EECE-4710 "IoT and TinyML"

Preventing Overfitting

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BE THE DIFFERENCE.

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Preventing Overfitting

+Data

+Data

+Data

+Data

But what to do if we do not have more data?

- Data Augmentation (artificial)
- Transfer Learning
- Early Stopping
- Dropout Regularization

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Preventing Overfitting

More Data, Data Augmentation (artificial)

Overfitting generally occurs when there are a small number of training examples. Data augmentation takes the approach of generating additional training data from your existing examples by augmenting them using random transformations that yield believable-looking images. This helps expose the model to more aspects of the data and generalize better.

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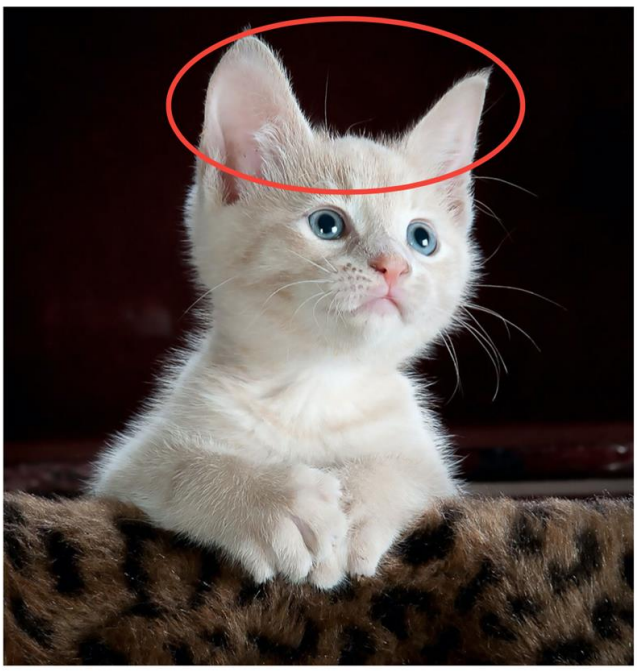

Training

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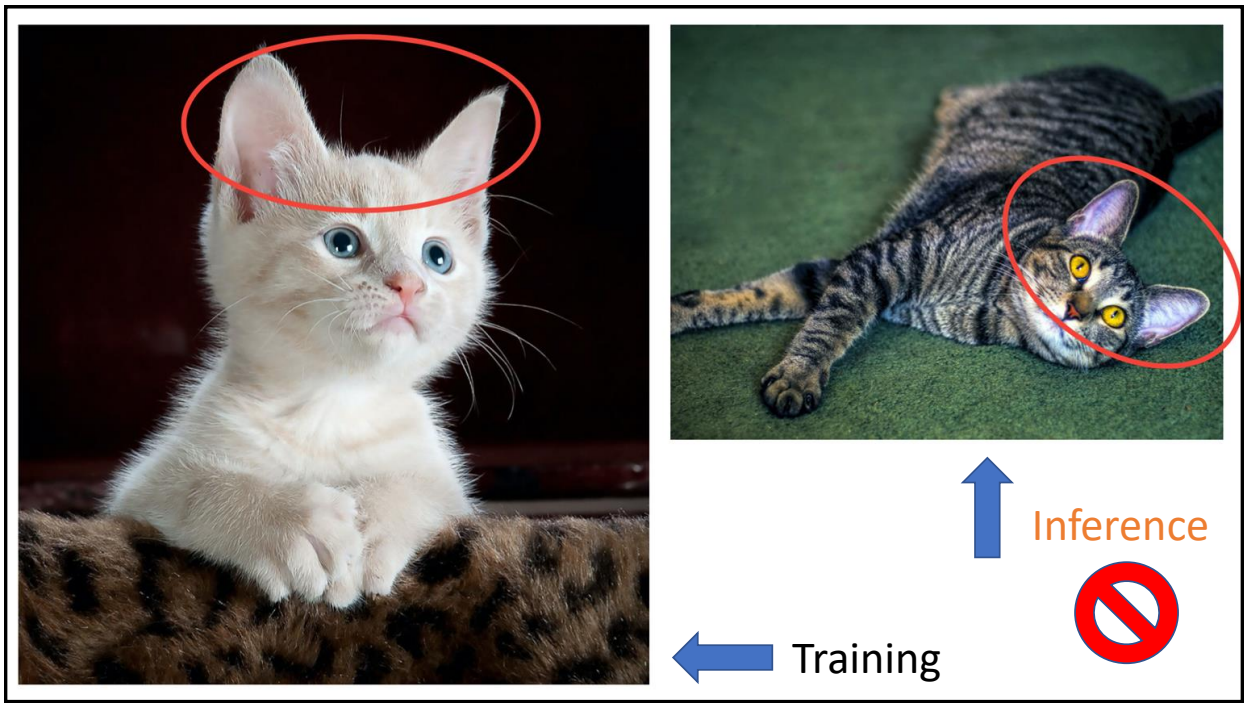
Inference
Training

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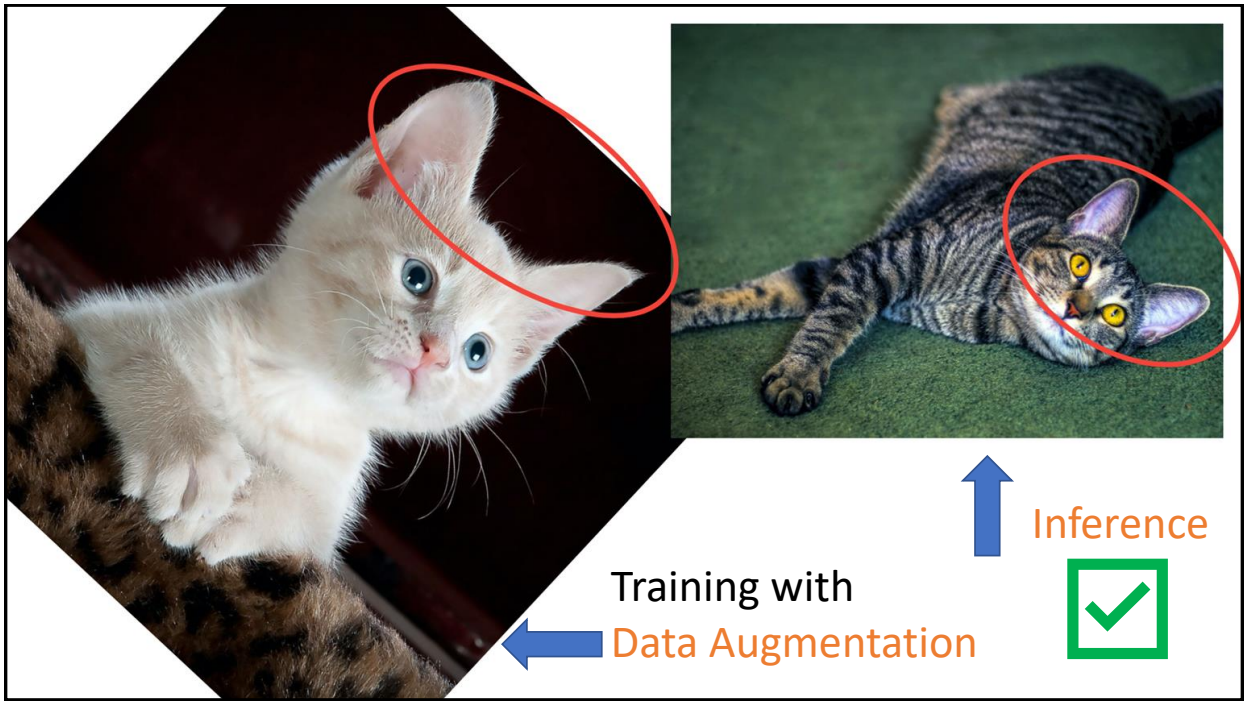
Inference
Training with
Data Augmentation

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Using Keras Preprocessing Layers

```
data_augmentation = tf.keras.Sequential([
  layers.RandomFlip("horizontal_and_vertical"),
  layers.RandomRotation(0.2),
])
```

```
plt.figure(figsize=(10, 10))
for i in range(9):
  augmented_image = data_augmentation(image)
  ax = plt.subplot(3, 3, i + 1)
  plt.imshow(augmented_image[0])
  plt.axis("off")
```

A variety of preprocessing layers you can use for data augmentation including:

- tf.keras.layers.RandomContrast
- tf.keras.layers.RandomCrop
- tf.keras.layers.RandomZoom
- ...

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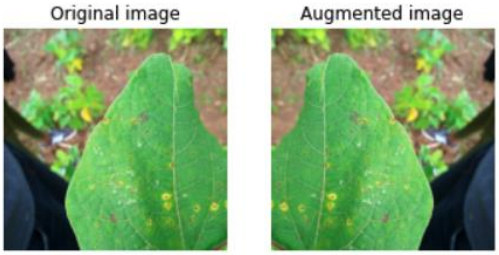
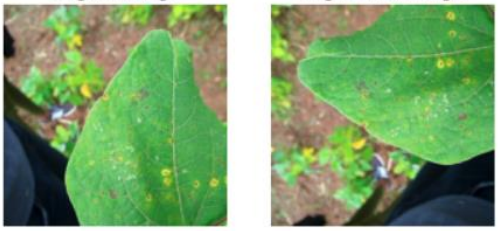
Using tf.image

```
flipped = tf.image.flip_left_right(image)
visualize(image, flipped)
```




```
rotated = tf.image.rot90(image)
visualize(image, rotated)
```



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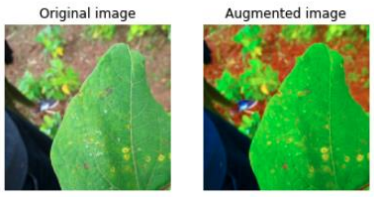
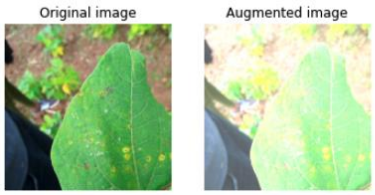
Using tf.image

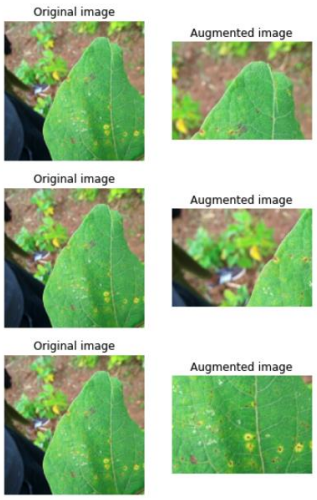
```
saturated = tf.image.adjust_saturation(image, 3)
visualize(image, saturated)
```




```
bright = tf.image.adjust_brightness(image, 0.4)
visualize(image, bright)
```




```
for i in range(3):
  seed = (i, 0)  # tuple of size (2,)
  stateless_random_crop = tf.image.stateless_random_crop(
      image, size=[210, 300, 3], seed=seed)
  visualize(image, stateless_random_crop)
```



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Data Augmentation

Code Time!

IESTI01_data_augmentation.ipynb

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Preventing Overfitting

Early Stopping & Dropout Regularization

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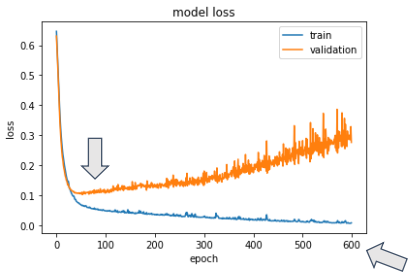
Early Stopping

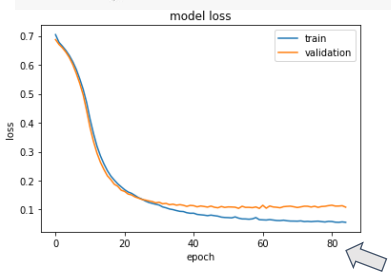
```
from tensorflow.keras.callbacks import EarlyStopping

early_stop = EarlyStopping(monitor='val_loss',
                           mode='min',
                           verbose=1,
                           patience=25)
```

```
history = model.fit(X_train,
                    y_train,
                    epochs=600,
                    validation_data=(X_test, y_test),
                    verbose=1
                    )
```




```
history = model.fit(x=X_train,
                    y=y_train,
                    epochs=600,
                    validation_data=(X_test, y_test),
                    verbose=1,
                    callbacks=[early_stop]
                    )
```



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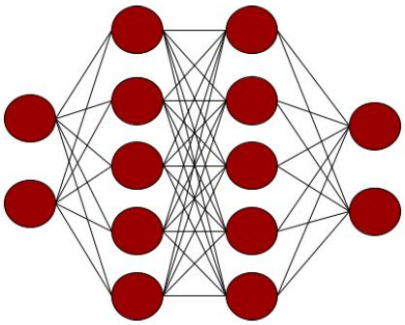
Dropout Regularization

```
model = tf.keras.models.Sequential([
                    tf.keras.layers.Flatten(input_shape=(28,28)),
                    tf.keras.layers.Dense(256, activation=tf.nn.relu),
                    tf.keras.layers.Dense(128, activation=tf.nn.relu),
                    tf.keras.layers.Dense(64, activation=tf.nn.relu),
                    tf.keras.layers.Dense(10, activation=tf.nn.softmax)])
```



Fashion MNIST Dataset

- 20 Epochs
- 94.0% Accuracy on Train Data
- 88.5% Accuracy on Validation Data

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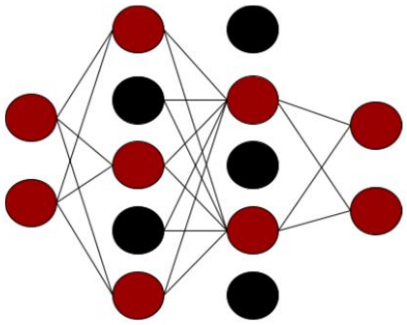
Dropout Regularization

```
model = tf.keras.models.Sequential([
                    tf.keras.layers.Flatten(input_shape=(28,28)),
                    tf.keras.layers.Dense(256, activation=tf.nn.relu),
                    tf.keras.layers.Dropout(0.2),
                    tf.keras.layers.Dense(128, activation=tf.nn.relu),
                    tf.keras.layers.Dropout(0.2),
                    tf.keras.layers.Dense(64, activation=tf.nn.relu),
                    tf.keras.layers.Dropout(0.2),
                    tf.keras.layers.Dense(10, activation=tf.nn.softmax)])
```



Fashion MNIST Dataset

- 20 Epochs
- 89.5% Accuracy on Train Data
- 88.3% Accuracy on Validation Data

Removing a random number of neurons and connections (in this example, 20%), reduces the chances of the neurons becoming overspecialized and the model will generalize better, reducing the overfit.

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Breast Cancer BINARY Classification
Wisconsin Diagnostic Breast Cancer (WDBC)
Code Time!

Breast_Cancer_Classification.ipynb

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Preventing Overfitting
Transfer Learning

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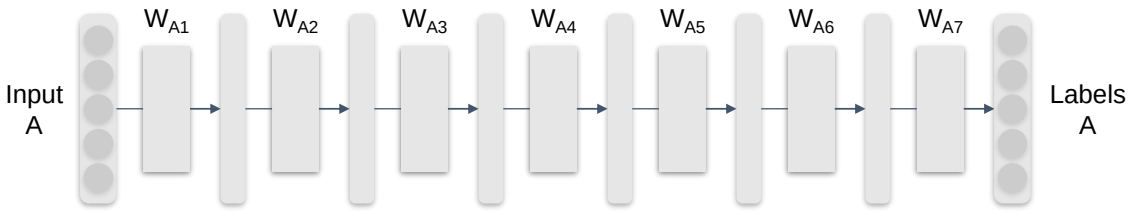
End Result of Training



Result of training is to learn the weights of neural network model.

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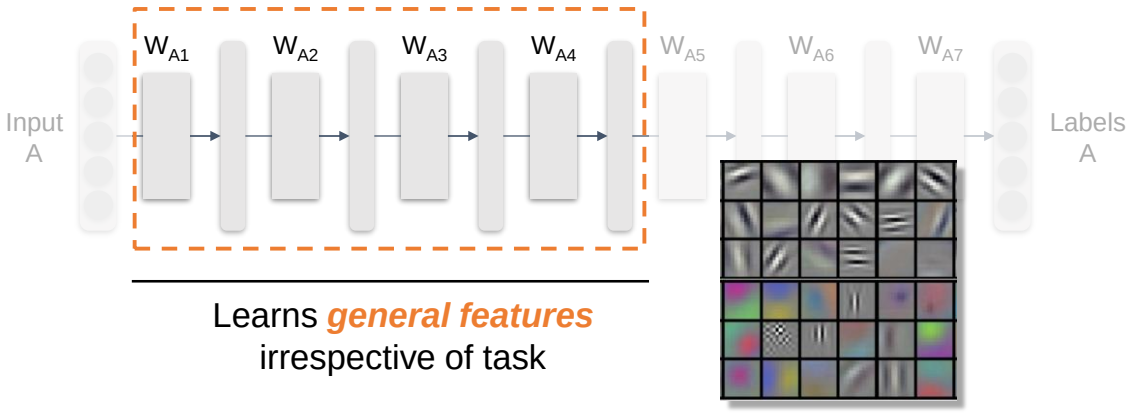
End Result of Training



Learns ***general features***
irrespective of task

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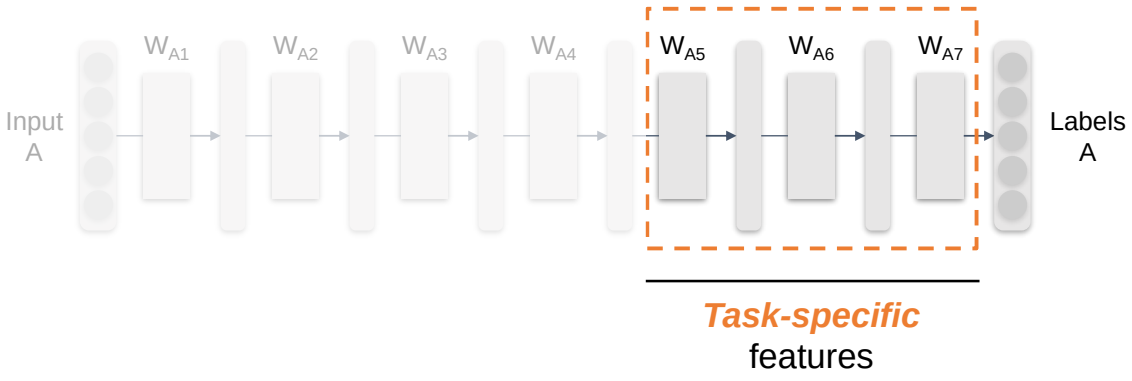
End Result of Training



Task-specific
features

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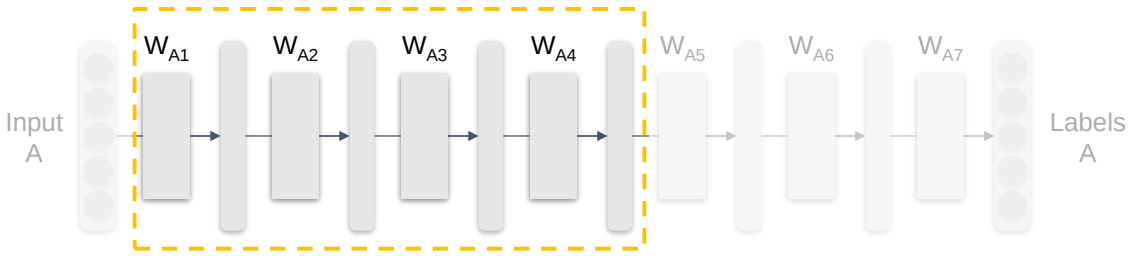
Transfer Learning

Reuse (freeze general feature extraction)



Learns ***general features***
irrespective of task

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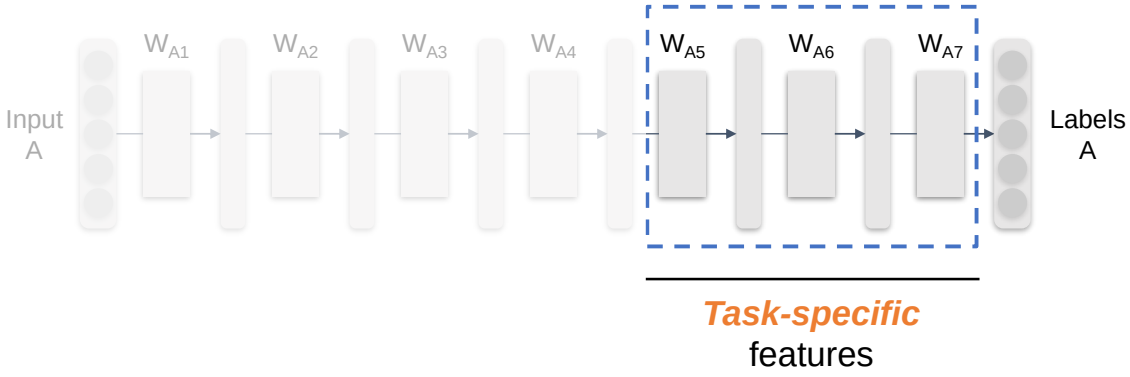
Transfer Learning

Train **only** last few layers



Task-specific features

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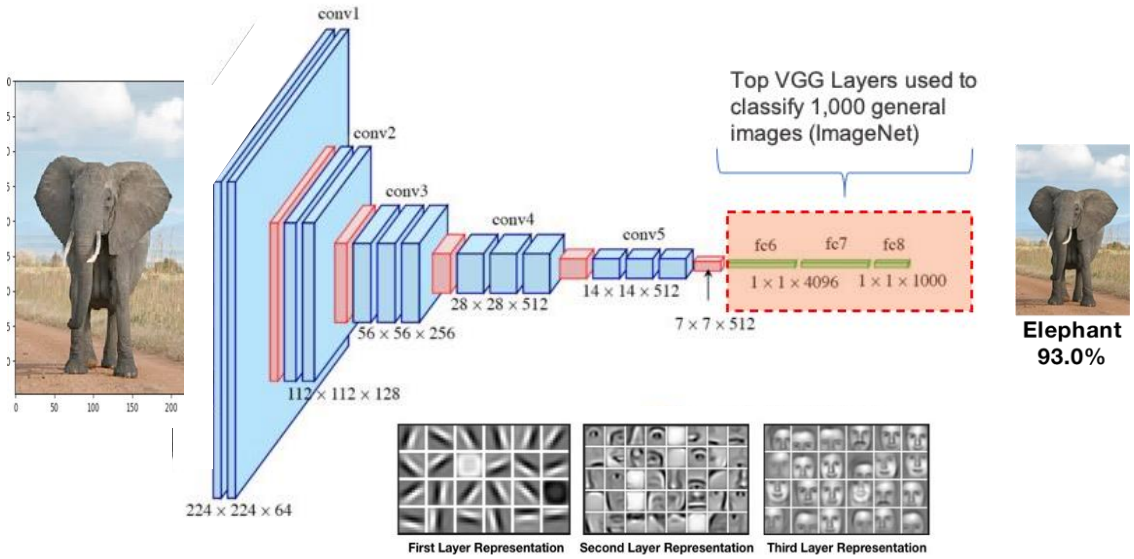
Example: VGG-16 Convolutional Neural Network Model



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VGG-16

- ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is an annual computer vision competition. Each year, teams compete on two tasks:
  - The first is to detect objects within an image coming from 200 classes, which is called **object localization**.
  - The second is to classify images, each labeled with one of 1000 categories, which is **called image classification**.
- VGG-16 was proposed by Karen Simonyan and Andrew Zisserman of the Visual Geometry Group Lab of Oxford University in 2014 in the paper "VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION".
  - This model won 1st and 2nd place in the above categories in the 2014 ILSVRC challenge.

https://www.mygreatlearning.com/blog/introduction-to-vgg16/
https://www.geeksforgeeks.org/vgg-16-cnn-model/

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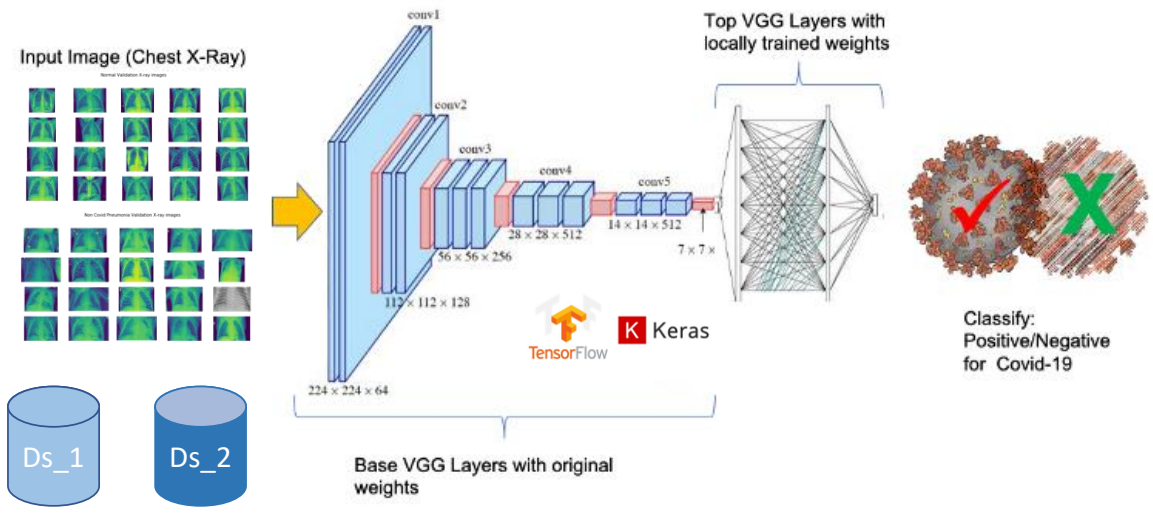
Training the model (Transfer Learning)



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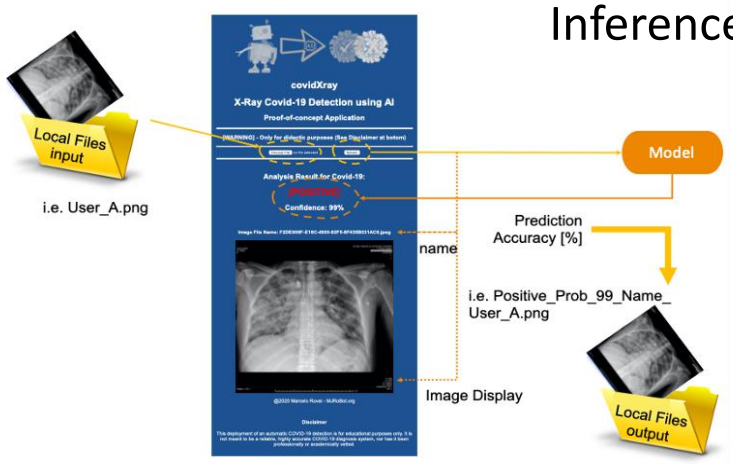
covidXray

Detecting Covid-19 in Chest X-Ray images

https://github.com/Mjrovai/covid19Xray

Inference



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Credits

- A previous edition of this course was developed in collaboration with Dr. Susan C. Schneider of Marquette University.
- We are very grateful and thank all the following professors, researchers, and practitioners for jump-starting courses on TinyML and for sharing their teaching materials:

- Prof. Marcelo Rovai - TinyML - Machine Learning for Embedding Devices, UNIFEI
  - https://github.com/Mjrovai/UNIFEI-IESTI01-TinyML-2022.1
- Prof. Vijay Janapa Reddi - CS249r: Tiny Machine Learning, Applied Machine Learning on Embedded IoT Devices, Harvard
  - https://sites.google.com/g.harvard.edu/tinyml/home
- Prof. Rahul Mangharam – ESE3600: Tiny Machine Learning, Univ. of Pennsylvania
  - https://tinyml.seas.upenn.edu/#
- Prof. Brian Plancher - Harvard CS249r: Tiny Machine Learning (TinyML), Barnard College, Columbia University
  - https://a2r-lab.org/courses/cs249r_tinyml/

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References

- Additional references from where information and other teaching materials were gathered include:

- Applications & Deploy textbook: “TinyML” by Pete Warden, Daniel Situnayake
  - https://www.oreilly.com/library/view/tinyml/9781492052036/
- Deploy textbook “TinyML Cookbook” by Gian Marco Iodice
  - https://github.com/PacktPublishing/TinyML-Cookbook
- Jason Brownlee
  - https://machinelearningmastery.com/
- TinyMLedu
  - https://tinyml.seas.harvard.edu/
- Professional Certificate in Tiny Machine Learning (TinyML) – edX/Harvard
  - https://www.edx.org/professional-certificate/harvardx-tiny-machine-learning
- Introduction to Embedded Machine Learning - Coursera/Edge Impulse
  - https://www.coursera.org/learn/introduction-to-embedded-machine-learning
- Computer Vision with Embedded Machine Learning - Coursera/Edge Impulse
  - https://www.coursera.org/learn/computer-vision-with-embedded-machine-learning