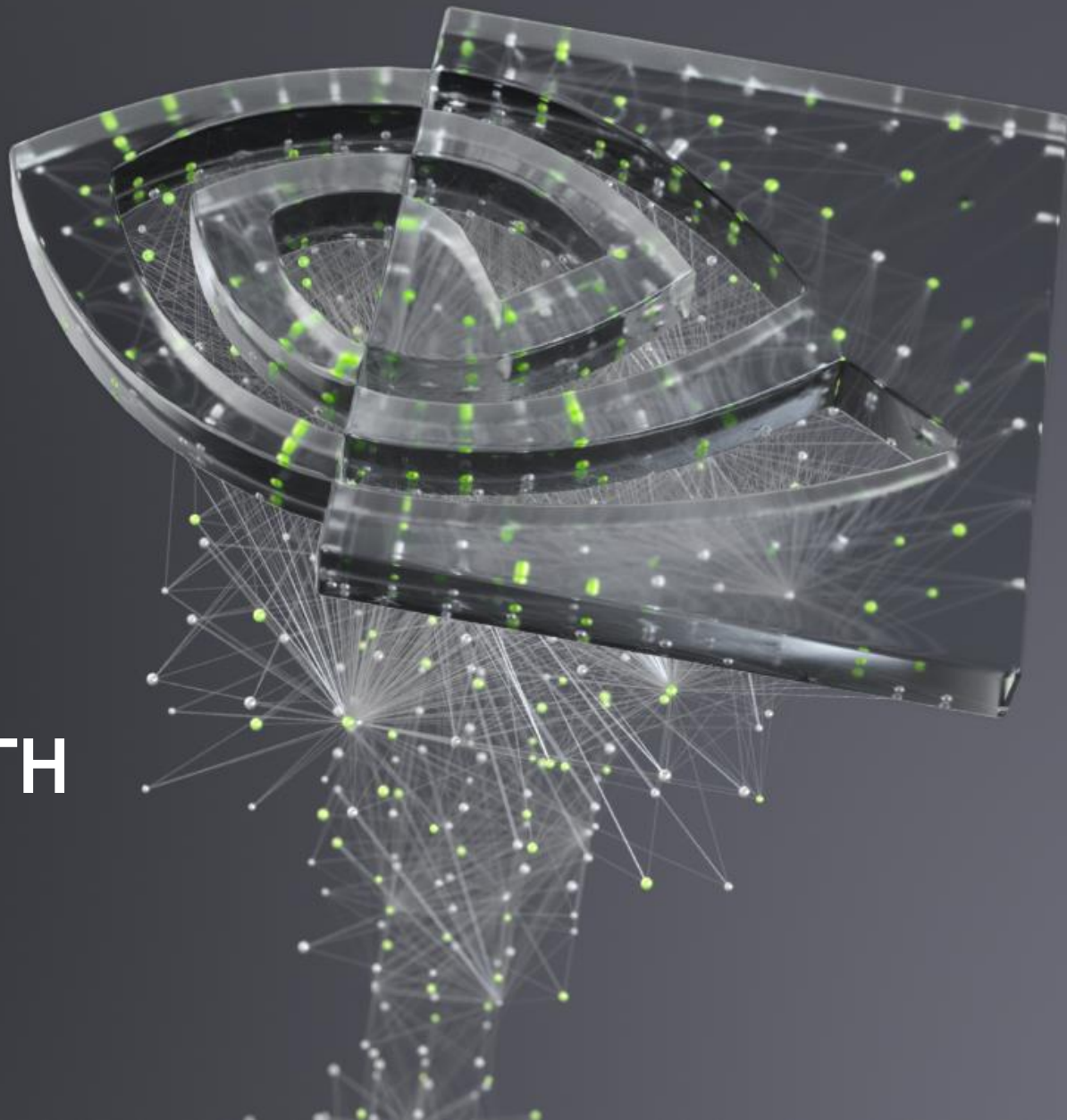




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GETTING STARTED WITH IMAGE SEGMENTATION





WHAT THIS COURSE IS

Neural Networks for Medical Imaging

Discussion/Demonstration of Image Segmentation using Deep Learning

Transposed Convolutional Neural Networks

Hands-on exercises using TensorFlow for CNN training and evaluation of Image Segmentation workflow

Modern Deep Learning Frameworks

Get practice using TensorFlow 2 and the Keras API



WHAT THIS COURSE ISN'T

An introduction to Deep Neural Networks

A mathematical explanation of Convolution and CNNs

A survey of all the features and options of TensorFlow



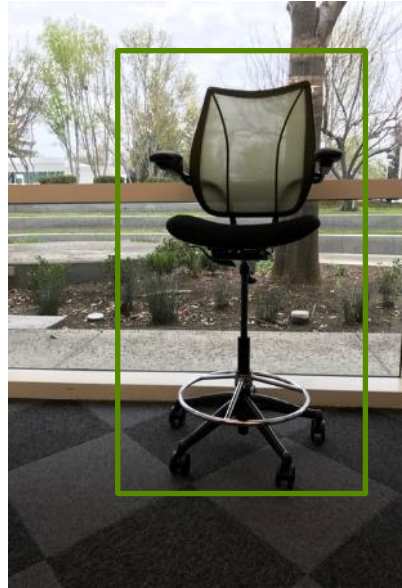
IMAGE SEGMENTATION

COMPUTER VISION TASKS

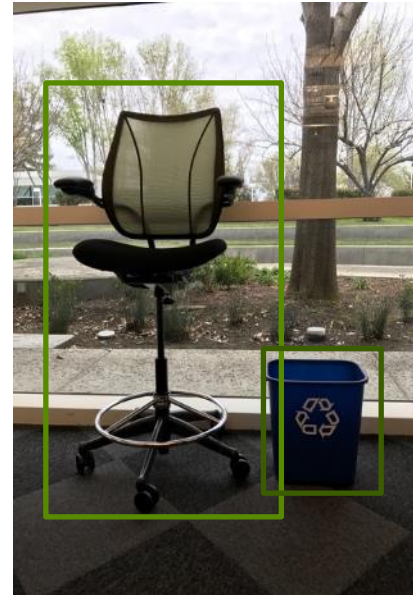
**Image
Classification**



**Image
Classification +
Localization**



Object Detection



**Image
Segmentation**



(inspired by a slide used in cs231n lecture from Stanford University)

IMAGE SEGMENTATION

- “Segmentation” sometimes used to describe similar but slightly different tasks
- In this lab, semantic segmentation will be performed
 - i.e., in an image, each pixel will be placed into one of multiple classes
- In a sense it’s a classification problem where each pixel has a class, vs image recognition where each image (collection of pixels) has a class
- Specifically we’ll be looking at medical imaging data and attempting to determine where the left ventricle (LV) is
 - i.e., for each pixel is it part of LV or not?



TENSORFLOW

WHAT IS TENSORFLOW?

Created by Google, [tensorflow.org](https://www.tensorflow.org)

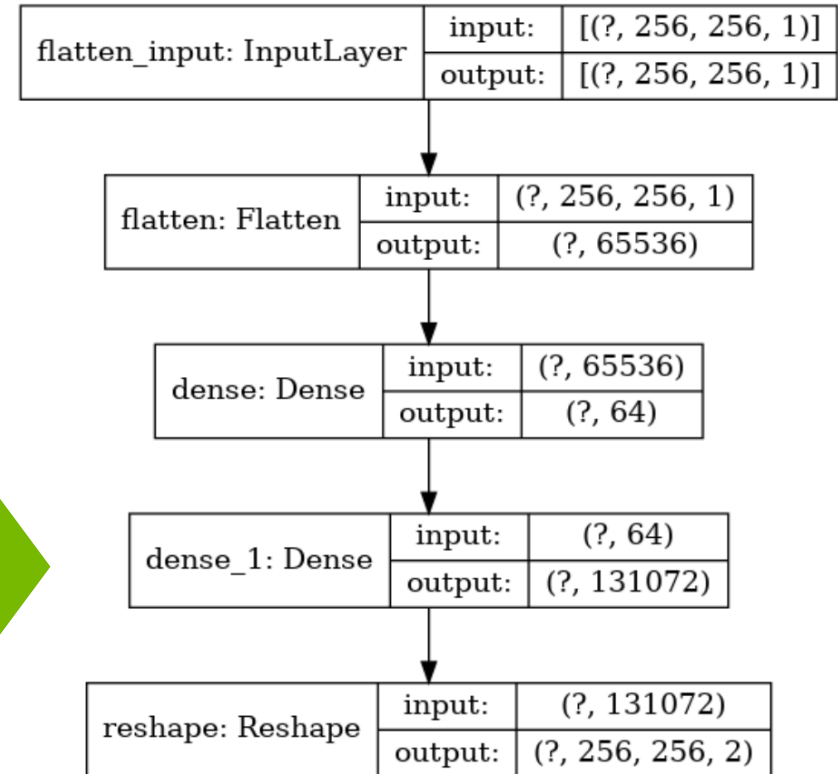
- “Open source software library for machine intelligence”
 - Available on GitHub
- Flexibility—express your computation as a data flow graph
 - If you can express it in TF syntax, you can run it
- Portability—CPUs and GPUs, workstation, server, mobile
- Language options—Python, C++, Go, Java
- Performance—Tuned for performance on CPUs and GPUs
 - Assign tasks to different hardware devices
 - Uses CUDNN

WHAT IS KERAS?

Created by keras.io

- “Keras is a deep learning API written in Python, running on top of the machine learning platform TensorFlow”
 - Comes preinstalled with TensorFlow 2

```
# set up the model architecture
model = tf.keras.models.Sequential([
    Flatten(input_shape=[256, 256, 1]),
    Dense(64, activation='relu'),
    Dense(256*256*2, activation='softmax'),
    Reshape((256, 256, 2))
])
```



SAMPLE WORKFLOW

1

Prepare the Data
TFRecords

2

Build the Keras Model

3

Train the Model

4

Evaluate the Model
DICE, TensorBoard



THE LAB

Dataset

- Cardiac MRI short-axis (SAX) scans
 - Sunnybrook cardiac images from earlier competition
http://smial.sri.utoronto.ca/LV_Challenge/Data.html
 - "Sunnybrook Cardiac MR Database" is made available under the CC0 1.0 Universal license described above, and with more detail here:
<http://creativecommons.org/publicdomain/zero/1.0/>
 - Attribution:
 - Radau P, Lu Y, Connelly K, Paul G, Dick AJ, Wright GA. "Evaluation Framework for Algorithms Segmenting Short Axis Cardiac MRI." The MIDAS Journal -Cardiac MR Left Ventricle Segmentation Challenge, <http://hdl.handle.net/10380/3070>

Image Example

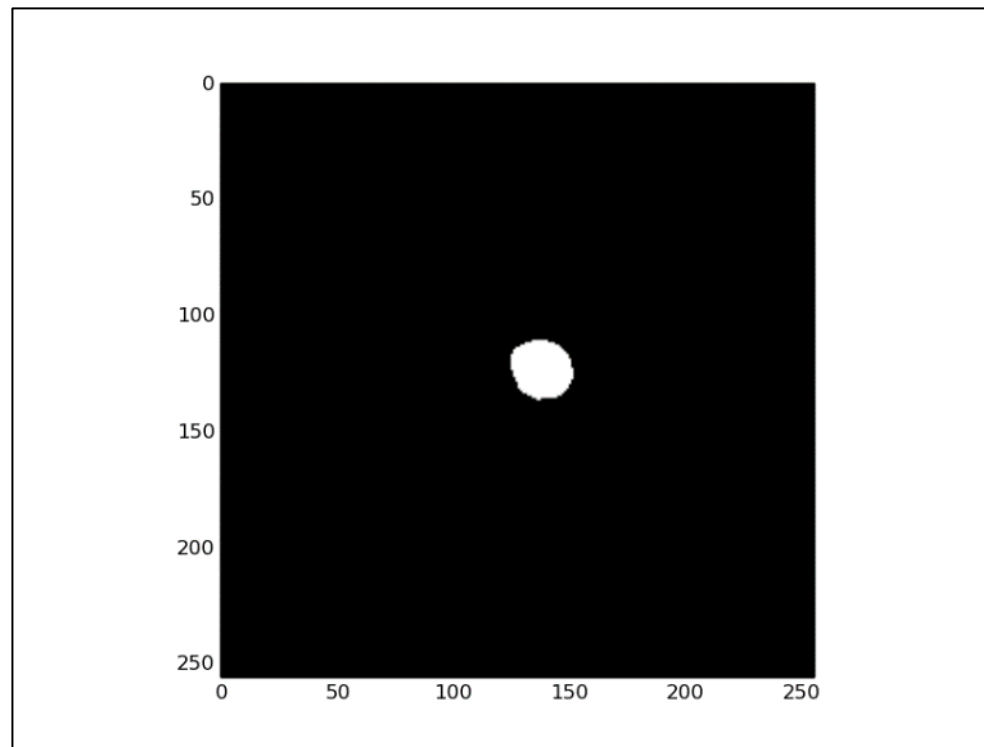
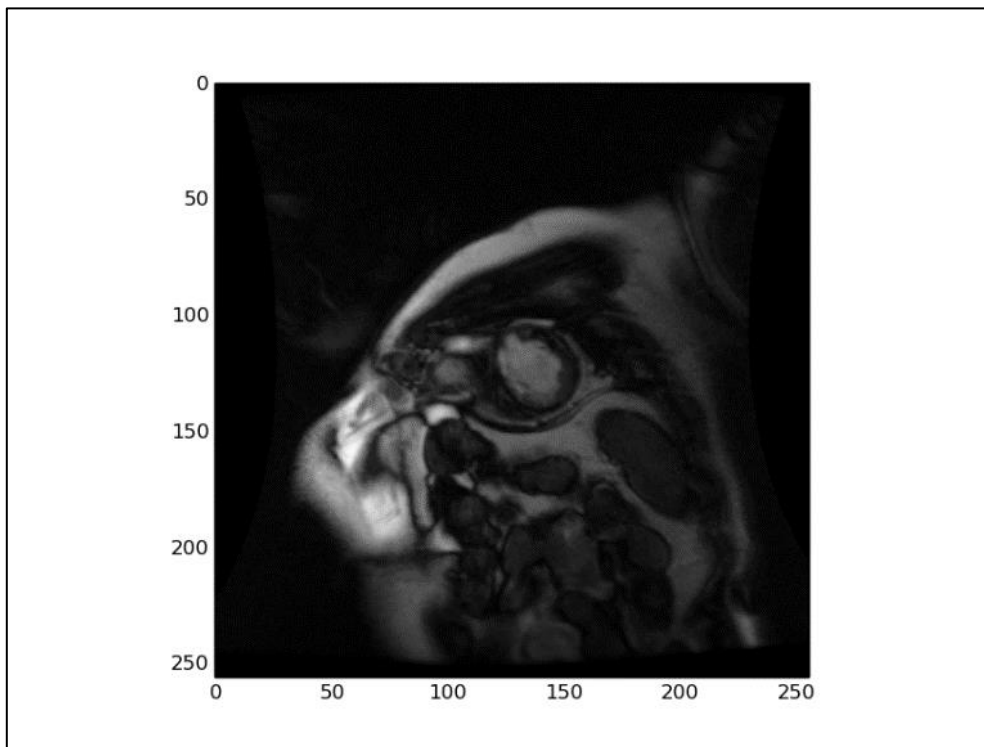
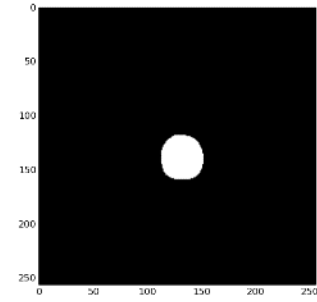
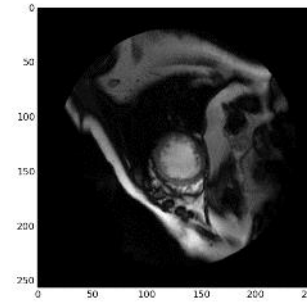
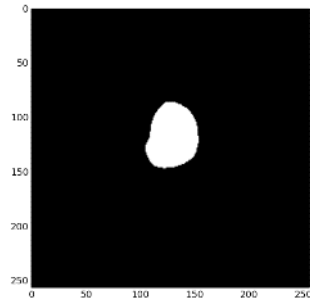
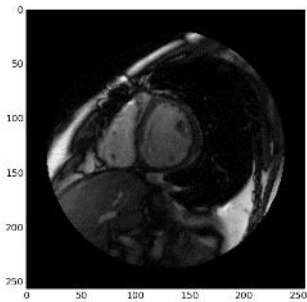
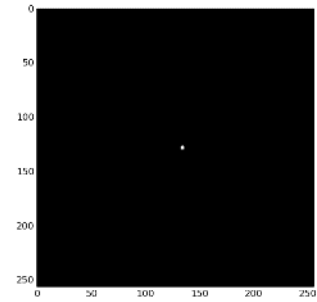
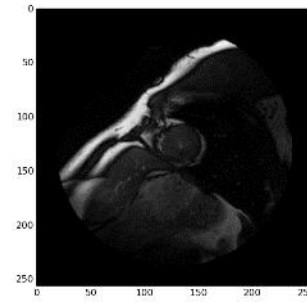
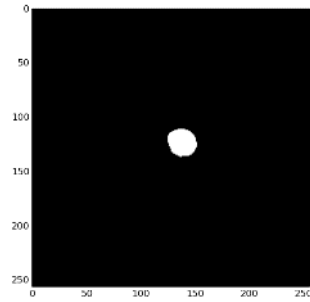
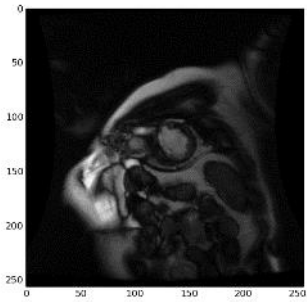


Image Examples

Complete images and expertly labeled contours of LV



Data Details

- Original images are 256 x 256 grayscale DICOM format
- Output is a tensor of size 256 x 256 x 2
 - Each pixel belongs to one of two classes
- Training set consist of 234 images
- Validation set consist of 26 images

Background Data Setup

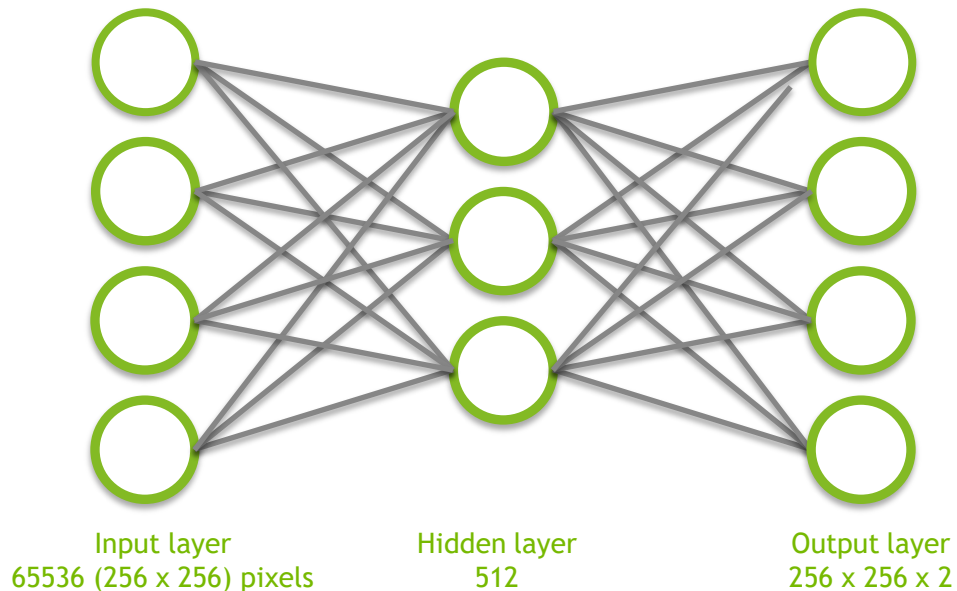
- Lots of guidance and code for how to setup/extract data taken from here:
 - <https://www.kaggle.com/c/second-annual-data-science-bowl/details/deep-learning-tutorial>
- Images and contours have been extracted from the raw data and packaged up for ingest into TensorFlow
- TensorFlow data records provided but raw data is NOT provided for this lab
 - If interested you can download yourself



Lab Tasks

TASK 1

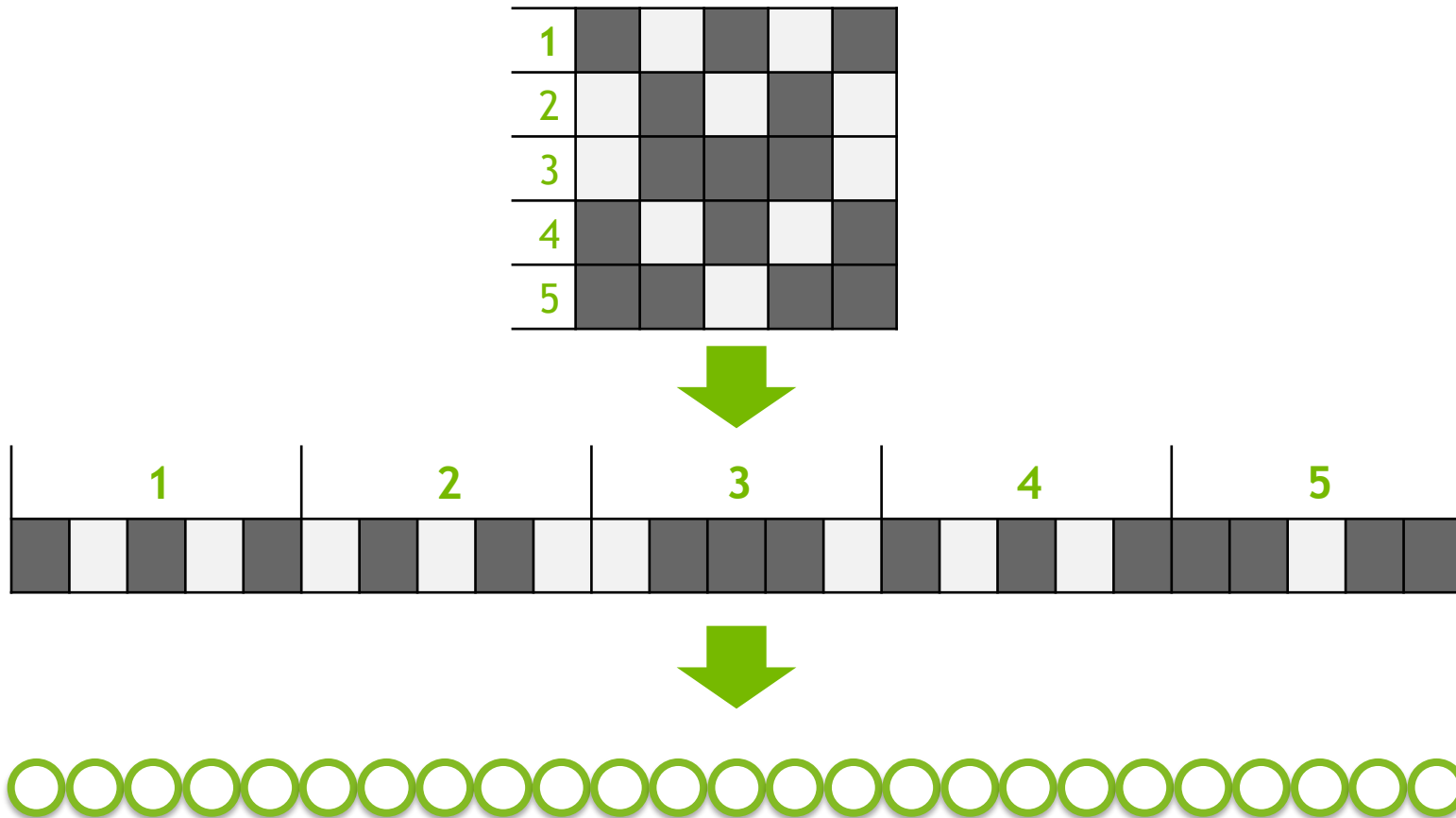
Ensure things are working properly!



- Train and test a fully-connected neural network with one hidden layer
- For the loss computation we'll use TF built-in `sparse_softmax_cross_entropy_with_logits`
 - Computes softmax of the inference output then cross entropy against the correct labels

TASK 1

Ensure things are working properly!



TASK 2

Convolutional Layers

- Convolution layers
 - Previous example focused on each input pixel
 - What if features encompass multiple input pixels
 - Can use convolutions to capture larger receptive fields
- Pooling layers
 - Essentially a down-sampling method retaining information while eliminating some computational complexity

TASK 2

Convolutional Layers

2D Convolution

.0	.8	.6
.7	.5	.3
.0	.9	.0

.4

2D Transposed
Convolution

TASK 2

Convolutional Layers

2D Convolution

<div><div>.0</div><div>X 0.1</div></div>	<div><div>.8</div><div>X 0.2</div></div>	<div><div>.6</div><div>X 0.1</div></div>
<div><div>.7</div><div>X 0.0</div></div>	<div><div>.5</div><div>X 0.2</div></div>	<div><div>.3</div><div>X 0.0</div></div>
<div><div>.0</div><div>X 0.2</div></div>	<div><div>.9</div><div>X 0.1</div></div>	<div><div>.0</div><div>X 0.1</div></div>

.4

TASK 2

Convolutional Layers

.0 X 0.0	.8 X 2.0	.6 X 1.5
.7 X 1.7	.5 X 1.2	.3 X 0.7
.0 X 0.0	.9 X 2.2	.0 X 0.0

.4

2D Transposed
Convolution



TASK 2

Convolutional Layers

Max Pooling

.0	.8	.6
.7	.5	.3
.0	.9	.0

.9

TASK 2

Convolutional Layers

- Finish the CNN, replace “FIXME”
 - You need to figure out the dimensions
- Convolution1, 5x5 kernel, stride 2; Maxpooling1, 2x2 window, stride 2
- Convolution2, 5x5 kernel, stride 2; Maxpooling2, 2x2 window, stride 2
- Convolution3, 3x3 kernel, stride 1; Convolution4, 3x3 kernel, stride 1
- Score_classes, 1x1 kernel, stride 1; Upscore (DeConv), 31x31 kernel, stride 16
- Optional / Time Permitting: Experiment with num_epochs

TASK 3

The DICE Metric

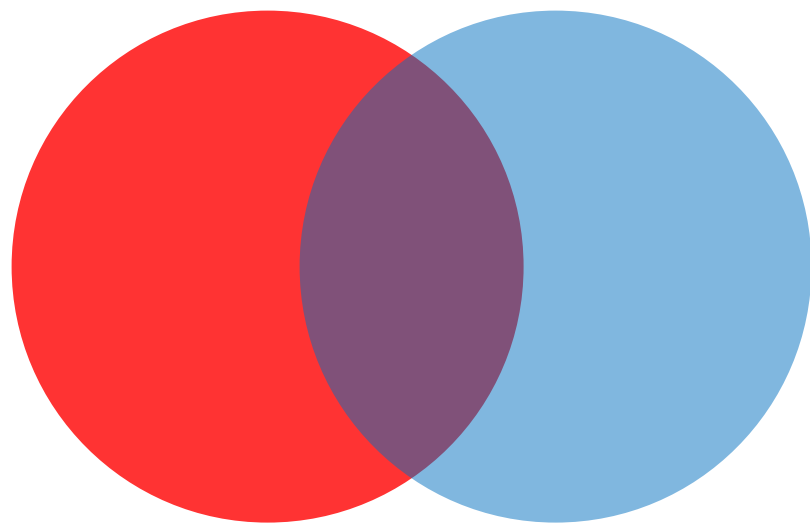
- Metric to compare the similarity of two samples:

$$\frac{2A_{nl}}{A_n + A_l}$$

- Where:
 - A_n is the area of the contour predicted by the network
 - A_l is the area of the contour from the label
 - A_{nl} is the intersection of the two
 - The area of the contour that is predicted correctly by the network
 - 1.0 means perfect score.
- More accurately compute how well we're predicting the contour against the label
- We can just count pixels to give us the respective areas

TASK 3

The DICE Metric



2 x The
Purple Area

Area of the
Red Circle + Area of the
Blue Circle

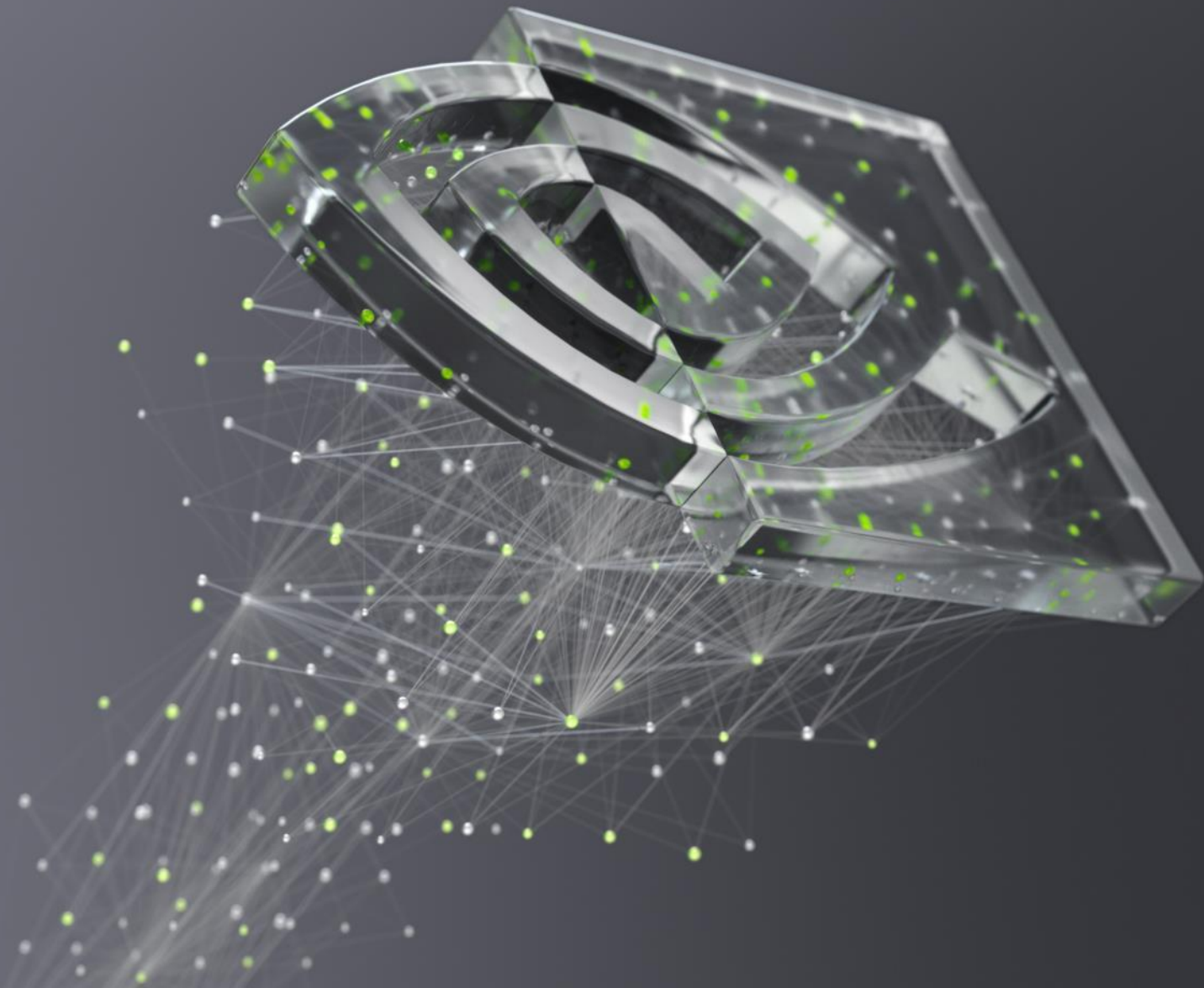
TASK 3

Parameter Search

- `learning_rate`: initial learning rate
- `decay_rate`: the rate that the initial learning rate decays
 - e.g., 1.0 is no decay, 0.5 means cut the decay rate in half each number of (decay) steps
- `decay_steps`: number of steps to execute before changing learning rate
- `num_epochs`: number of times to cycle through the input data
- `batch_size`: keep at 1 for now
- Experiment with **`learning_rate`**, **`decay_rate`**, **`decay_steps`**, **`num_epoch`**
- Record the parameters that give you the best Dice score



Start the Lab!

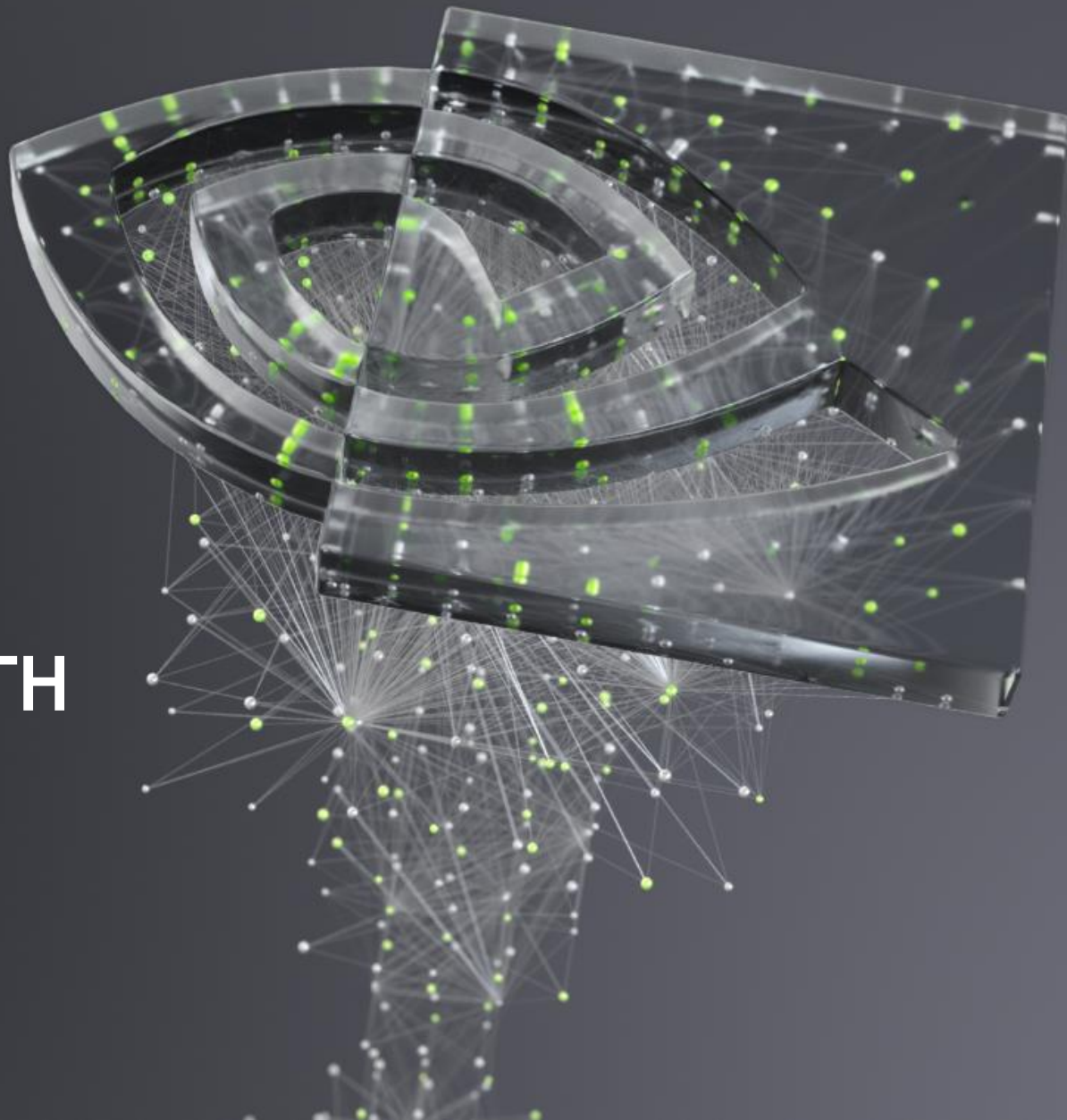


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GETTING STARTED WITH IMAGE SEGMENTATION SOLUTIONS



Task 1 - Solution

```
# set up the model architecture
model = tf.keras.models.Sequential([
    Flatten(input_shape=[256, 256, 1]),
    Dense(64, activation='relu'),
    Dense(256*256*2, activation='softmax'),
    Reshape((256, 256, 2))
])

# specify how to train the model with algorithm, the loss function and metrics
model.compile(
    optimizer='adam',
    loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
    metrics=['accuracy'])
```


Task 1 Training Output - 1 Epoch

Train for 234 steps, validate for 26 steps

Epoch 1/20

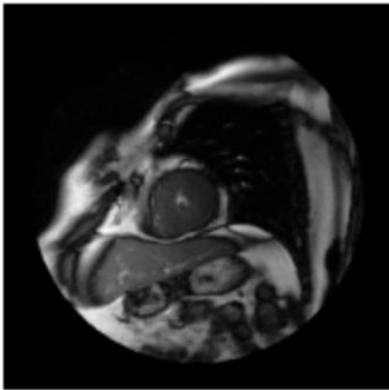
WARNING:tensorflow:Method (on_train_batch_end) is slow compared to the batch update (0.270887). Check your callbacks.

1/234 [.....] - ETA: 2:12 - loss: 0.6931 - accuracy: 0.5012WARNING:tensorflow:Method (on_train_batch_end) is slow compared to the batch update (0.191189). Check your callbacks.

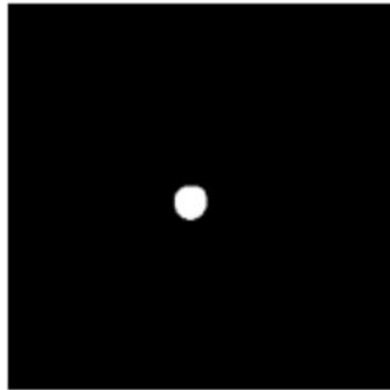
2/234 [.....] - ETA: 1:19 - loss: 0.6931 - accuracy: 0.4996WARNING:tensorflow:Method (on_train_batch_end) is slow compared to the batch update (0.111491). Check your callbacks.

220/234 [=====>..] - ETA: 0s - loss: 0.6931 - accuracy: 0.5048

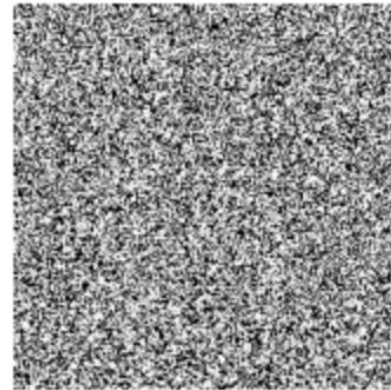
Input Image



Label



Predicted Label



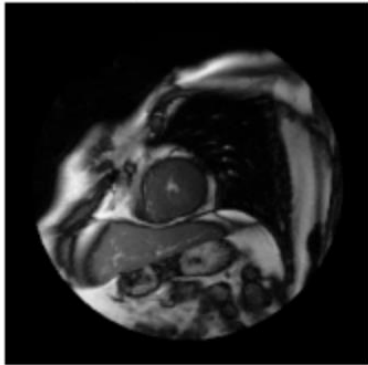
Sample Prediction after epoch 1

Task 1 Training Output - 20 Epochs

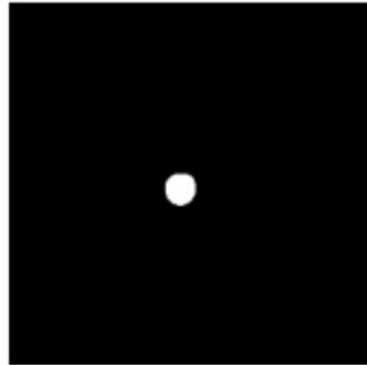
Epoch 20/20

226/234 [=====>..] - ETA: 0s - loss: 0.6931 - accuracy: 0.9864

Input Image



Label



Predicted Label



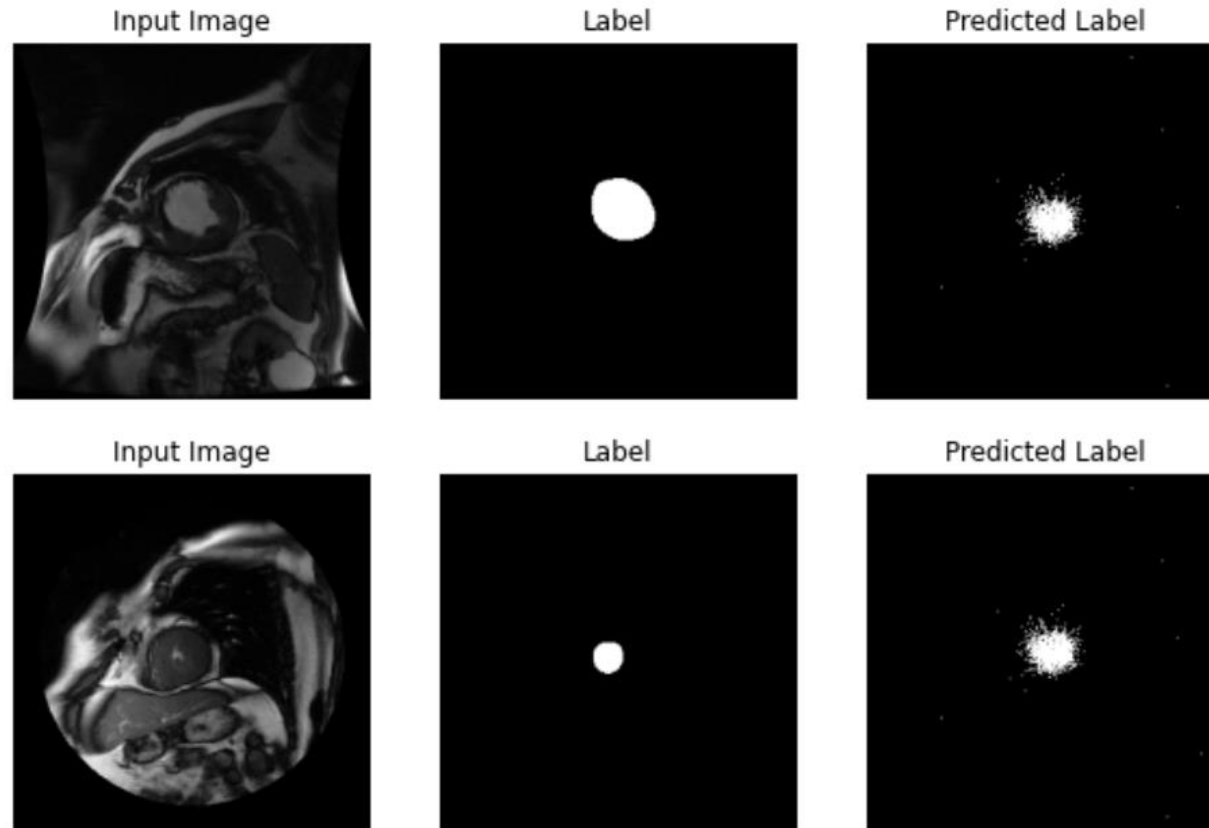
Sample Prediction after epoch 20

234/234 [=====] - 2s 9ms/step - loss: 0.6931 - accuracy: 0.9865 - val_loss: 0.6931 - val_accuracy: 0.9865

0.9865



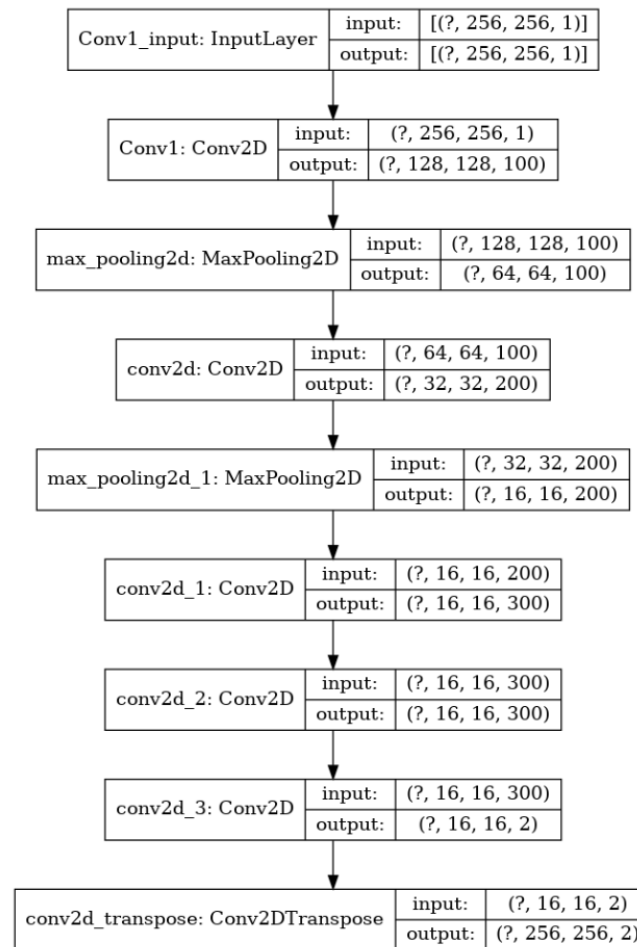
Task 1 Training Output - Good Result?



Task 2 - Solution

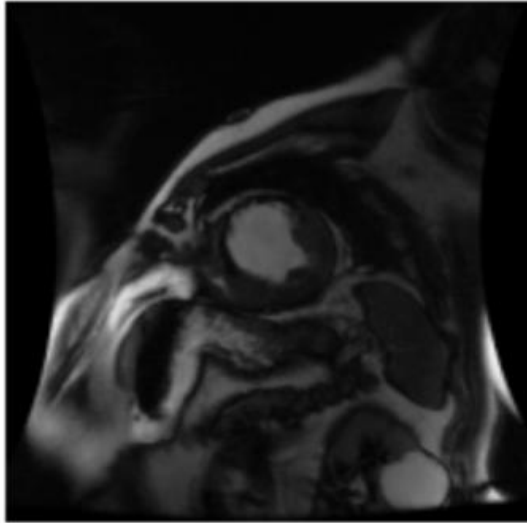
```
layers = [  
    Conv2D(input_shape=[256, 256, 1],  
          filters=100,  
          kernel_size=5,  
          strides=2,  
          padding="same",  
          activation=tf.nn.relu,  
          name="Conv1"),  
    MaxPool2D(pool_size=2, strides=2, padding="same"),  
    Conv2D(filters=200,  
          kernel_size=5,  
          strides=2,  
          padding="same",  
          activation=tf.nn.relu),  
    MaxPool2D(pool_size=2, strides=2, padding="same"),  
    Conv2D(filters=300,  
          kernel_size=3,  
          strides=1
```

... and repeat ...

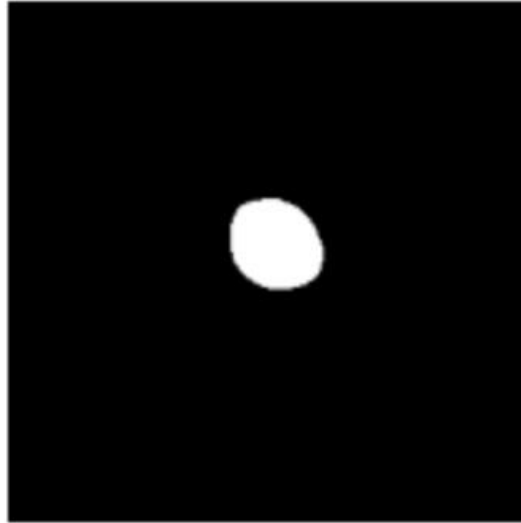


Task 2 Training Output - No Training

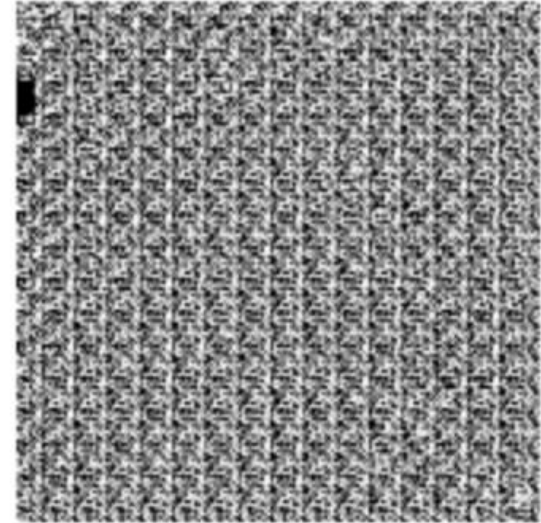
Input Image



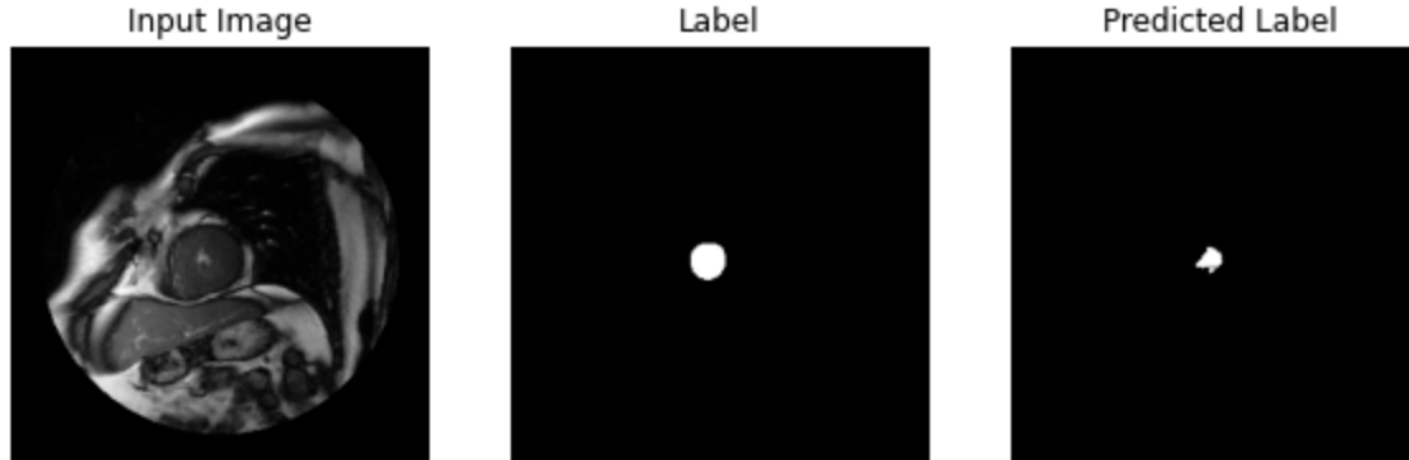
Label



Predicted Label



Task 2 Training Output - 20 Epochs

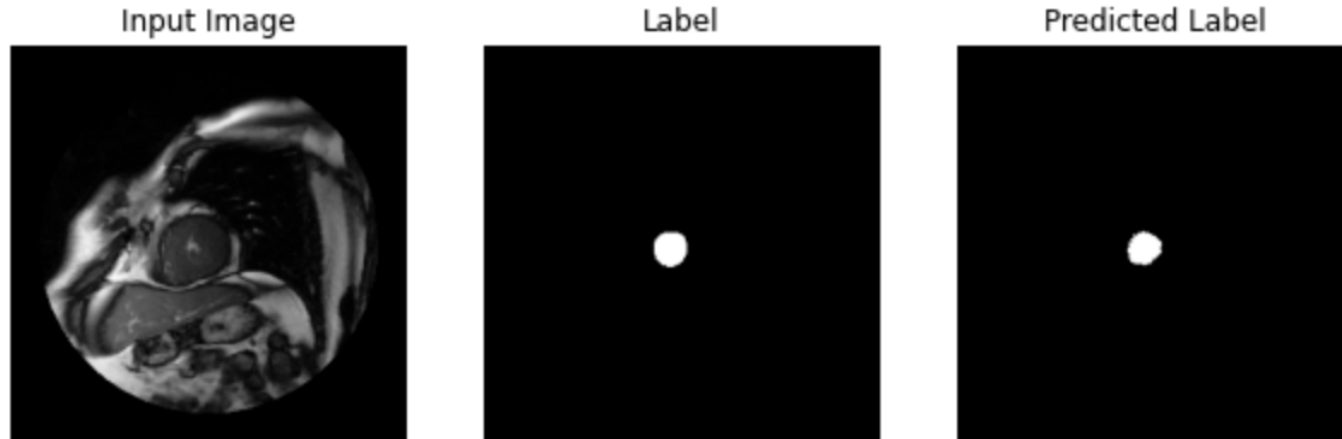


Sample Prediction after epoch 20

```
234/234 [=====] - 2s 7ms/step - loss: 0.0040 - accuracy: 0.9983 - val_loss: 0.0100 -  
val_accuracy: 0.9969
```



Task 3 - 30 Epochs



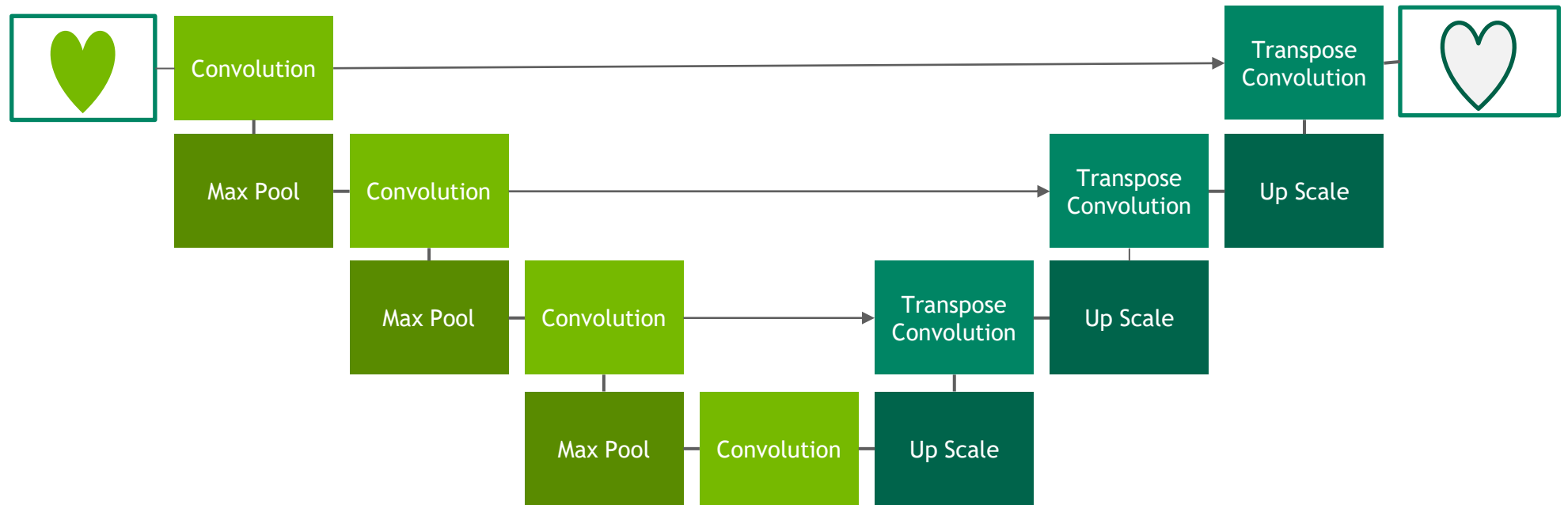
Sample Prediction after epoch 30

```
234/234 [=====] - 1s 6ms/step - loss: 0.0019 - dice_coef: 0.9583 - accuracy: 0.9992  
- val_loss: 0.0104 - val_dice_coef: 0.8519 - val_accuracy: 0.9975
```



Task 3 Parameter Search - Solution

You tell us!



U-Net

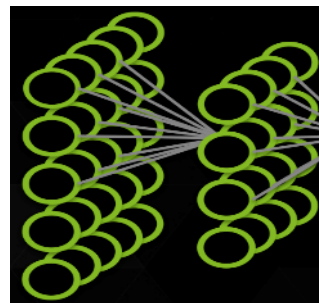
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View upcoming workshops and request a workshop onsite at
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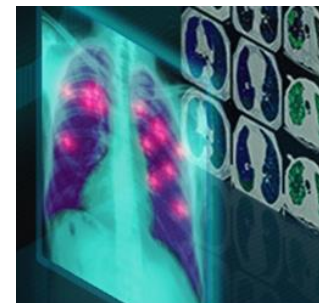
Educators can join the University Ambassador Program to teach DLI courses on campus and access resources. Learn more at
www.nvidia.com/dli



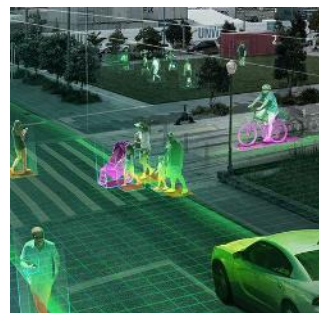
Fundamentals



Autonomous Vehicles



Healthcare



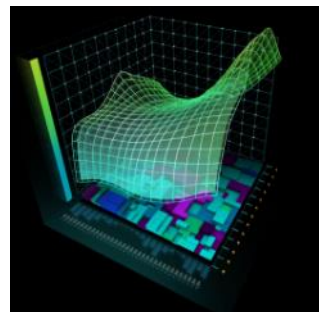
Intelligent Video Analytics



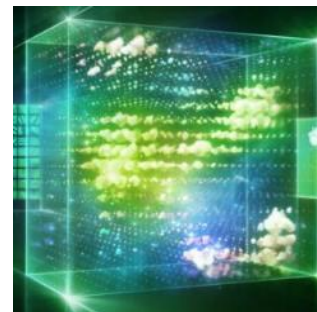
Robotics



Game Development & Digital Content



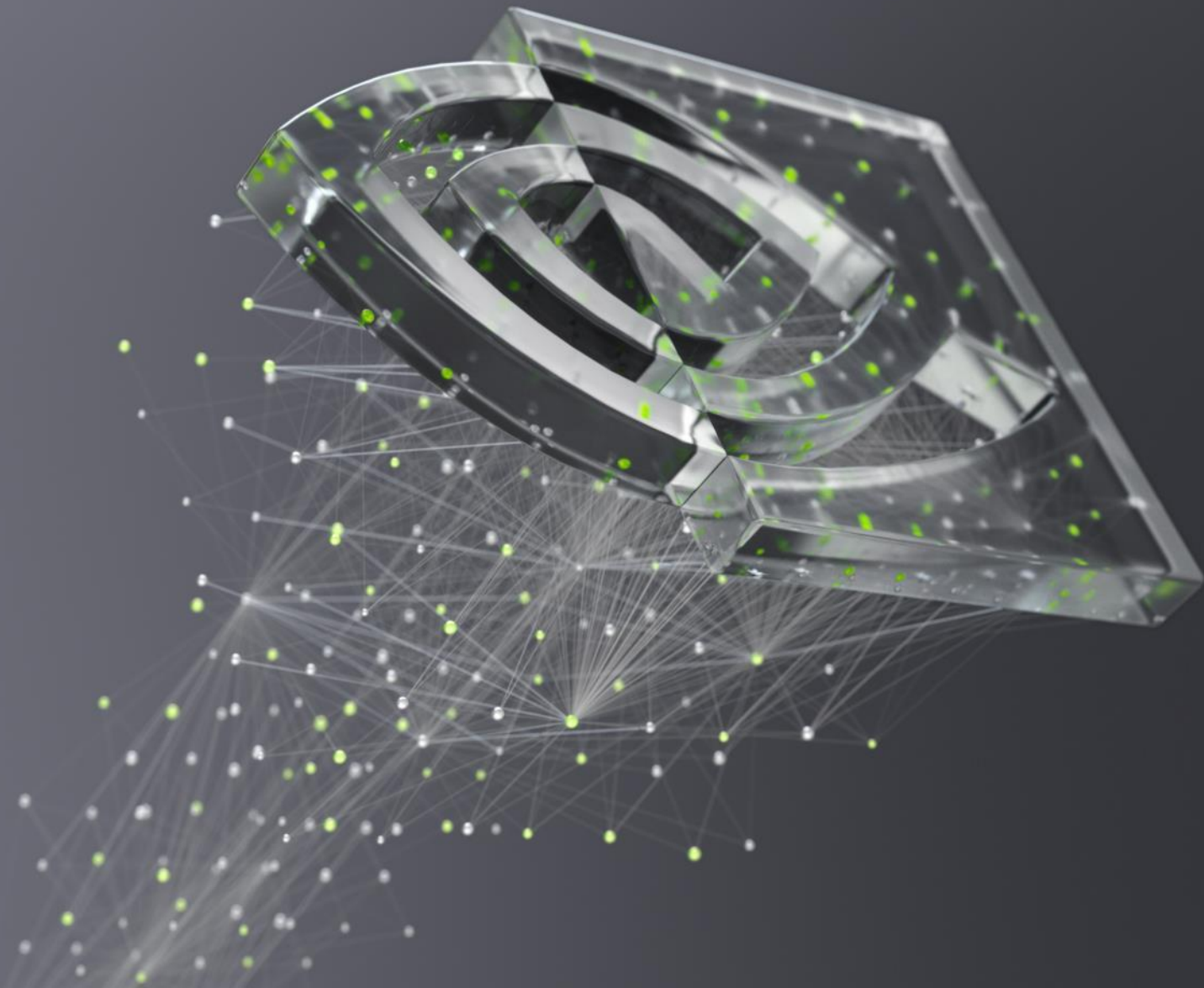
Finance



Accelerated Computing



Virtual Reality



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