Convolutional Neural Network: Module 2 - Pre-trained Network

Artificial Intelligence

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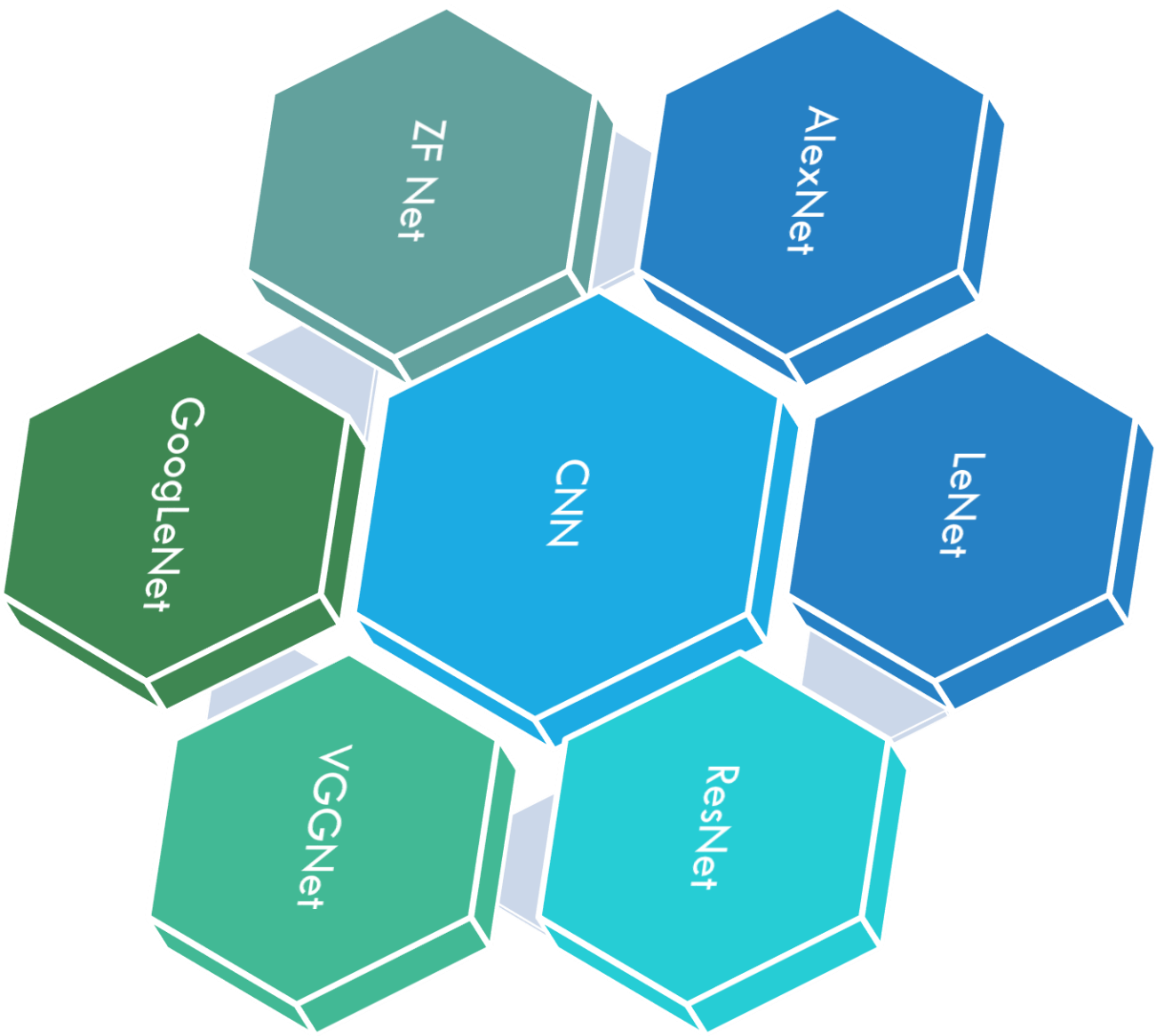
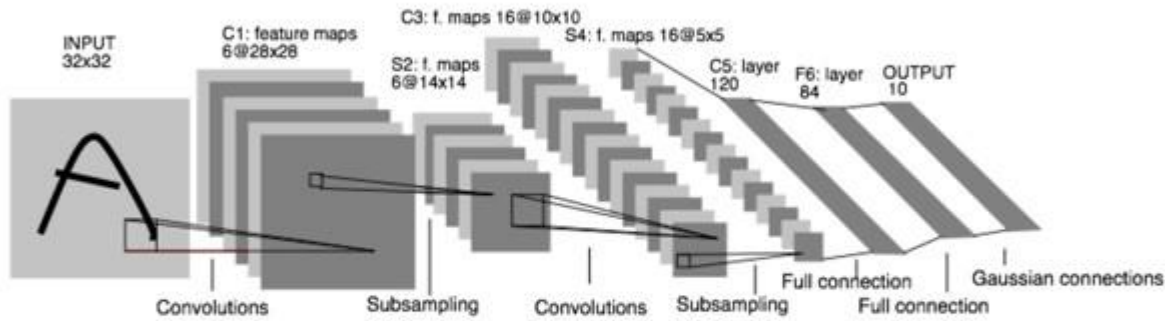
Existing Networks



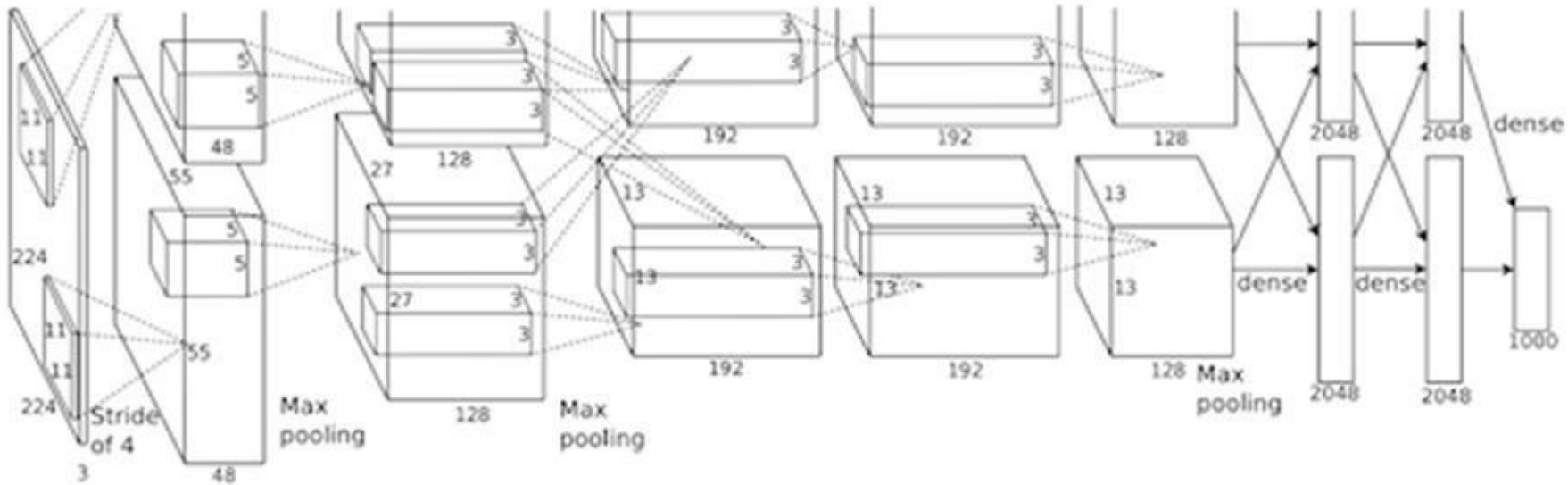
- **LeNet**. The first successful applications of Convolutional Networks were developed by Yann LeCun in 1990's. Of these, the best known is the LeNet architecture that was used to read zip codes, digits, etc.

Convolutional Networks: 1989



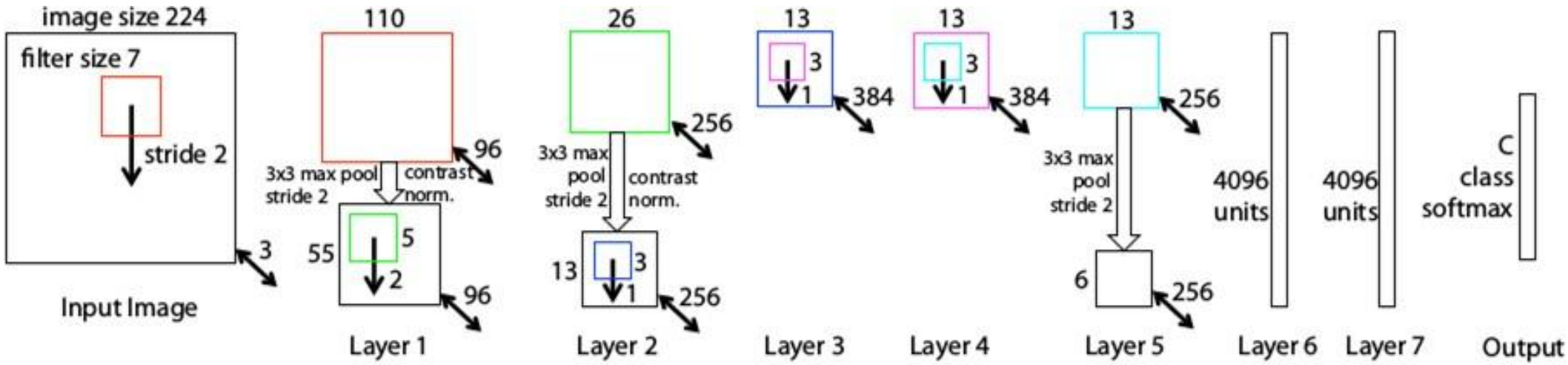
LeNet: a layered model composed of convolution and subsampling operations followed by a holistic representation and ultimately a classifier for handwritten digits. [LeNet]

- **AlexNet**. The first work that popularized Convolutional Networks in Computer Vision was the AlexNet, developed by Alex Krizhevsky, Ilya Sutskever and Geoff Hinton. The AlexNet was submitted to the ImageNet ILSVRC challenge in 2012 and significantly outperformed the second runner-up (top 5 error of 16% compared to runner-up with 26% error). The Network had a very similar architecture to LeNet, but was deeper, bigger, and featured Convolutional Layers stacked on top of each other (previously it was common to only have a single CONV layer always immediately followed by a POOL layer).



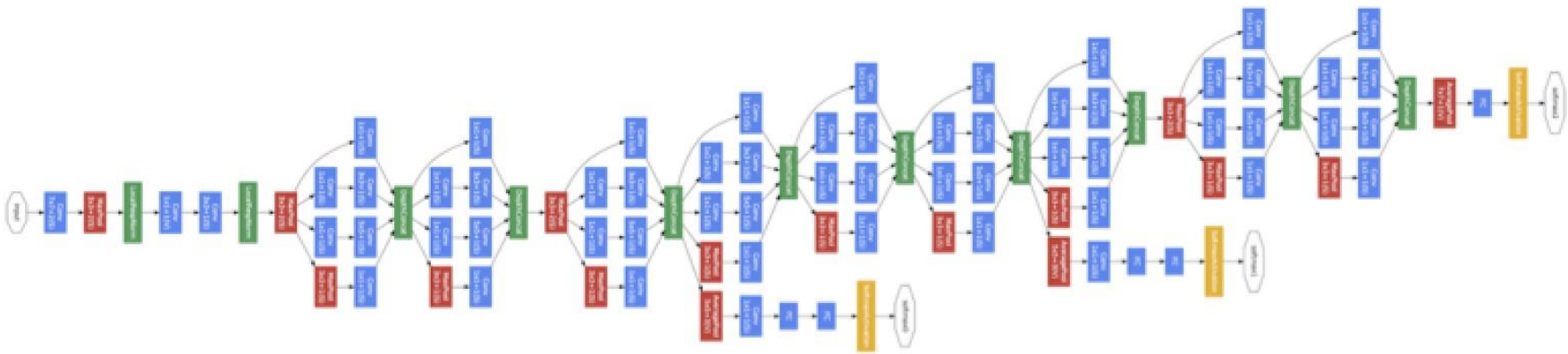
AlexNet architecture (May look weird because there are two different "streams". This is because the training process was so computationally expensive that they had to split the training onto 2 GPUs)

- **ZF Net**. The ILSVRC 2013 winner was a Convolutional Network from Matthew Zeiler and Rob Fergus. It became known as the ZFNet (short for Zeiler & Fergus Net). It was an improvement on AlexNet by tweaking the architecture hyperparameters, in particular by expanding the size of the middle convolutional layers and making the stride and filter size on the first layer smaller.



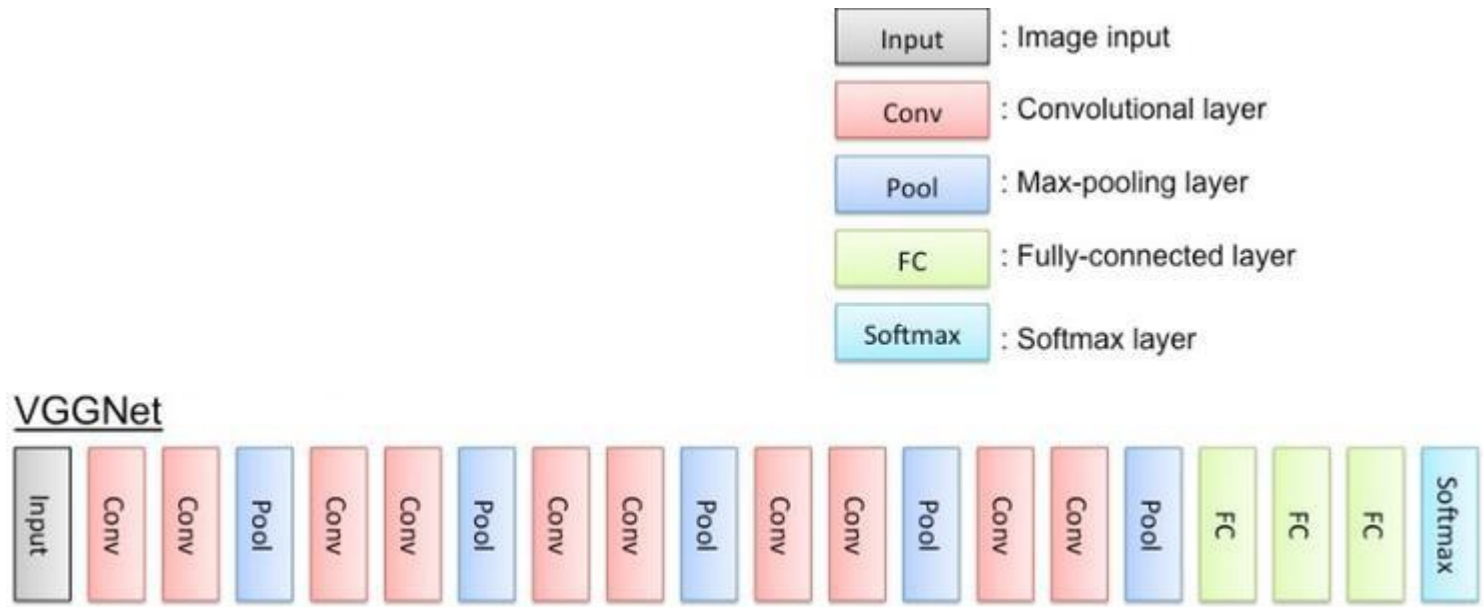
ZF Net Architecture

- **GoogLeNet**. The ILSVRC 2014 winner was a Convolutional Network from Szegedy et al. from Google. Its main contribution was the development of an *Inception Module* that dramatically reduced the number of parameters in the network (4M, compared to AlexNet with 60M). Additionally, this paper uses Average Pooling instead of Fully Connected layers at the top of the ConvNet, eliminating a large amount of parameters that do not seem to matter much. There are also several followup versions to the GoogLeNet, most recently Inception-v4.

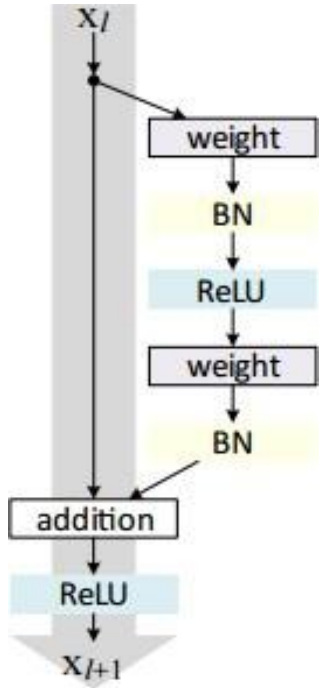


Convolution
Pooling
Softmax
Other

- **VGGNet**. The runner-up in ILSVRC 2014 was the network from Karen Simonyan and Andrew Zisserman that became known as the VGGNet. Its main contribution was in showing that the depth of the network is a critical component for good performance. Their final best network contains 16 CONV/FC layers and, appealingly, features an extremely homogeneous architecture that only performs 3x3 convolutions and 2x2 pooling from the beginning to the end. Their pretrained model is available for plug and play use in Caffe. A downside of the VGGNet is that it is more expensive to evaluate and uses a lot more memory and parameters (140M). Most of these parameters are in the first fully connected layer, and it was since found that these FC layers can be removed with no performance downgrade, significantly reducing the number of necessary parameters.



- **ResNet**. Residual Network developed by Kaiming He et al. was the winner of ILSVRC 2015. It features special *skip connections* and a heavy use of batch normalization. The architecture is also missing fully connected layers at the end of the network. The reader is also referred to Kaiming's presentation (video, slides), and some recent experiments that reproduce these networks in Torch. ResNets are currently by far state of the art Convolutional Neural Network models and are the default choice for using ConvNets in practice (as of May 10, 2016). In particular, also see more recent developments that tweak the original architecture from Kaiming He et al. Identity Mappings in Deep Residual Networks (published March 2016).



```python
# import the necessary packages
from keras.applications import ResNet50
from keras.applications import InceptionV3
from keras.applications import Xception # TensorFlow ONLY
from keras.applications import VGG16
from keras.applications import VGG19
from keras.applications import imagenet_utils
from keras.applications.inception_v3 import preprocess_input
from keras.preprocessing.image import img_to_array
from keras.preprocessing.image import load_img
import numpy as np
import argparse
import cv2
```

Import Package

```
# initialize the input image shape (224x224 pixels) along with
# the pre-processing function (this might need to be changed
# based on which model we use to classify our image)
inputShape = (224, 224)
preprocess = imagenet_utils.preprocess_input

# define a dictionary that maps model names to their classes
# inside Keras
'''
MODELS = {
    "vgg16": VGG16,
    "vgg19": VGG19,
    "inception": InceptionV3,
    "xception": Xception, # TensorFlow ONLY
    "resnet": ResNet50
}
'''

# load our the network weights from disk (NOTE: if this is the
# first time you are running this script for a given network, the
# weights will need to be downloaded first -- depending on which
# network you are using, the weights can be 90-575MB, so be
# patient; the weights will be cached and subsequent runs of this
# script will be *much* faster)
Network = VGG16
model = Network(weights="imagenet")
```

Initialize Network

```
val = 0
for i in range(0,11):
    #load data
    val = val + 1
    print("[INFO] loading and pre-processing image...")
    pathDir = "images/" +str(val) + ".jpg"
    image = load_img(pathDir, target_size=inputShape)#Keras processing image module
    image = img_to_array(image)
    # expand dimension to feed as (1,224,224,3)
    image = np.expand_dims(image, axis=0)
    print(image.shape) # to check matrix dimension which suitable for tensorflow
    print(model.summary())
    # pre-process image
    image = preprocess(image)
    # classify the image
    print("[INFO] classifying image with")
    preds = model.predict(image)  #keras method to predict
    P = imagenet_utils.decode_predictions(preds) # keras.application.imagenet_utils

    # display image with classification
    for (i, (imagenetID, label, prob)) in enumerate(P[0]):
        print("{}. {}: {:.2f}%".format(i + 1, label, prob * 100))

    orig = cv2.imread(pathDir)
    (imagenetID, label, prob) = P[0][0]
    orig = cv2.resize(orig, (300, 300))
    cv2.putText(orig, "Label: {}, {:.2f}%".format(label, prob * 100),(10, 30),
                cv2.FONT_HERSHEY_SIMPLEX, 0.8, (0, 255, 0), 2)
    cv2.imshow("Classification", orig)
    cv2.waitKey(0)
```

Initialize Network