

Paper 2: Using Deep Convolutional Networks for Gesture Recognition in American Sign Language

- Results
 - 82.5% accuracy on found dataset
 - 67% accuracy on made dataset
- Conclusions
 - Need more training data
- Future Work
 - Predict text based on sequential context

Paper 3: American Sign Language Character Recognition using Convolution Neural Network

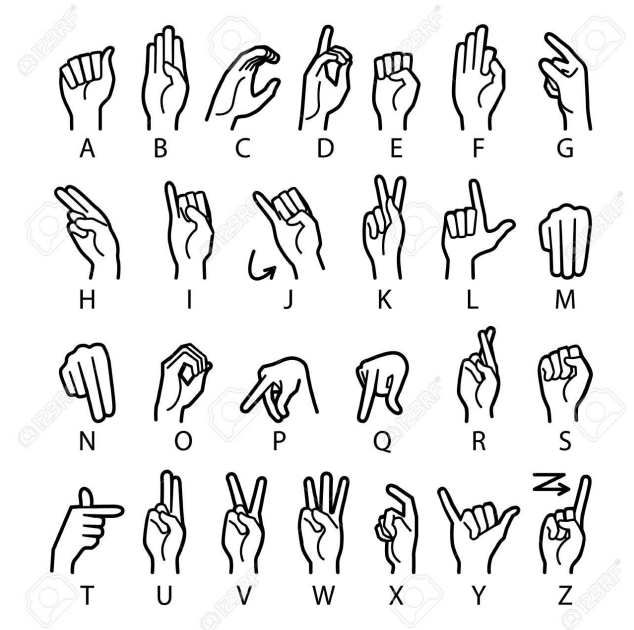
- Model
 - VGG16
 - Loss: Didn't mention
 - Optimizer: SGD with "momentum"
 - Pretrained on imagenet, retrained last layer on ASL dataset.
 - 1 Dataset

Paper 3: American Sign Language Character Recognition using Convolution Neural Network

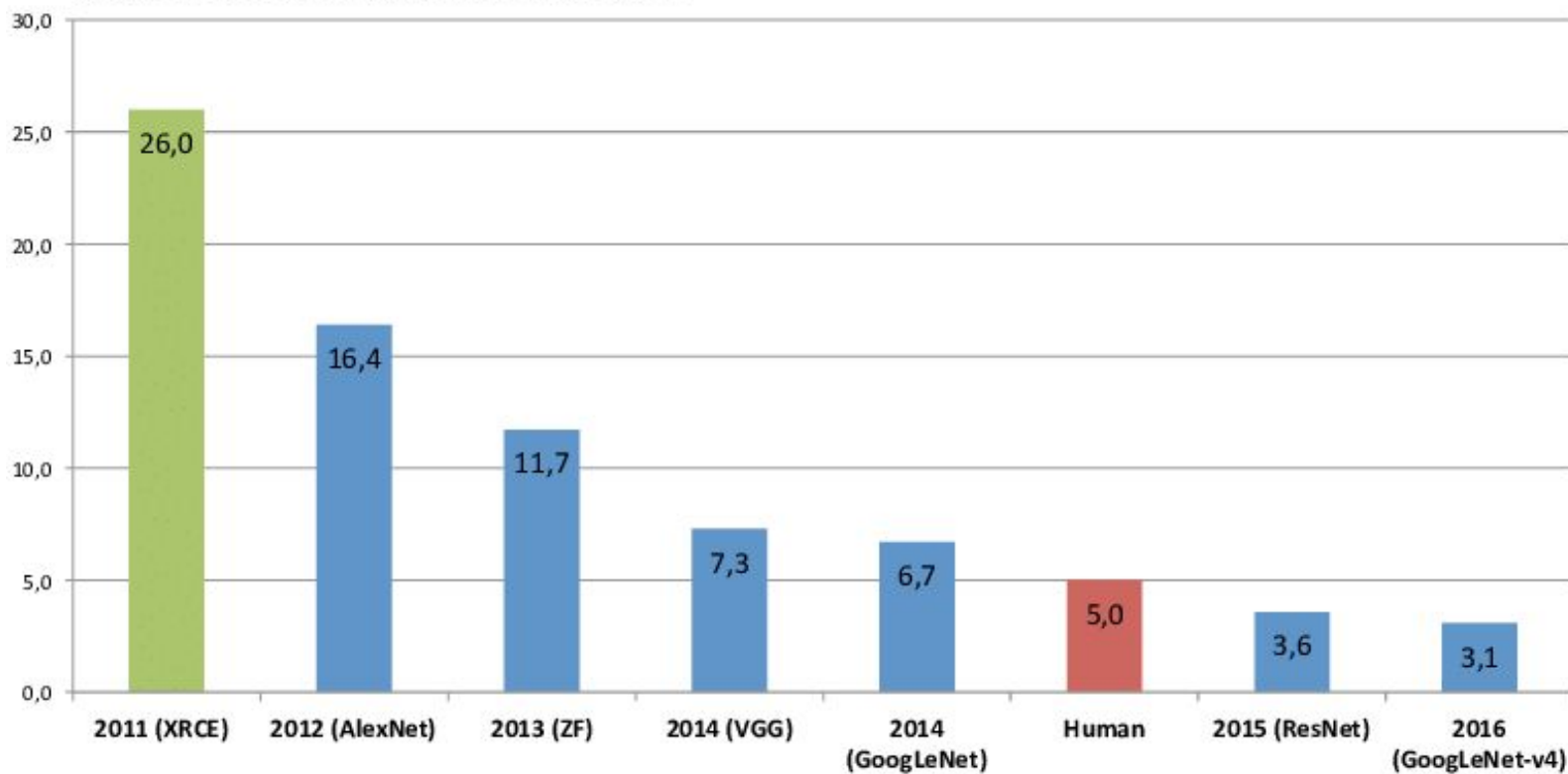
- Results
 - 95.54% accuracy
- Conclusion
 - CNN's are remarkably good at identifying sign language.
- Model overfitted

Our Goals

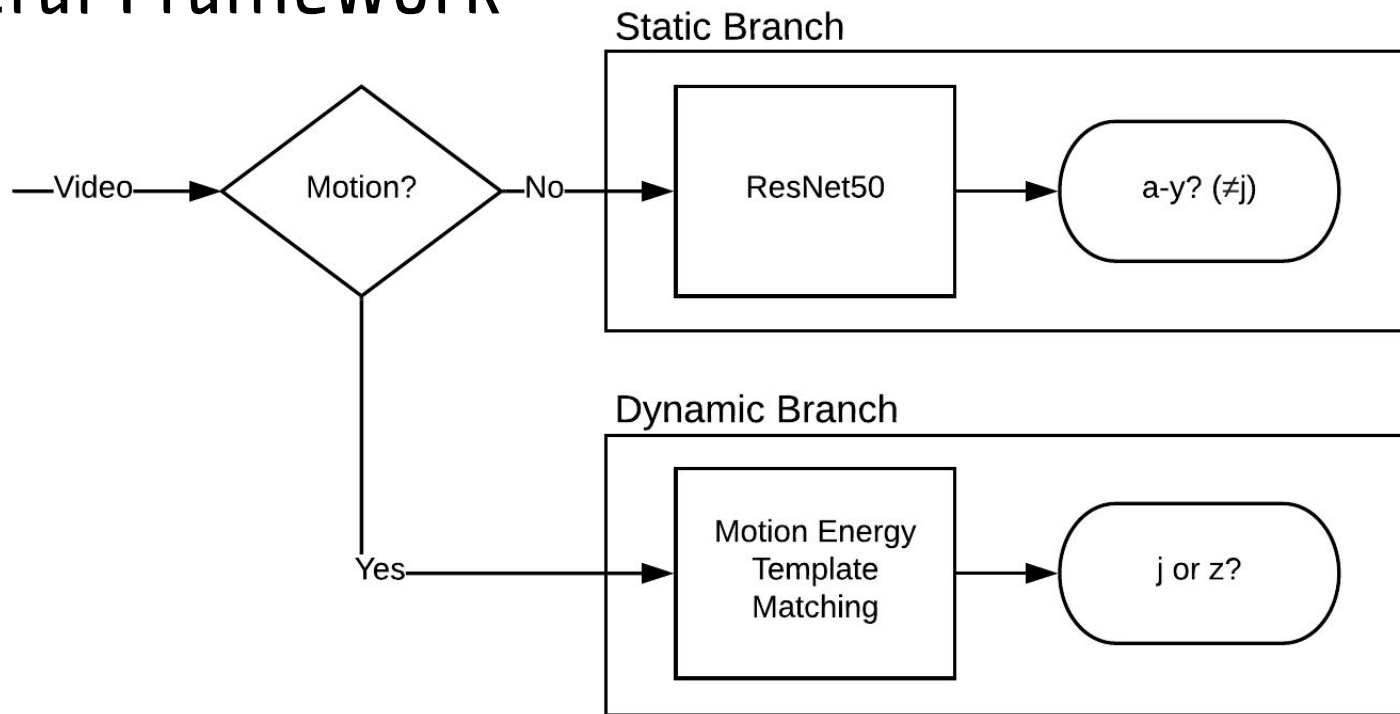
- Interpret both static and dynamic alphabet signs
- Use CNN to determine letters excluding j and z
- Use another classifier to determine if j or z



ImageNet Classification Error (Top 5)

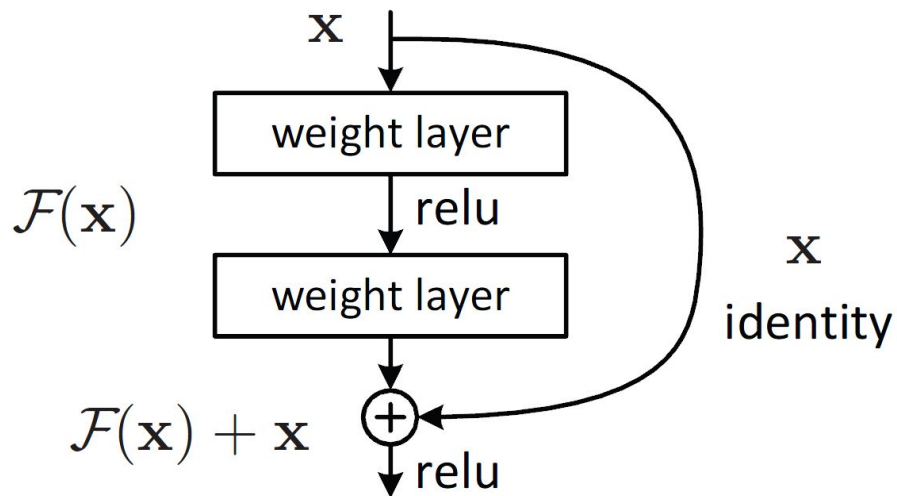


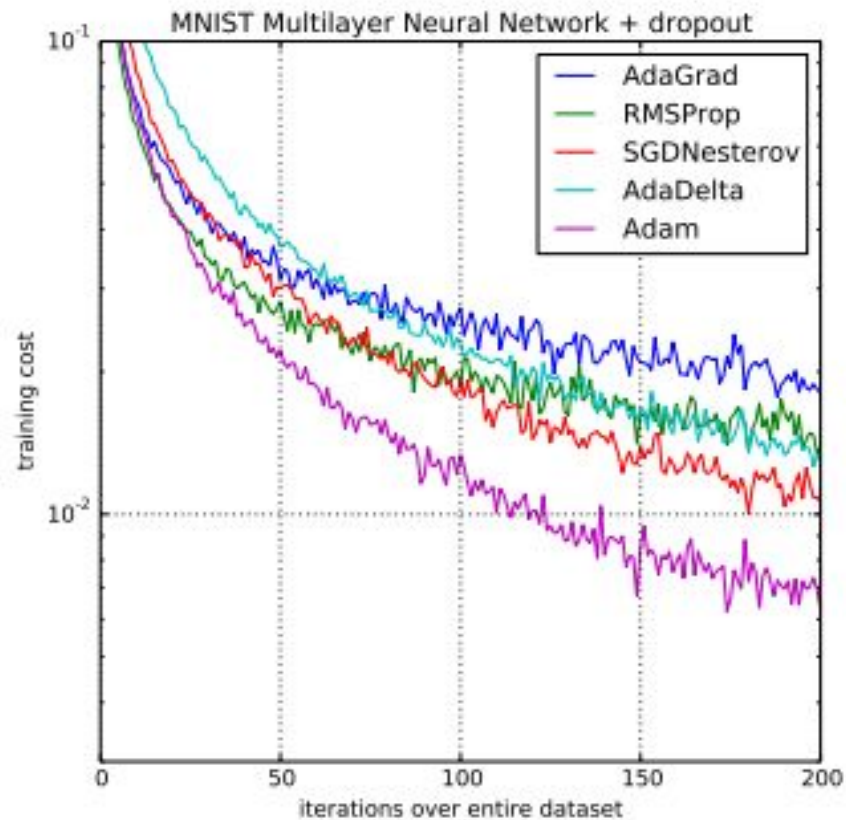
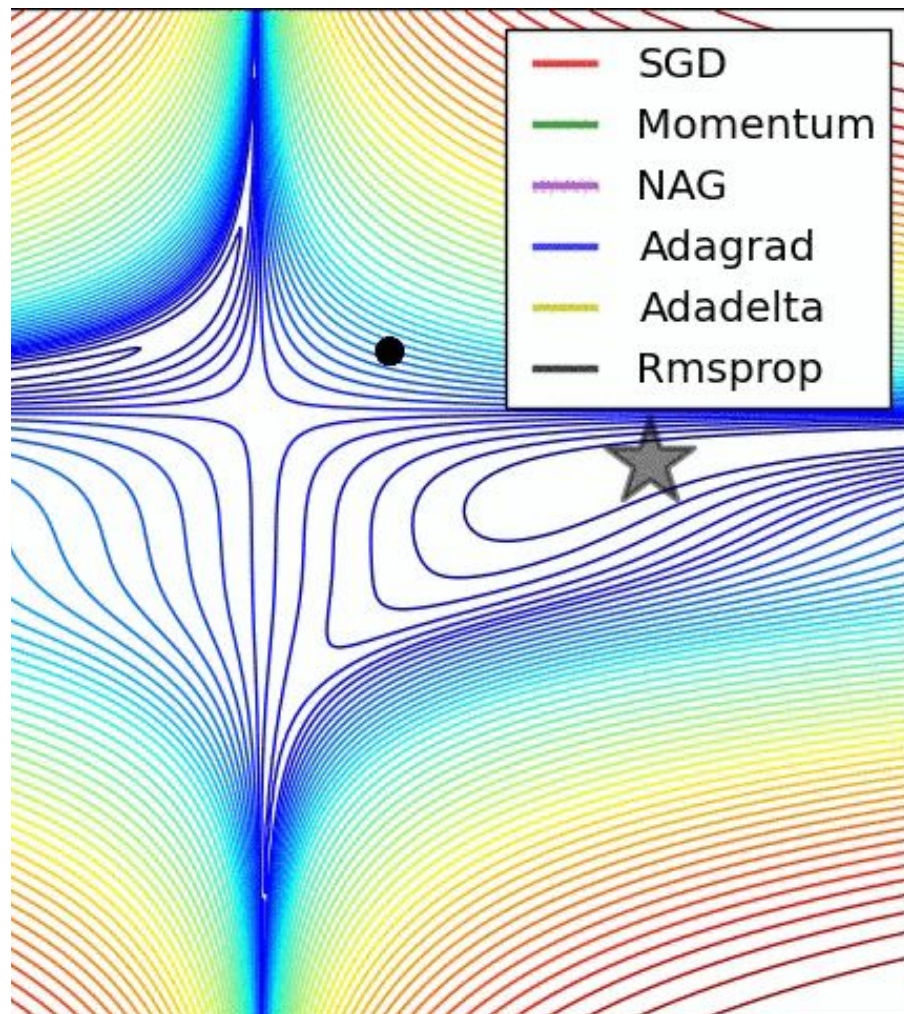
General Framework



Static

- ResNet50
 - Predicts based on a single frame
 - Training
 - Loss: categorical_crossentropy
 - Optimizer: Adam
 - 50 Epochs
 - Modified regularization

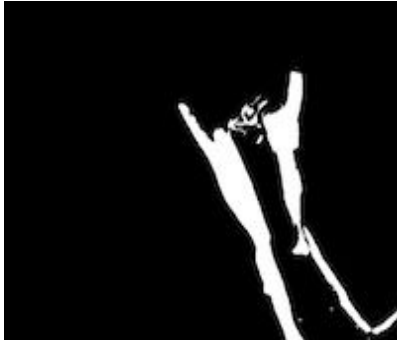




Dynamic

Classifying Dynamic Gestures

- J and Z
- Motion Energy History
- OpenCV Template Matching





Results and Conclusions

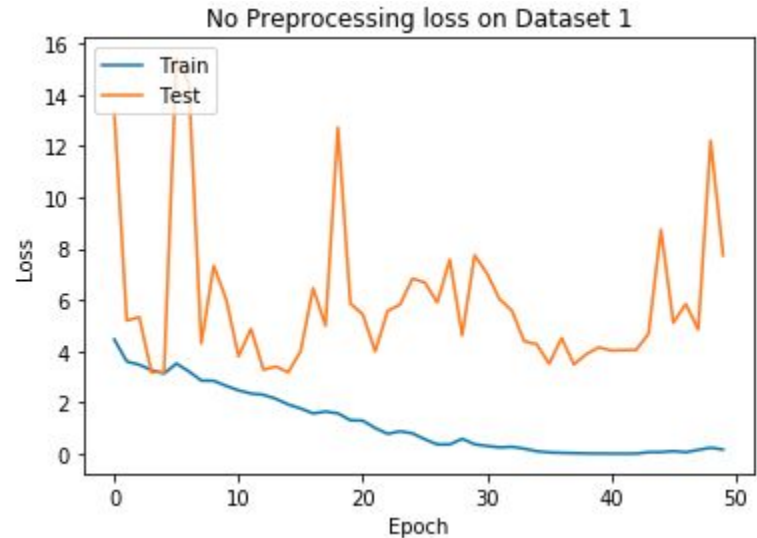
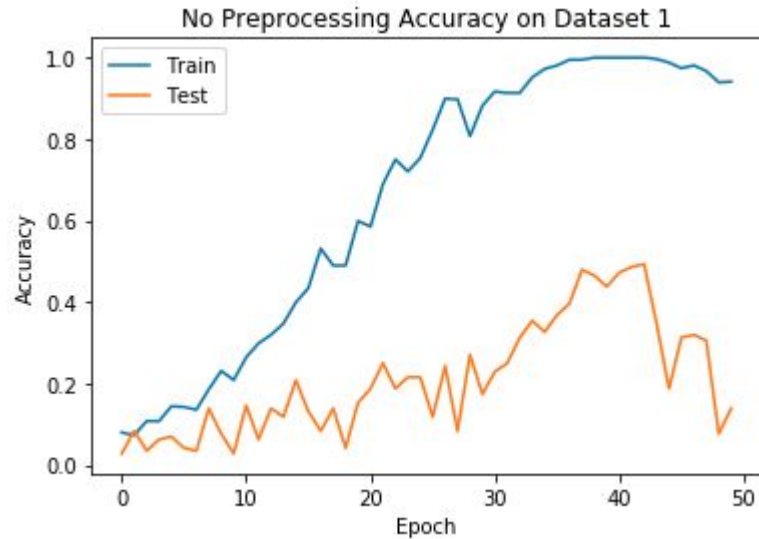


J or Z

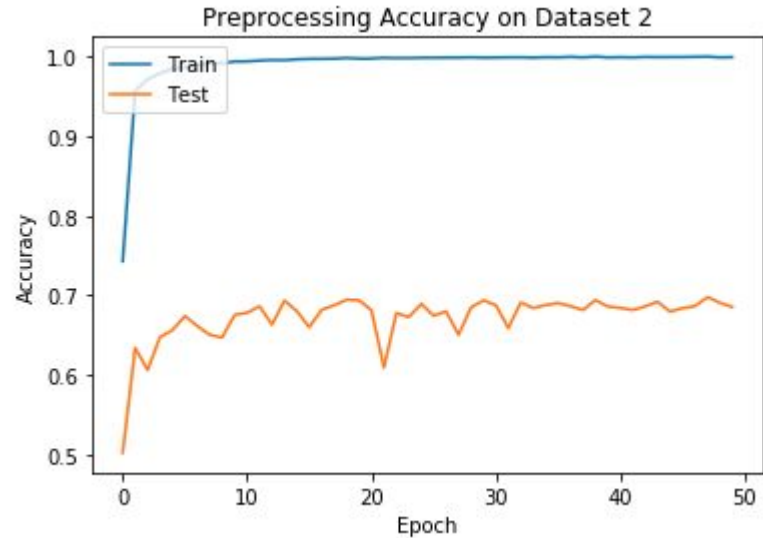
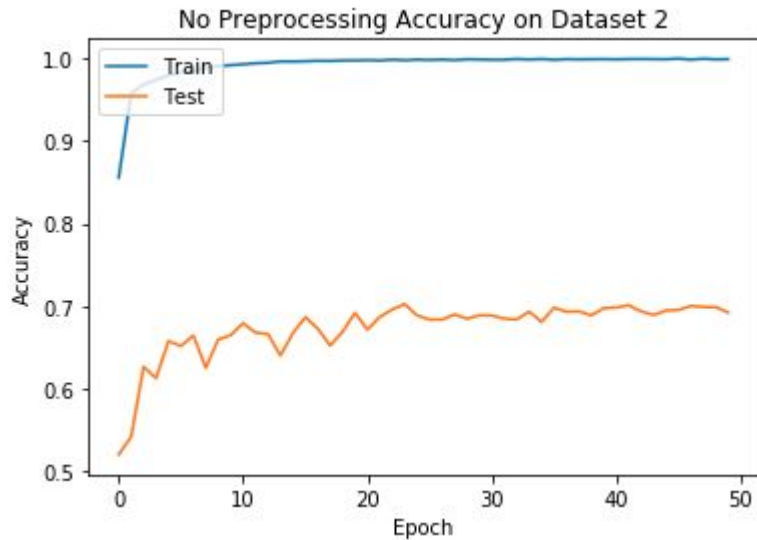
- Accurate overall from experimentation
- Hard to quantitatively measure accuracy due to issues
 - Forearm matching
 - Environmental conditions



Dataset 1: Accuracy and Loss

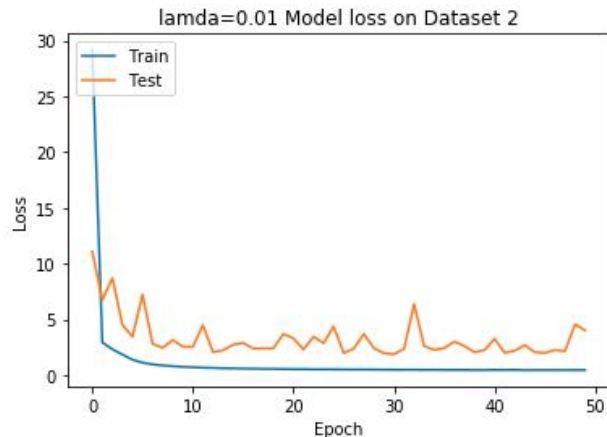
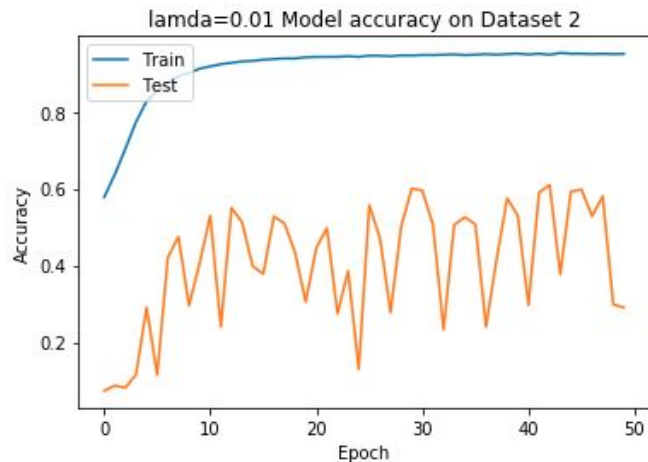


Dataset 2: Accuracy with/without Preprocessing



Dataset 2: Accuracy and Loss with Regularization

```
# Apply weight decay terms to l2 regularizer
decay = 0.001
for layer in self.model.layers:
    if isinstance(layer, keras.layers.Conv2D) or isinstance(layer, keras.layers.Dense):
        layer.add_loss(keras.regularizers.l2(decay)(layer.kernel))
    if hasattr(layer, 'bias_regularizer') and layer.use_bias:
        layer.add_loss(keras.regularizers.l2(decay)(layer.bias))
```





Demo

Conclusions

- Our methods did not provide an improvement over the other papers results
- Dataset plays a huge role
- Dynamic gestures work better with graphical models (HMMs, etc.)

Future Work

- Implement Real-time recognition using motion detection
- Improve CNN accuracy (Better dataset? Tuning? Coarticulation)
- Use motion tracking on top of pattern matching for J and Z
- Implement words and sentences



Questions?



Pictures

https://www.researchgate.net/figure/Winner-results-of-the-ImageNet-large-scale-visual-recognition-challenge-LSVRC-of-the_fig7_324476862

<https://www.dlology.com/blog/quick-notes-on-how-to-choose-optimizer-in-keras/>

<https://machinelearningmastery.com/adam-optimization-algorithm-for-deep-learning/>