Transfer Learning for American Sign Language Dataset

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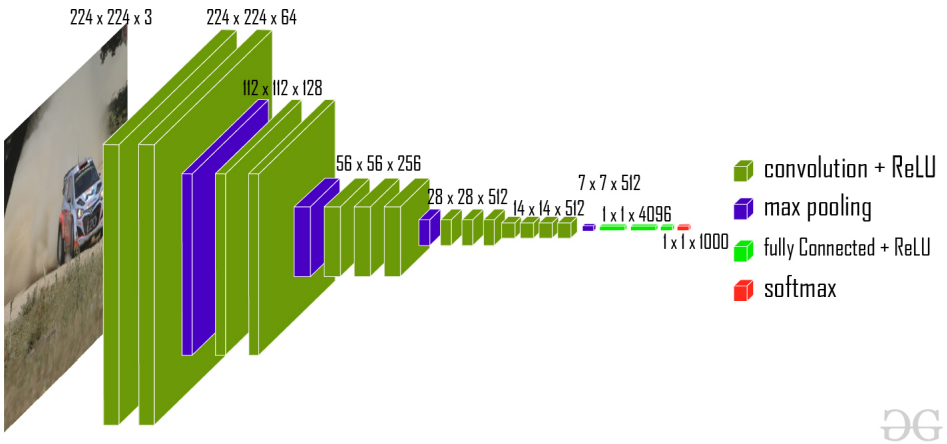
Introduction

Transfer learning is a machine learning technique that allows a pre-trained neural network model to be fine-tuned on a smaller, task-specific dataset. The use of transfer learning has become increasingly prevalent in the field of deep learning, specifically in image recognition, natural language processing, and reinforcement learning. The purpose of this final project is to investigate the effectiveness of transfer learning when applied to the task of classifying ASL hand gestures. There is an abundance of great research studying transfer learning, such as Weiss et al. (2016). We will build on these foundational studies and surveys to learn how transfer learning can be applied to our specific problem. Transfer learning has lots of potential for reducing computation required in deep learning projects, making time for computation a topic of this study. The primary goal of this paper is to evaluate the effectiveness of transfer learning, comparing the performance of the fine-tuned pre-trained models from a model we make without transfer learning. I find transfer learning particularly interesting as an individual, sometimes we feel limited to projects we can do alone because of the limited amount of data an individual can collect, computation power an individual has access to. Using transfer learning we can leverage research of others and in a literal sense open up the number of possibilities that your average person has in research and development.

Methods

For the training of the model, convolutional neural networks (CNNs) will be used. While we will be testing multiple pre-trained neural networks, we will only be talking about the architecture of VGG16, and how it is modified to solve our new task. First lets talk about how image classification works. Pretending that image classification is a black box for a second, the task of image classification is given an input image x, and outputs a single class that the image most likely falls into. For example, if we consider a model trained on the popular ImageNet dataset, given an image the model tries to guess which of the 1000 classes the image most likely is. Enter the VGG16 model for the ImageNet dataset.

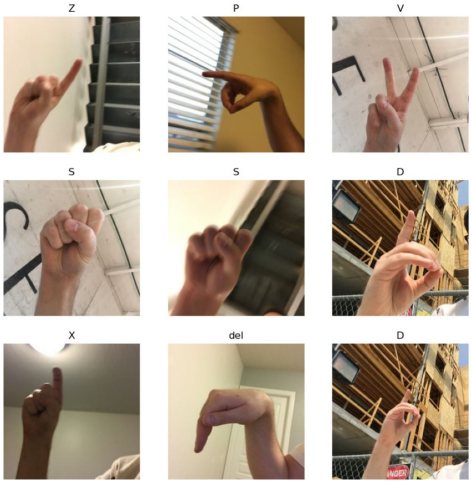


https://www.geeksforgeeks.org/vgg-16-cnn-model/

The above shows the network architecture of the VGG16 model which was trained using the ImageNet dataset. This dataset contains 224x224 images with RGB channels, this gives us an

input tensor of 224x224x3. As this is an example of a CNN, we then see a series of convolution layers using a ReLU activation followed by max pooling layers. This architecture shows 5 convolution/pooling operations, in some cases there are 2 convolutions before pooling and sometimes 3 convolutions. After this series of operations we have a 7x7x512 feature map. Then, this output is flattened to make it a 1x25088 feature vector. Following this is 3 fully connected layers, finally giving us a 1x1000 output. Using the softmax, we get the class predicted for our image. We can imagine the final output vector as $\hat{y} = [\hat{y_0}; \hat{y_1}; \hat{y_2}; ...; \hat{y_{999}}]$, which contains scores of each class, taking the $softmax(\hat{y})$ gives us the probability of each class. The max of the softmax is the predicted class. So why is this useful to us? How can we use this model to predict the classes for the ASL dataset? Essentially, the reason this is so useful, as I mentioned above, we create a feature map before our actual classification. The features in this map can be useful for a new model. ImageNet has a load of classes [2], we can assume by VGG16's very high accuracy that it has a good understanding of the natural world, and thus maybe understands what a hand looks like, meaning where a hand is in the image is not a feature that our fine-tuned model will have to learn. Compared to a model that we train from scratch, will have to use it's limited dataset to figure out more simple features. We cut off the flattening and then dense layers at the end of the neural network and create our own, we then fit the model using the ASL images and are given a new model.

This study uses two main datasets, one directly and one indirectly. While we do not actually use the dataset the ImageNet dataset, I think it is still important to explain it here to gain a full grasp of transfer learning's value. ImageNet is a dataset consisting of approximately 14 million images that each belong to one of 1000 classes [3]. ImageNet was first created to establish a good benchmark test to be used for object categorization. Researchers work hard to develop new and better algorithms to organize and annotate video and image data, better tools require better data to train their algorithms on. We can imagine how a model build using ImageNet can be used to categorize our pictures, think about this as the technology that allows us to search all the pictures on our iPhones for those containing a cat. The second dataset used is ASL Alphabet Test, found on Kaggle. This dataset contains 870 images, each of which contain a hand making the shape of an ASL letter (with some variation). There are twenty-nine possible classes, these include all the letters A-Z as well as "del", "space", and "nothing". This gives us a total of 30 images per class, with a total of 29 classes providing 870 images. Nine random images were selected and are displayed below, above them shows their respective classes.



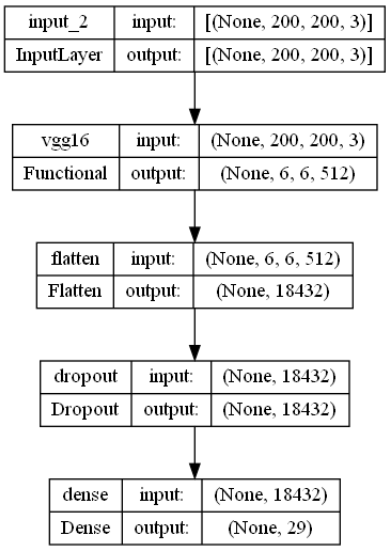
This data was split into three subsets: 609 images for training, 174 images for validation, 87 images for test, a 70:20:10 split. This split ensures that our model is trained and validated using different sets of data, allowing us to evaluate its generalization performance on unseen images. These splits are also important for another reason, data augmentation.

With such a limited dataset, data augmentation is quite useful. Through data augmentation we are able to create a more robust model that is accustomed to more variable data. Data augmentation is a technique that applies random transformations to the images, in this case: flipping, rotating, zooming, adjusting contrast and random translation. These transformations allow us to artificially expand the training dataset. To break down these transformations a bit more descriptively:

- Random horizontal flipping
- Random rotation within a range of ±20% of the original angle
- Random zoom, with a zoom range of ±20% along both the horizontal and vertical axes
- Random contrast adjustment, with a contrast range of ±20%
- Random translation, with a translation range of ±20% along both the horizontal and vertical axes

By incorporating the data augmentation layer into our fine-tuning process, we aimed to increase the models' ability to generalize to unseen data, improving the accuracy on the test dataset by approximately 21%.

Now to get into the training of the model. We used the VGG16 model as our based model, pre-trained on the ImageNet dataset as mentioned above. We added a custom prediction layer with the number of outputs equal to the number of classes in our dataset (29) and a softmax activation function for multi-class classification. The final model included the following layers:



- **input_4:** Input layer, this represents the image with dimensions 200x200 with 3 channels (RGB)
- **vgg16:** VGG16 base model (without the top classification layer)
- **flatten_1:** Flatten layer to convert the feature maps into a 1D tensor
- **dropout_1:** Dropout layer with a rate of 0.2 to regularize the model and prevent overfitting
- **dense_1:** Dense layer (prediction layer) with 29 output units and a softmax activation function

The model was then compiled using the Adam optimizer with a learning rate of 0.001 and the sparse categorical cross-entropy loss function. To quickly explain the Adam (Adaptive Moment Estimation) optimizer, it adapts the learning rate for each weight in the model individually, making it more efficient and effective for deep neural networks. It computes adaptive learning rates for each parameter using the first and second moments (the mean and centered variance) of the gradients. These are estimated with exponential moving averages. The primary benefits of Adam are faster convergence, improved handling of sparse gradients, and robustness to noisy data. Sparse categorical cross-entropy loss is used for multi-class classification tasks where the target variable consists of integer class labels rather than one-hot-encoded vectors. It computes the cross-entropy loss between the predicted class probabilities and the true class labels. This is useful when working with lots of classes, as it avoids the need for one-hot encoding the target labels, in this case with 29 classes we could've gotten away with encoding though. The models' performance was evaluated based on its accuracy during training. The model was trained for 25 epochs, using the training dataset and validating its performance on the validation set.

Results