Gesture Recognition

Utilizing Deep Learning with Faster-RCNN

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Project Description

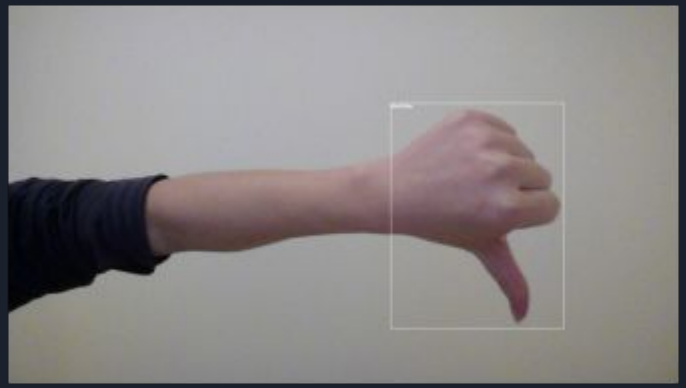
- Hand Gesture Recognition (Like, Dislike, Okay, and Stop)
- Object detection solution
  - Identify gesture location
  - Classify gesture
- Potential use of this application includes: ASL translation and self-driving car
- Language and tools:
  - Development Environment: Google Colab
  - Implementation Format: Jupyter Notebook
  - Language: Python
  - Libraries: Pytorch

Materials

Datasets

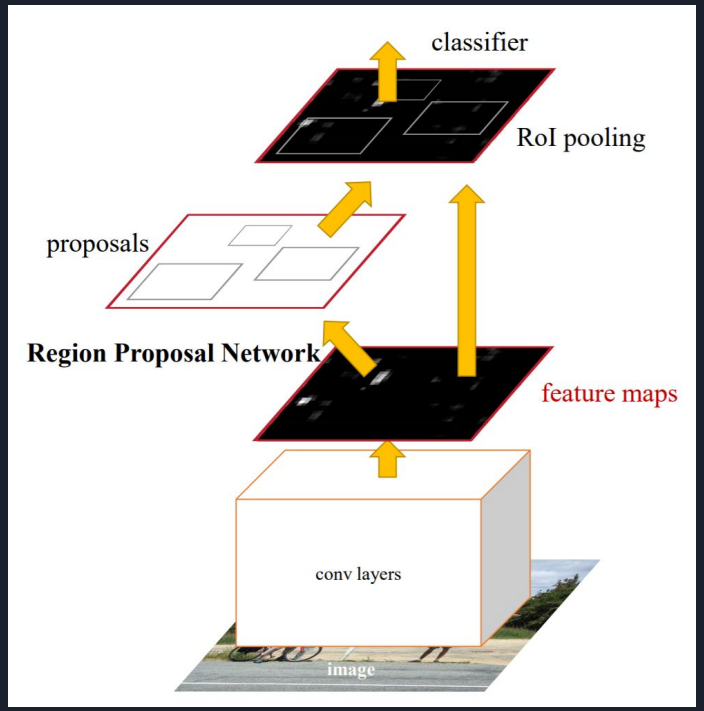
- Several datasets made, including simple and complex variants
- Hand-crafted, including photos and annotations
  - Script to automate train/test/validation set splits
- Annotations in YOLO format, done using MakeSense.ai
  - Class, X Position, Y Position, Width, Height
  - 0 0.543505 0.523965 0.170343 0.450980
- Over 1000 images in total!

Original Dataset - Highly varied in subject and background



Simplified Dataset - Focus on gestures, simple background

Architecture

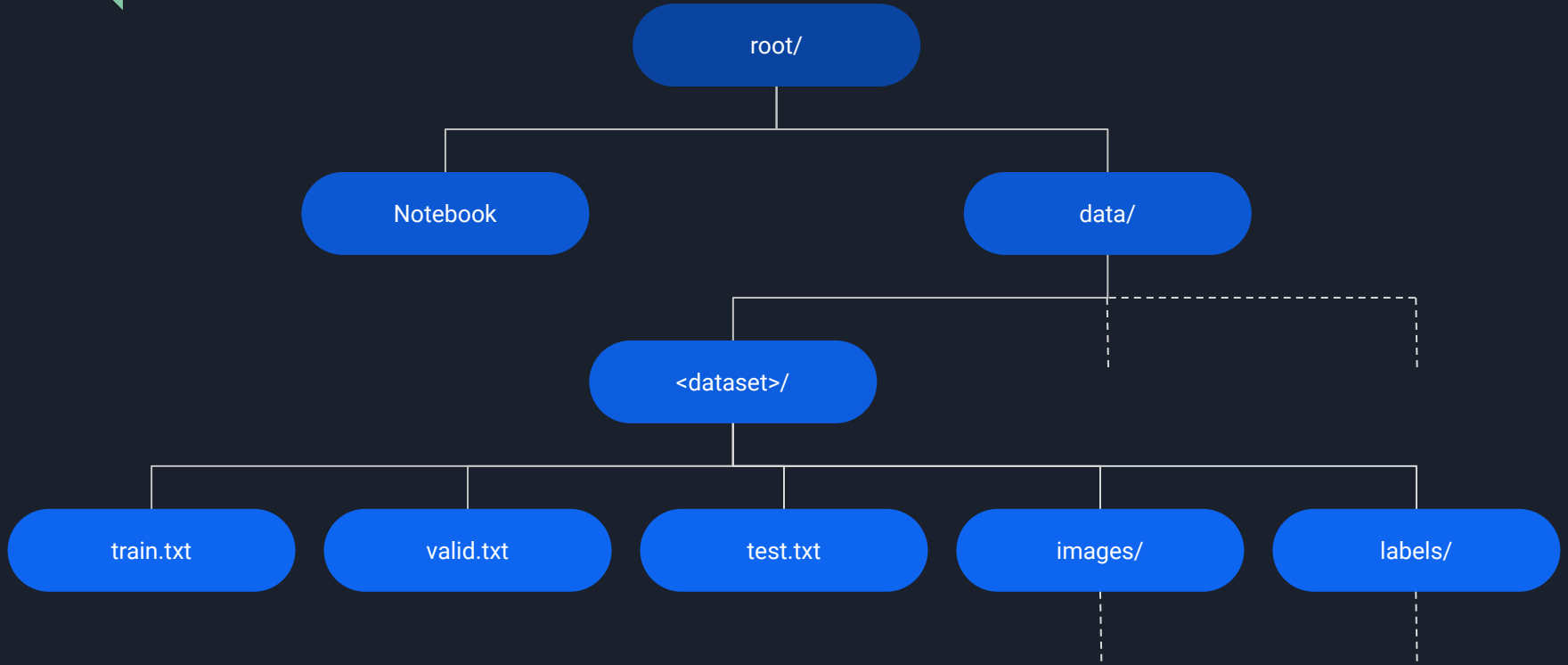


- Faster-RCNN used for final pipeline
  - ResNet 50 backbone for classification
  - RPN (Region Proposal Network) for object detection
  - Shared convolutional layers between the two
- Pre-built PyTorch Implementation
- Pretrained weights on backbone (ResNet50 classifier)
  - Weights pre-trained on ImageNet dataset

Image from Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks @ https://arxiv.org/pdf/1506.01497.pdf

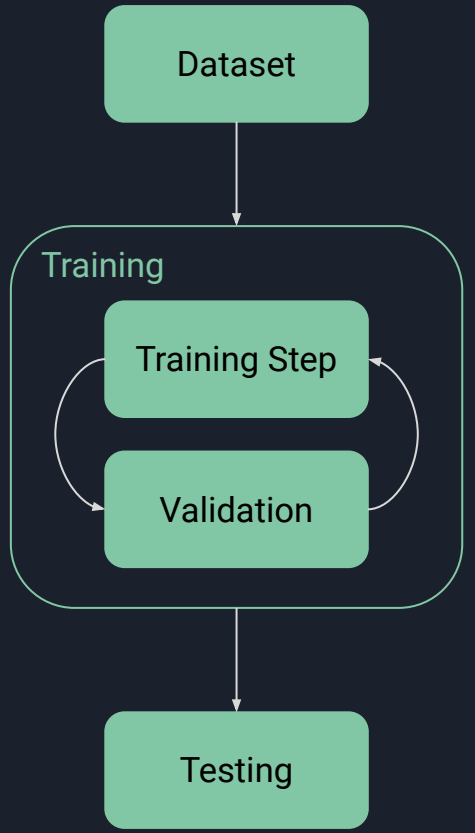
Methods

File Structure



Pipeline

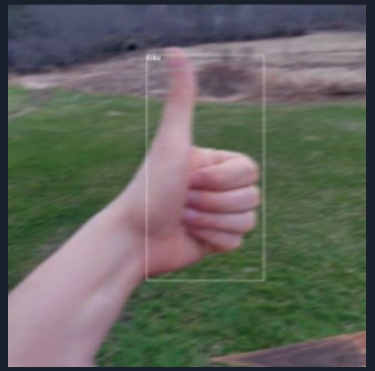
- Custom Dataset class to handle file structure
  - Getting items by text file, not folder structure
- Image and BBox augmentations added to increase data variance
  - Utilized Albumentations library
- Utilized Adam optimizer in training
  - Training set 70% of full dataset
  - Starting params: Learning Rate 0.0001, weight decay 0.0005
- Validate on validation set every training step
  - Validation set 10% of full dataset
  - Validate with NMS filtered classification loss
- Test
  - Test set 20% full dataset
  - Tested on NMS filtered classification accuracy, includes confusion matrix



Augmentations

- Augment existing dataset with image variations using Albumentations
- Transformation pattern includes:
  - Horizontal flip
  - Median Blur
  - Rotation
  - Grayscale

Example 1: Grayscale + Blur



Example 2: Horizontal Flip + Blur

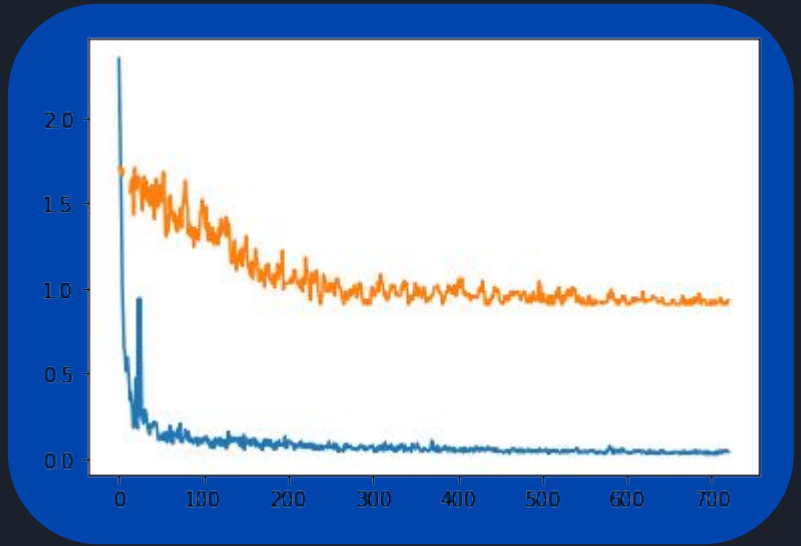
Validation & Testing

Validation:

- Validation set consists of 10% full dataset
- Validate on classification loss after NMS filtering
- Validate on all images of the validation set per training step
- Plot training and validation loss curves

Testing:

- Testing set consists of 20% full dataset
- Computing total and per class classification accuracy
- Producing confusion matrix



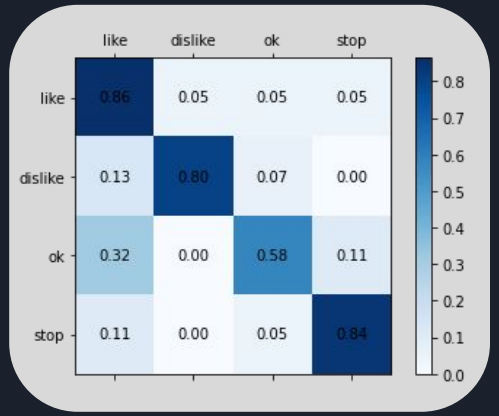
Results

Run 1: No transforms

Learning Rate: 0.0001, Weight Decay: 0.0005, Batch size: 4, Epochs: 2

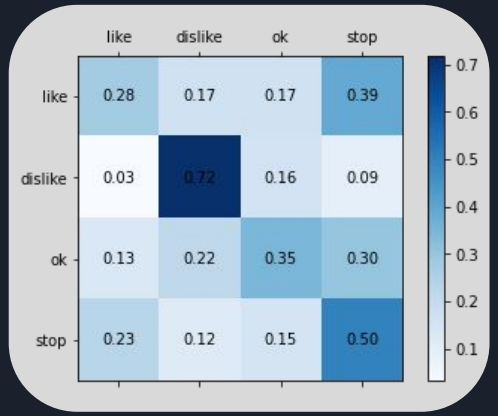
Basic Dataset:

- Average IoU:
  - 0.532
- Average Classification Accuracy given NMS filtering at 0.95 IoU
  - 77%



Advanced Dataset:

- Average IoU:
  - 0.4222
- Average Classification Accuracy given NMS filtering at 0.95 IoU
  - 49%

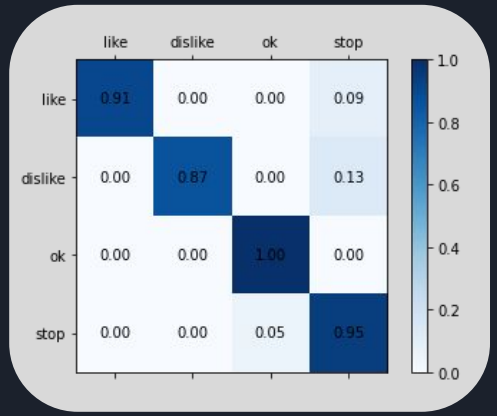


Run 2: No transforms

Learning Rate: 0.0001, Weight Decay: 0.0005, Batch size: 4, Epochs: 10

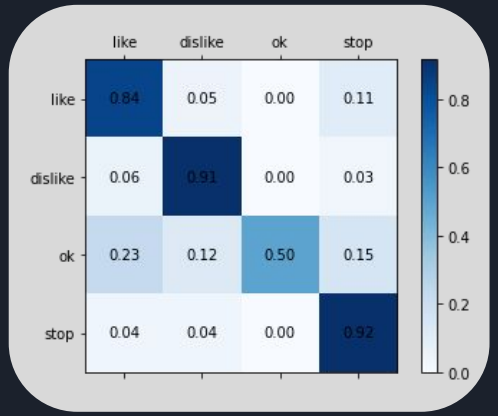
Basic Dataset:

- Average IoU:
  - 0.657
- Average Classification Accuracy given NMS filtering at 0.95 IoU
  - 95%



Advanced Dataset:

- Average IoU:
  - 0.4308
- Average Classification Accuracy given NMS filtering at 0.95 IoU
  - 80%

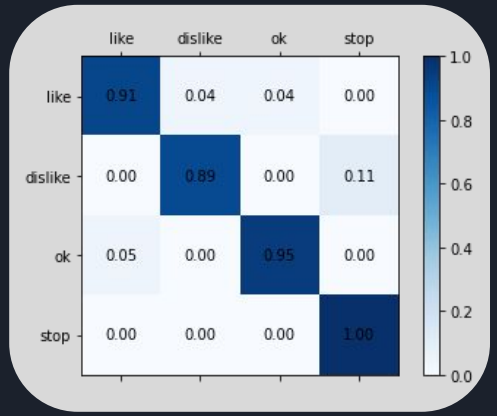


Run 3: With Transforms

Learning Rate: 0.0001, Weight Decay: 0.0005, Batch size: 4, Epochs: 20

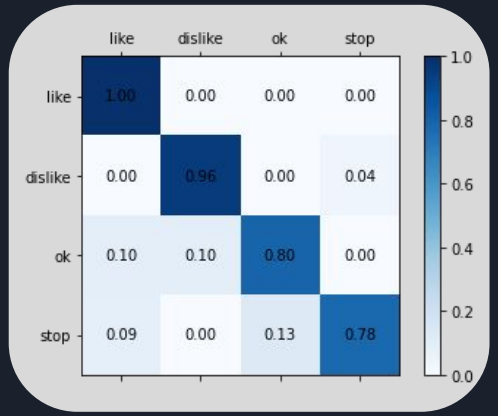
Basic Dataset:

- Average IoU:
  - 0.5955
- Average Classification Accuracy given NMS filtering at 0.95 IoU
  - 94%



Advanced Dataset:

- Average IoU:
  - 0.5849
- Average Classification Accuracy given NMS filtering at 0.95 IoU
  - 88%



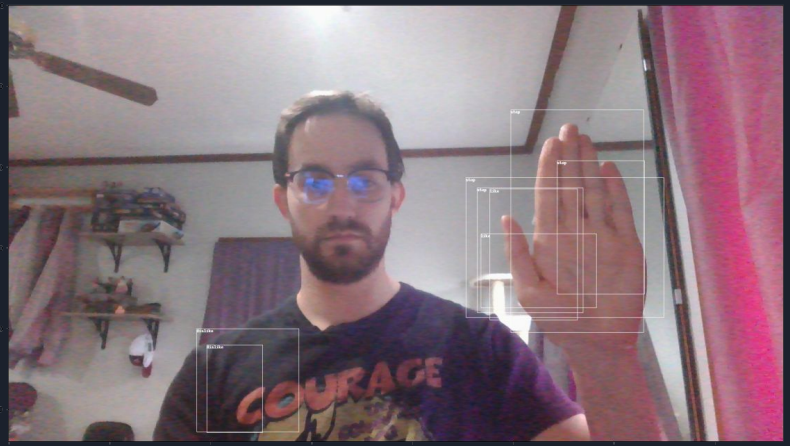
Example Output:

Basic dataset trained at:

LR 0.0001, Weight Decay 0.0005, 10 epochs

Advanced dataset trained at:

LR 0.0001, Weight Decay 0.0005, 10 epochs



Conclusion

- The model is capable to recognize hand gestures based on:
  - Relatively small dataset
  - Both simple and complex dataset
- High classification accuracy: 77 - 95%
- Object detection can be still improved: Average IoU 0.422 - 0.657

Discussion

Difficulties:

- Google Colab resource limitations
- Problems implementing and debugging original YOLOv3 implementation
  - Issues converting original pipeline to Faster-RCNN
- Learning to create good datasets from scratch
  - Annotation is time consuming
- Current augmentation pipeline fails for some data

Points of Note:

- NMS threshold was chosen to focus on classification accuracy
  - Reducing the threshold will give a better representation of the model's detection abilities

Outlooks

Improvements:

- Further increase the size of our dataset
  - Experiments have shown more data increases model performance
- Redesign validation and testing pipelines to increase performance
  - Compute and add more losses, such as objectness and bbox regression
- Evaluate on more metrics, such as precision and recall
- Increase model's detection capabilities

Avenues of Further Exploration:

- Increasing number of learned gestures
  - Potential applications: ASL translation