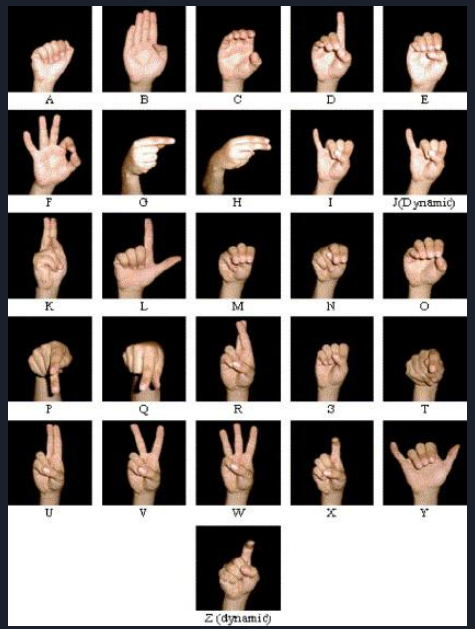
# AMERICAN SIGN LANGUAGE IMAGE CLASSIFICATION

ISHITA JAIN
JYOTHI GANJI
MIHIR GADGIL

# American Sign Language

- ASL is the natural language that serves as predominant sign language for hearing-impaired communities in US and most of Canada.
- ASL is most closely related to French Sign Language
- Originated in early 19th century in American School of the Deaf in West Hartford, Connecticut.
- Lots of study has been done on sign recognition in last few years, namely HMM (Hidden Markov Model), ANN (Artificial Neural Network) and SVM (Support Vector Machines)



# Dataset

- https://www.kaggle.com/datamunge/sign-language-mnist
- 27,455 samples in the training set, with features as pixel values
- Each image sample is 28x28 pixels
- Target is composed of 24 letters, excluding J and Z as they involve motion
- Each letter is encoded as a number from 0 to 25 (excluding 9 and 25)
- Fairly balanced classes, with minority class E with 957 samples and majority class R with 1294 samples
- Added two more images per class, using our own hands
- Test set size : 7,172 samples

# Initial Steps

- Initially worked with Keras
- Custom build architectures were tried which performs well
- But fails with test data and then, tried with pre-trained model “ResNet”

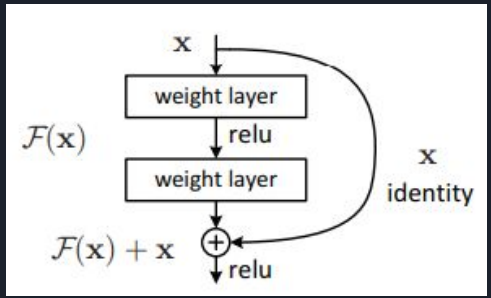
# Model

- ResNet 18
- Pre-trained on ImageNet (2012) dataset, with 1000 classes
- Last layer changed to 26 neurons linear layer
- Further trained on our dataset

# ResNet 18 Architecture

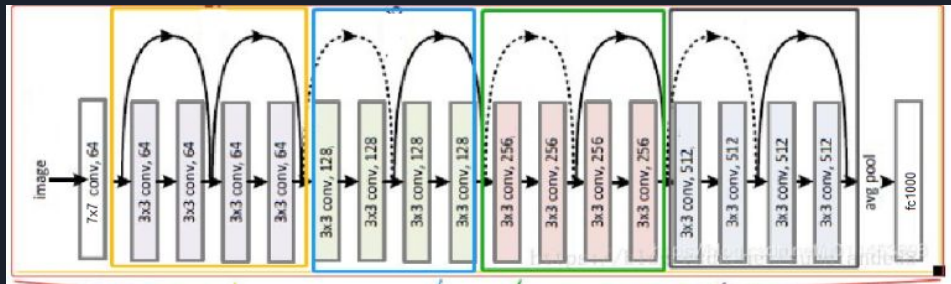
Residual Learning

- Hypothesis: it is easier to approximate the residual function (F(x) := H(x) - x) than to learn the original function (H(x))
- Learning by feedforward neural networks with “shortcut connections” by skipping one or more layers
- Shortcut connections help speed up the learning process




Residual Learning: a building block
(Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun, 2015)

# ResNet 18 Architecture (contd.)




| layer name | output size | 18-layer | 34-layer | 50-layer | 101-layer | 152-layer |
|---|---|---|---|---|---|---|
| conv1 | 112×112 | 7×7, 64, stride 2 | | | | |
| | | 3×3 max pool, stride 2 | | | | |
| conv2_x | 56×56 | $\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$ | $\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$ | $\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$ | $\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$ | $\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$ |
| conv3_x | 28×28 | $\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$ | $\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$ | $\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$ | $\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$ | $\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$ |
| conv4_x | 14×14 | $\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$ | $\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$ | $\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$ | $\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$ | $\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$ |
| conv5_x | 7×7 | $\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$ | $\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$ | $\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$ | $\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$ | $\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$ |
| | 1×1 | average pool, 1000-d fc, softmax | | | | |
| FLOPs | | $1.8\times10^9$ | $3.6\times10^9$ | $3.8\times10^9$ | $7.6\times10^9$ | $11.3\times10^9$ |

(Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun, 2015)

# Why ResNet18?

- Tried ResNet18, GoogleNet and DenseNet
- DenseNet runs out of VRAM
- GoogleNet similar results to ResNet
- But longer time to train

# Preprocessing

1. Grayscale to RGB: Expected by model
2. Resize: 28 x 28 to 224 x 224
3. Horizontal Flip: Simulate right and left hand
4. Rotate: Variations in hand orientation
5. Colour Jitter: Lighting conditions, different skin colours
6. Normalization: Expected by model

# Results

- Custom-built architectures
  - Decent performance on non augmented training data
  - Poor performance on test and augmented data
- ResNet 18 model performance on both training and testing data:
  - Validation loss (Cross Entropy): ~$10^{-4}$
  - Accuracy: 100%
  - F1-Score: 1.0
  - Cohen’s Kappa: 1.0

# References


1. https://www.kaggle.com/datamunge/sign-language-mnist.
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4. Nikam, Ashish S., and Aarti G. Ambekar. "Sign language recognition using image based hand gesture recognition techniques." 2016 Online International Conference on Green Engineering and Technologies (IC-GET). IEEE, 2016.
5. He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.