




MLHO

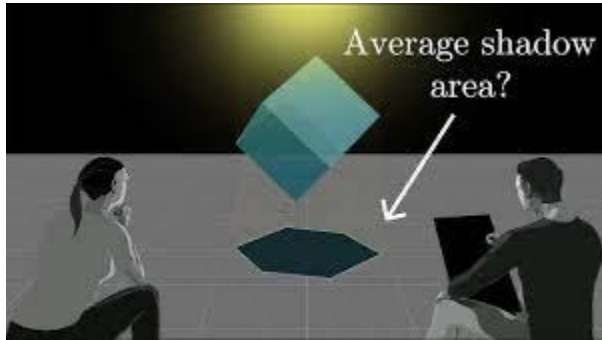
3D object recognition from 2D Projection



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Inspiration and Motivation

3Blue1brown: average area of a shadow



Source: <https://www.youtube.com/watch?v=ltLUadnCvi0>

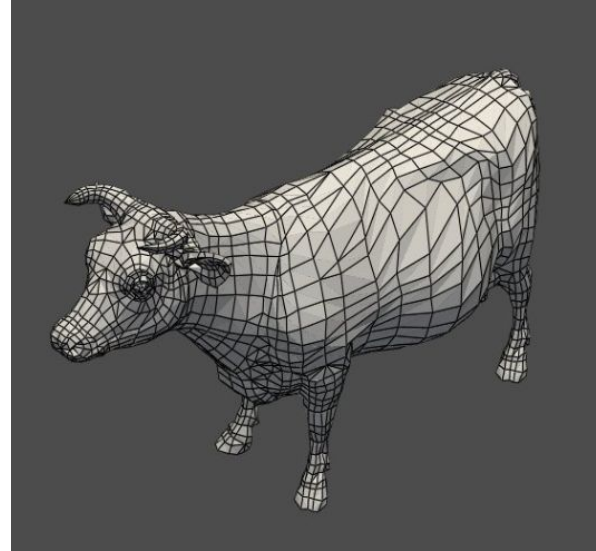
Question: Can we identify the original object from its shadow?



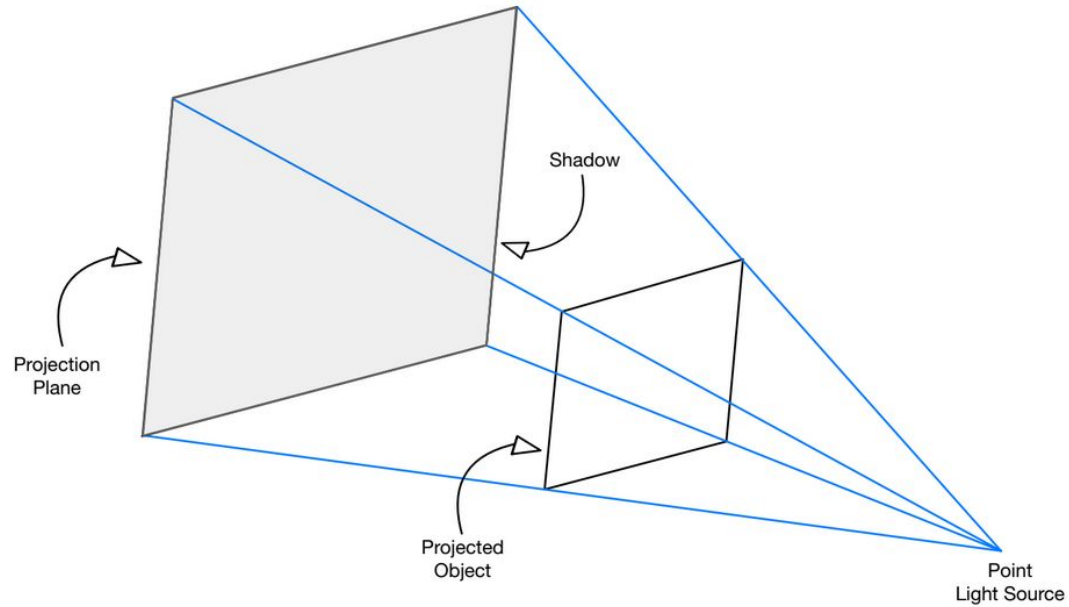
Data generation and preprocessing

3D Shapes

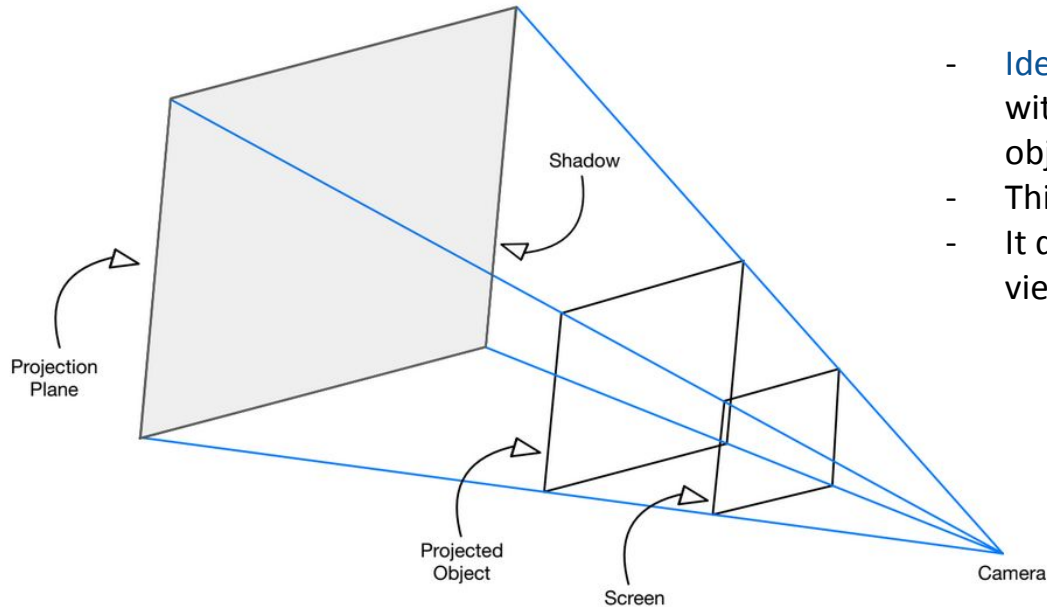
- Objects are constructed with polygons
- We have a 3D mesh for each object
- Objects include:
 - Cube
 - Pyramid
 - Tetrahedron
 - Diamond
 - Dodecahedron
 - Icosahedron
 - Torus
 - Cylinder
 - Cow
 - Human



Perspective Projection



Perspective Projection



- **Idea:** replace the light source with a viewer and project the object to the screen instead.
- This inverses the parity
- It doesn't matter because we view all orientations anyway

Perspective Projection

Results: We have shadows like this
with 1300 samples per shape

target: cube



target: tetrahedron



target: cow



target: pyramid



target: diamond



target: dodecahedron



target: icosahedron



target: torus



target: cylinder



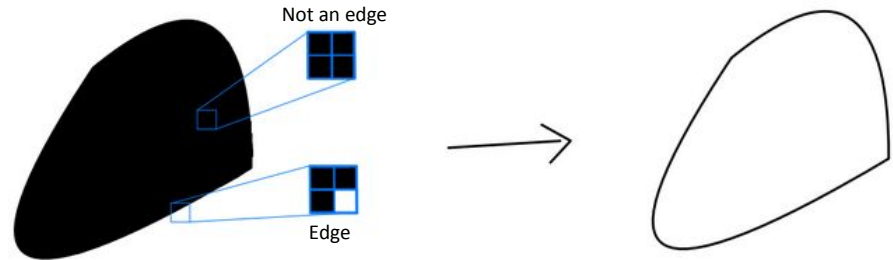
target: human



Preprocessing

Primitive edge detection:

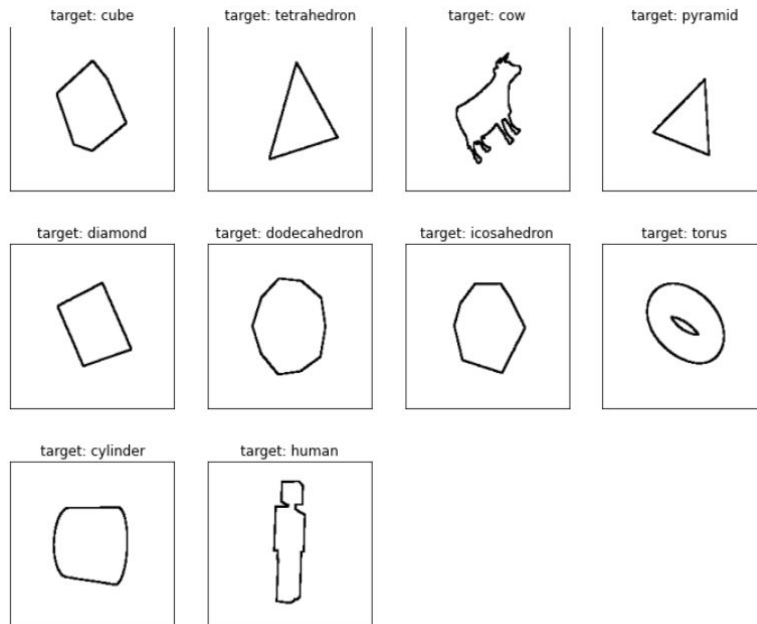
- Loop over all pixels in the image
- If a pixel has a different value than its neighbours consider it part of the edge



Preprocessing

Primitive edge detection:

Results

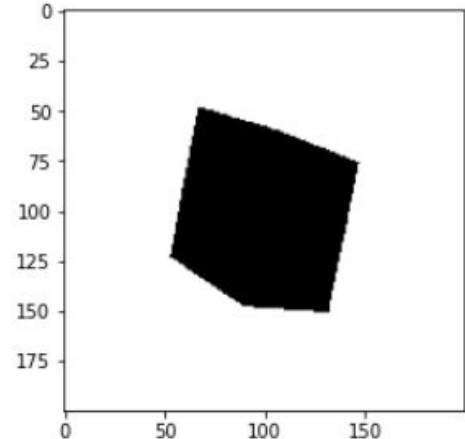
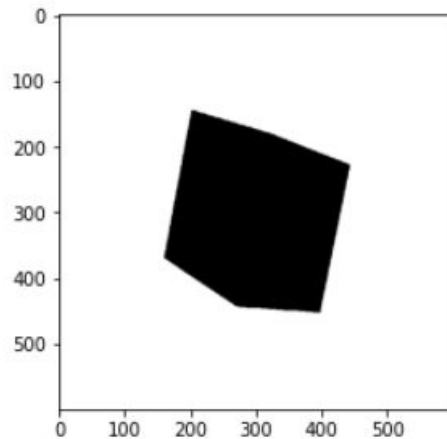


Preprocessing

Data compression:

- Cast pixel values as booleans
- Change (and reduce) the image resolution

-due to memory issues, all images converted to 200x200, dtype='bool'





Classification

Multinomial Logistic Regression

- Trained with L2 regularization
- Accuracy score ≈ 0.60

target: cow
predicted: cow



target: Tetrahedron
predicted: human



target: diamond
predicted: human



target: cow
predicted: cow



target: Pyramid
predicted: human



target: Cube
predicted: Cube



target: Cylinder
predicted: Cylinder



target: Cube
predicted: Cube



target: human
predicted: cow



target: diamond
predicted: Cube



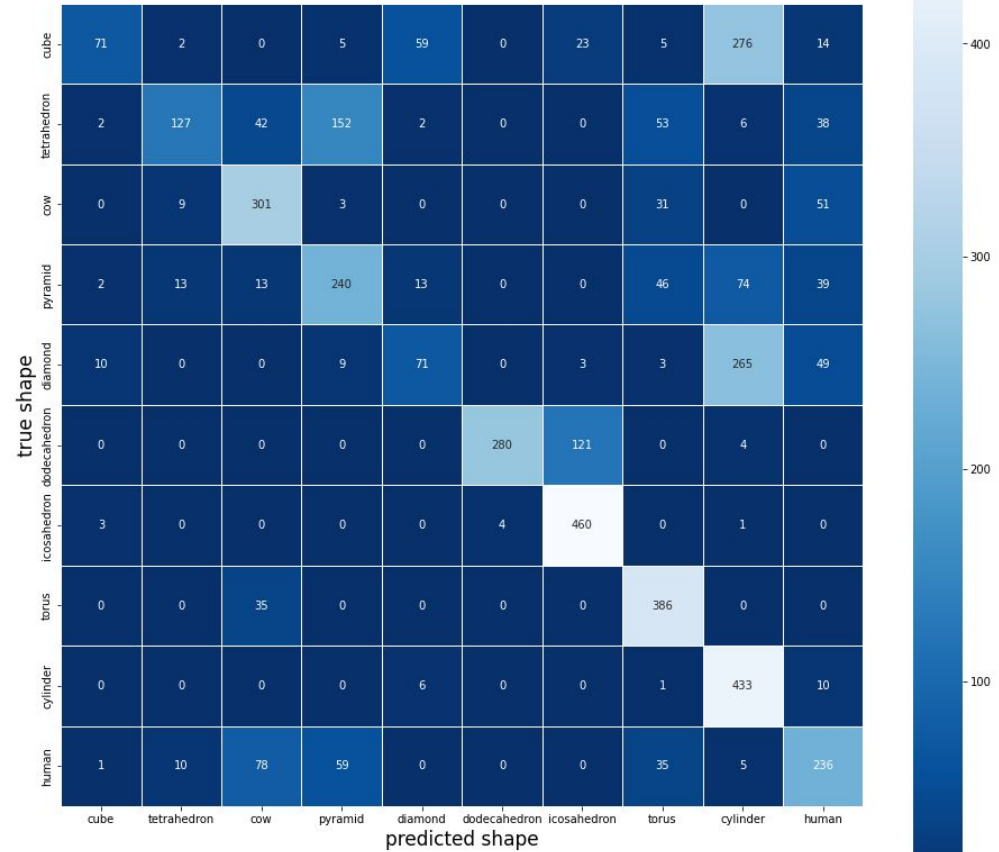
target: Cube
predicted: Cylinder



target: Cylinder
predicted: human



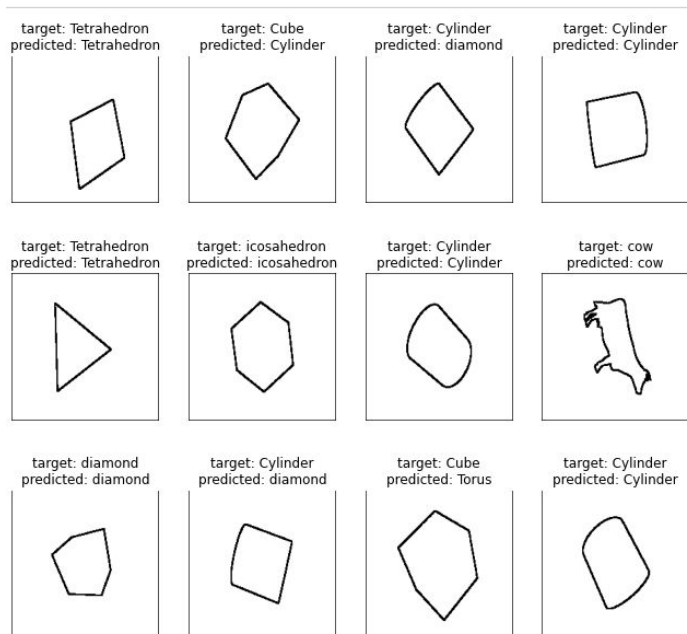
Multinomial Logistic Regression



Multinomial Logistic Regression

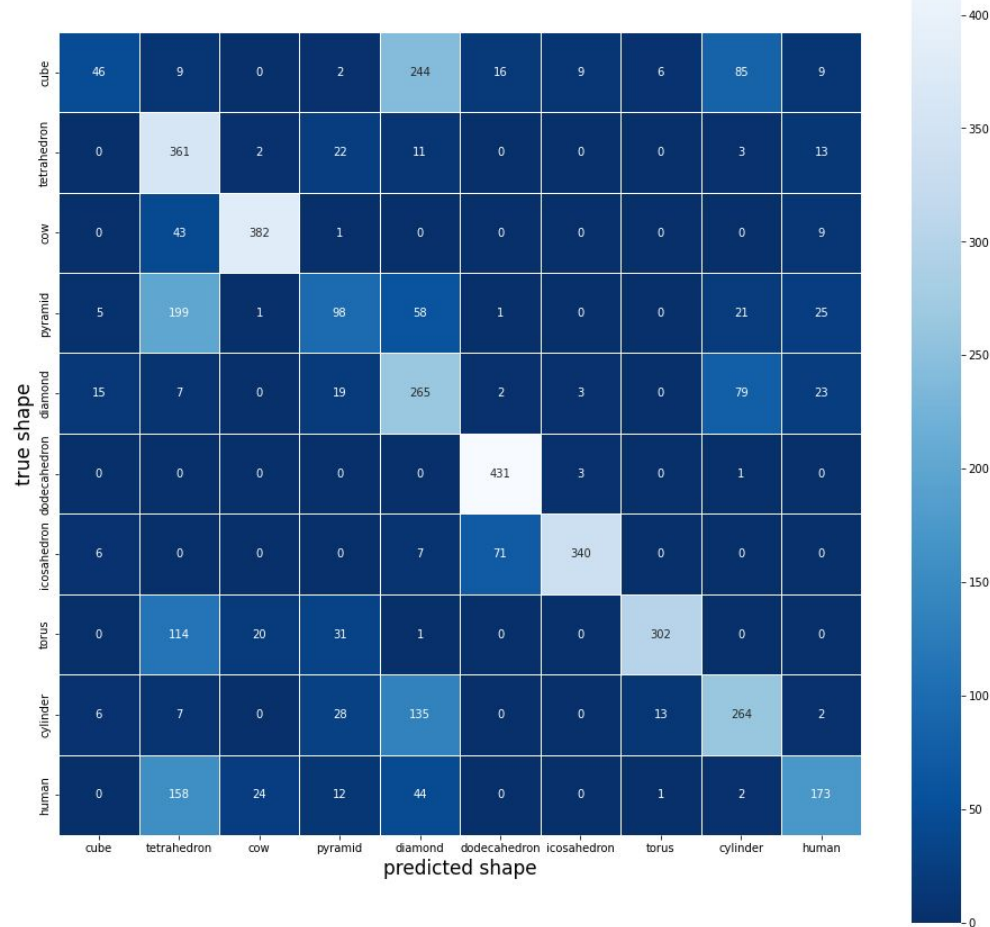
Slight improvement with the edges dataset

Score ≈ 0.62



Multinomial Logistic Regression

Edges Dataset





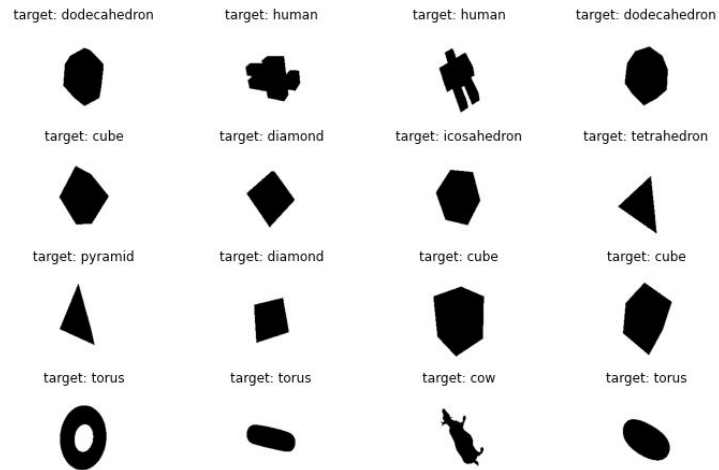
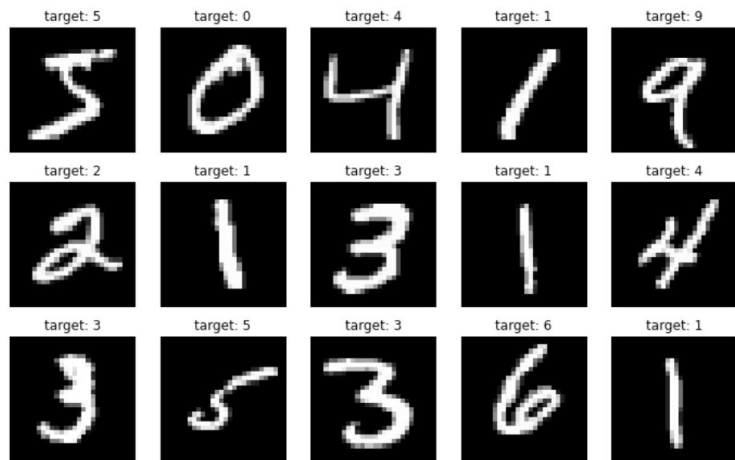
Deep Neural Network

- used Kaggle to train neural networks

- CNNs are default neural networks for image classification, but DNN could also be used

- in the class we did MNIST with DNN, we used 2 models that had 95% and 98% accuracy, but our dataset is more complex

MNIST vs Dataset

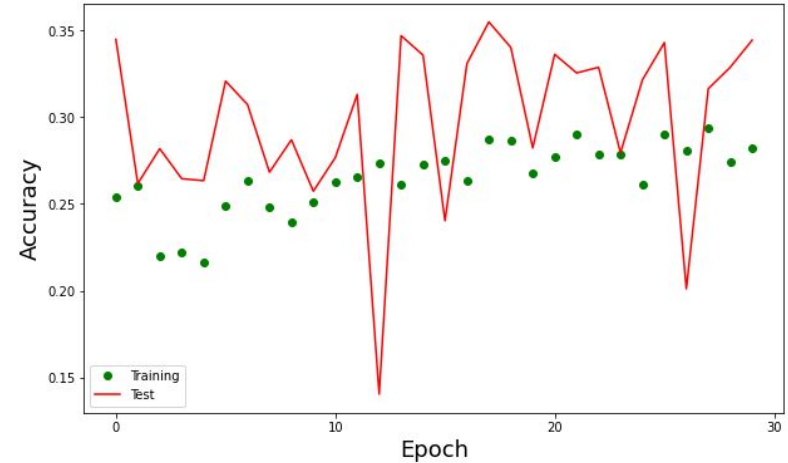
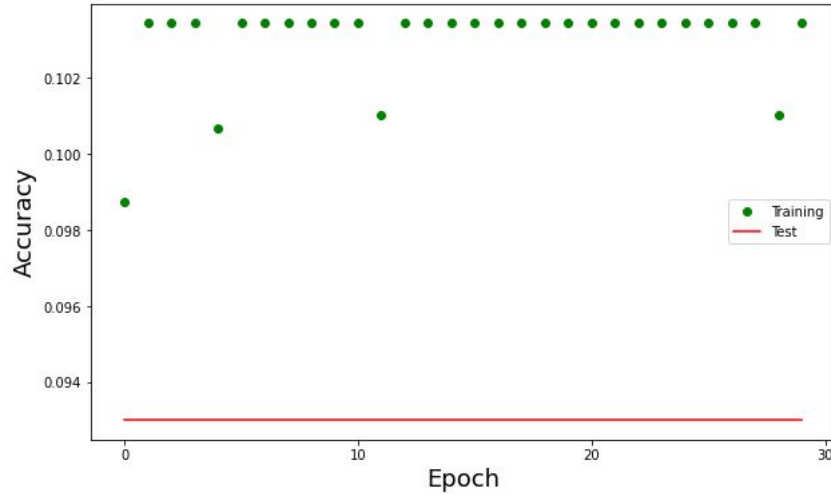


Models from the class

Layer (type)	Output Shape	Param #
=====	=====	=====
dense_28 (Dense)	(None, 15)	600015
dense_29 (Dense)	(None, 10)	160
=====	=====	=====
Total params: 600,175		
Trainable params: 600,175		
Non-trainable params: 0		

Layer (type)	Output Shape	Param #
=====	=====	=====
dense_23 (Dense)	(None, 512)	20480512
dropout_4 (Dropout)	(None, 512)	0
dense_24 (Dense)	(None, 512)	262656
dropout_5 (Dropout)	(None, 512)	0
dense_25 (Dense)	(None, 10)	5130
=====	=====	=====
Total params: 20,748,298		
Trainable params: 20,748,298		
Non-trainable params: 0		

Results with models from class



Model that worked the best

Layer (type)	Output Shape	Param #
dense_18 (Dense)	(None, 200)	72000200
dense_19 (Dense)	(None, 100)	20100
dropout_7 (Dropout)	(None, 100)	0
dense_20 (Dense)	(None, 50)	5050
dense_21 (Dense)	(None, 4)	204
Total params: 72,025,554		
Trainable params: 72,025,554		
Non-trainable params: 0		

-with dropout=0.2 and learning rate=0.00001, optimizer Adam, batch size = 40

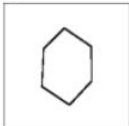
10 shapes

-All 10 shapes: cube, tetrahedron, cow, pyramid, diamond, dodecahedron, icosahedron, torus, cylinder, human

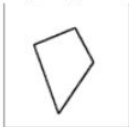
-1300 samples per shape

Edges and full shapes

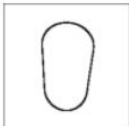
target: icosahedron



target: pyramid



target: cylinder



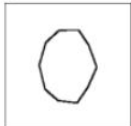
target: cylinder



target: cow



target: dodecahedron



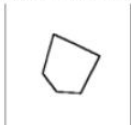
target: cow



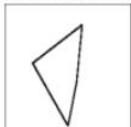
target: torus



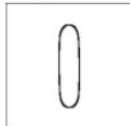
target: diamond



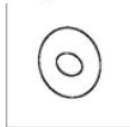
target: pyramid



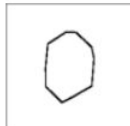
target: torus



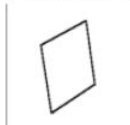
target: torus



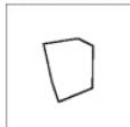
target: dodecahedron



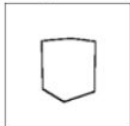
target: diamond



target: diamond



target: cube



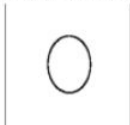
target: cow



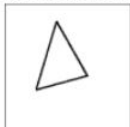
target: cylinder



target: cylinder



target: tetrahedron



target: dodecahedron



target: cow



target: icosahedron



target: tetrahedron



target: pyramid



target: icosahedron



target: tetrahedron



target: dodecahedron



target: icosahedron



target: tetrahedron



target: human



target: cow



target: icosahedron



target: torus



target: human



target: pyramid



target: torus



target: cube



target: diamond

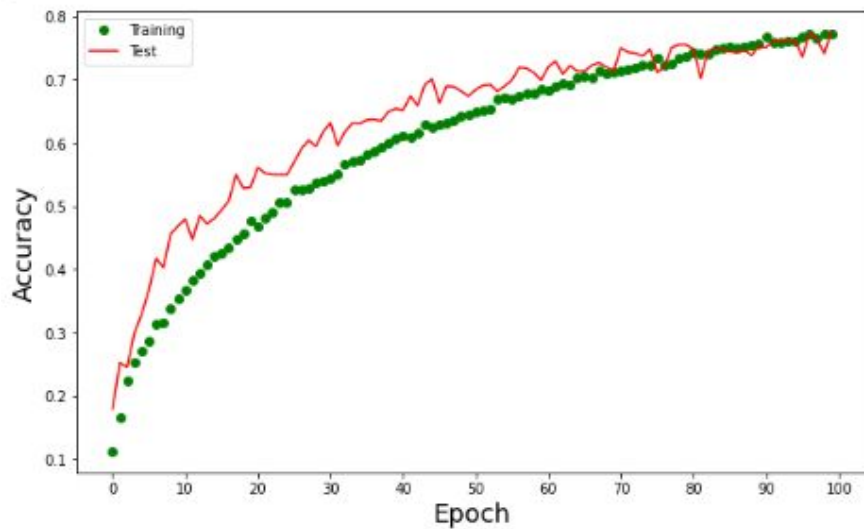


target: icosahedron

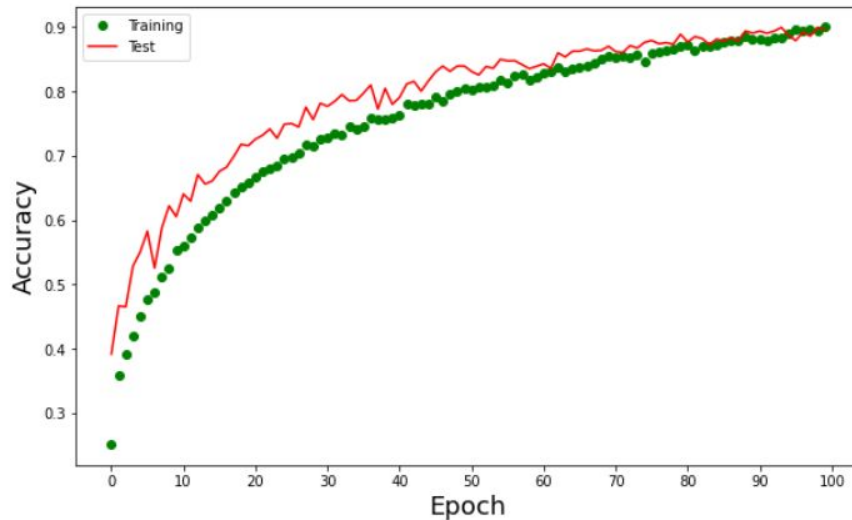


Results

Edges



Full shapes



Classification reports

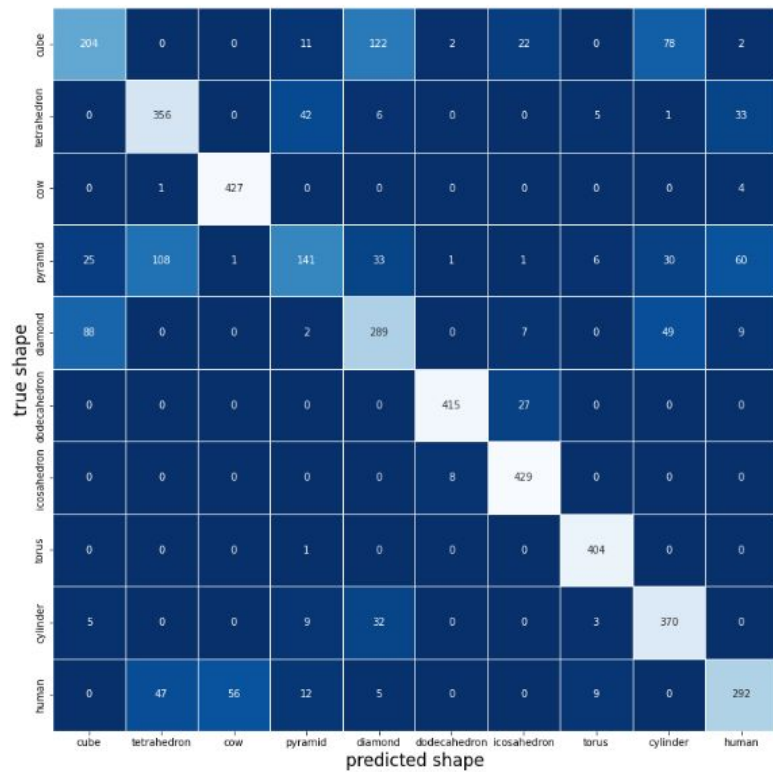
Edges

	precision	recall	f1-score	support
cube	0.63	0.46	0.53	441
tetrahedron	0.70	0.80	0.75	443
cow	0.88	0.99	0.93	432
pyramid	0.65	0.35	0.45	406
diamond	0.59	0.65	0.62	444
dodecahedron	0.97	0.94	0.96	442
icosahedron	0.88	0.98	0.93	437
torus	0.95	1.00	0.97	405
cylinder	0.70	0.88	0.78	419
human	0.73	0.69	0.71	421
accuracy			0.78	4290
macro avg	0.77	0.77	0.76	4290
weighted avg	0.77	0.78	0.76	4290

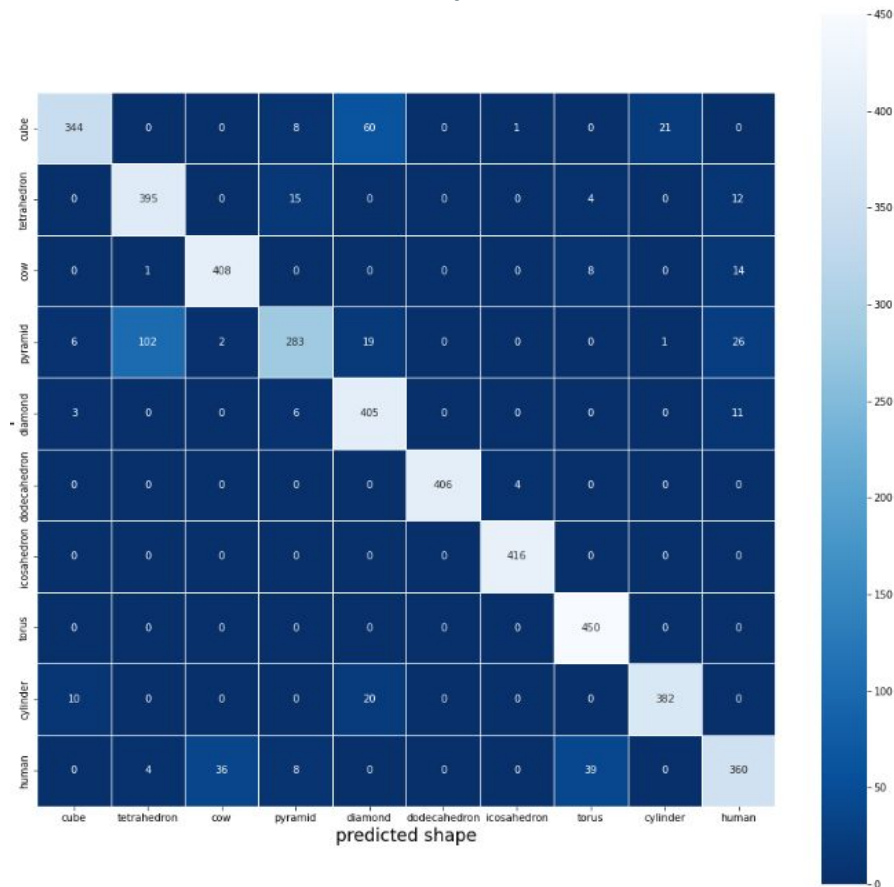
Full shapes

	precision	recall	f1-score	support
cube	0.95	0.79	0.86	434
tetrahedron	0.79	0.93	0.85	426
cow	0.91	0.95	0.93	431
pyramid	0.88	0.64	0.75	439
diamond	0.80	0.95	0.87	425
dodecahedron	1.00	0.99	1.00	410
icosahedron	0.99	1.00	0.99	416
torus	0.90	1.00	0.95	450
cylinder	0.95	0.93	0.94	412
human	0.85	0.81	0.83	447
accuracy			0.90	4290
macro avg	0.90	0.90	0.90	4290
weighted avg	0.90	0.90	0.89	4290

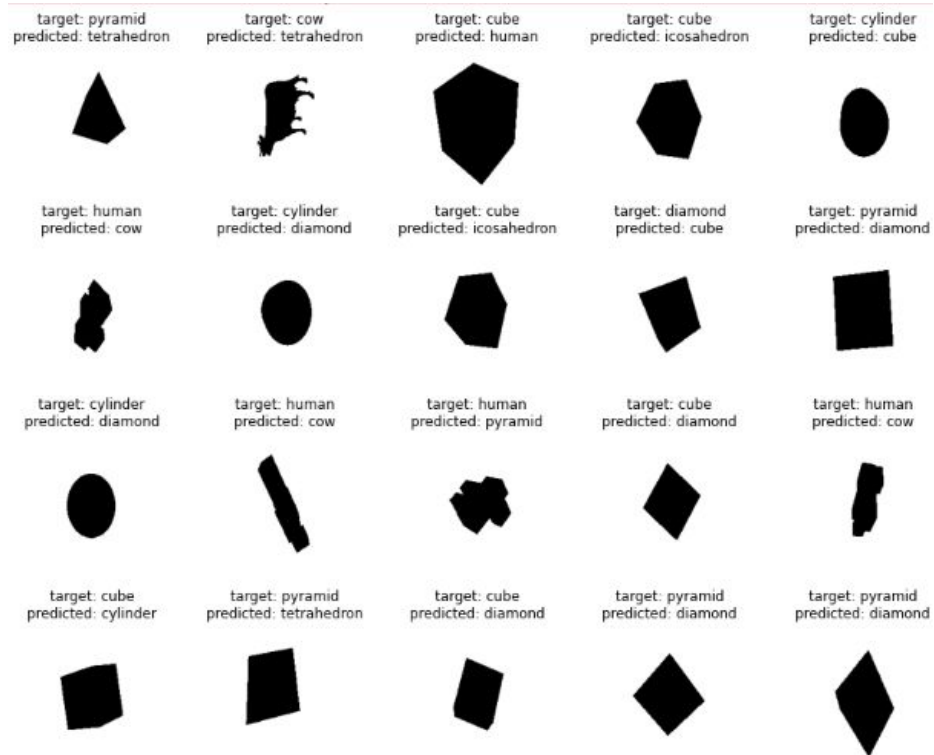
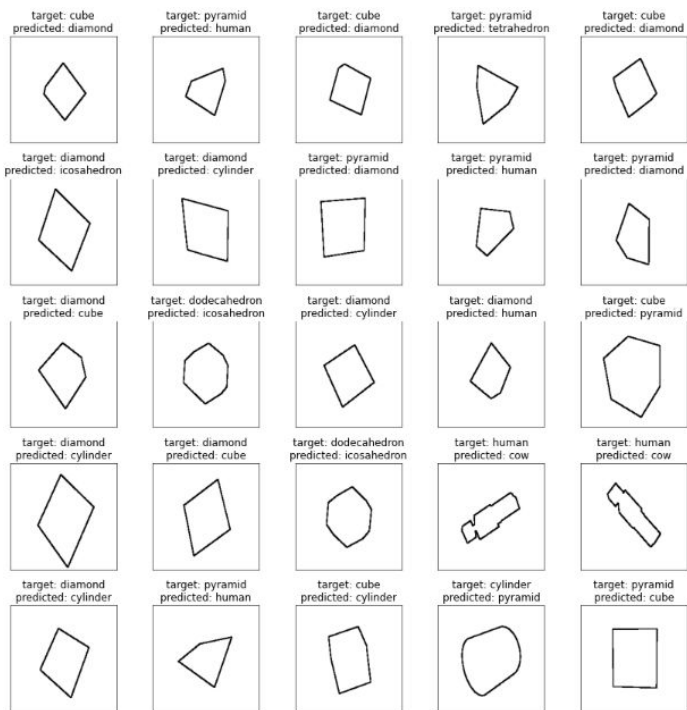
Edges



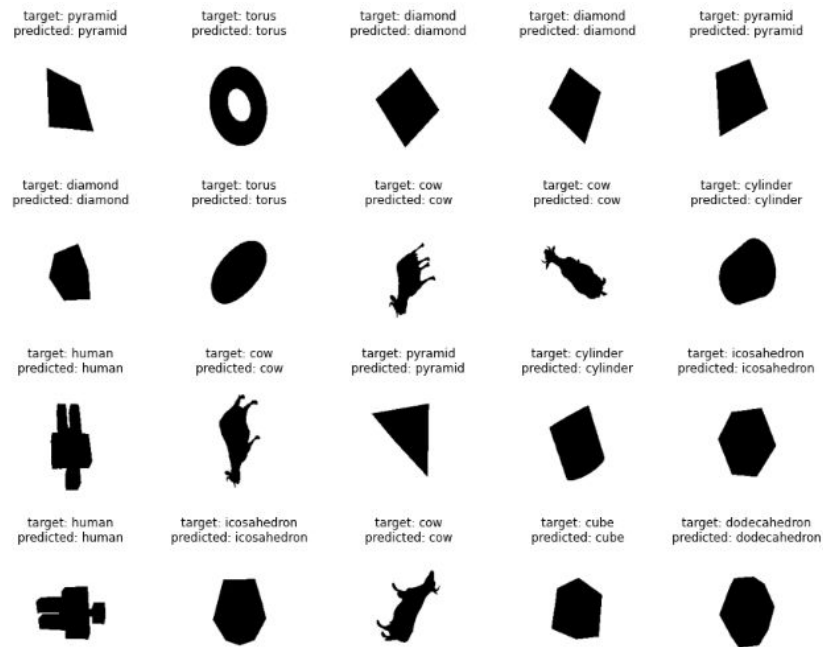
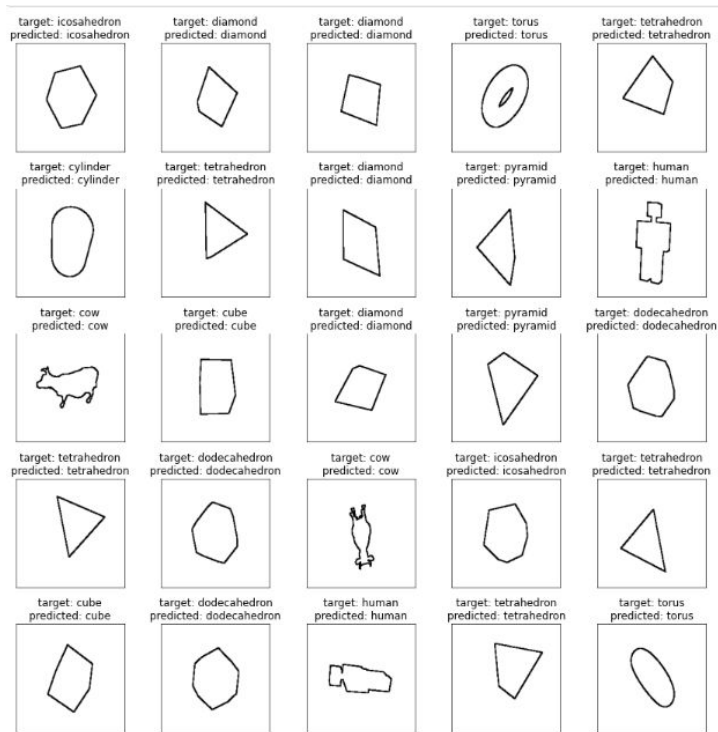
Full shapes



Wrong predictions



Correct predictions

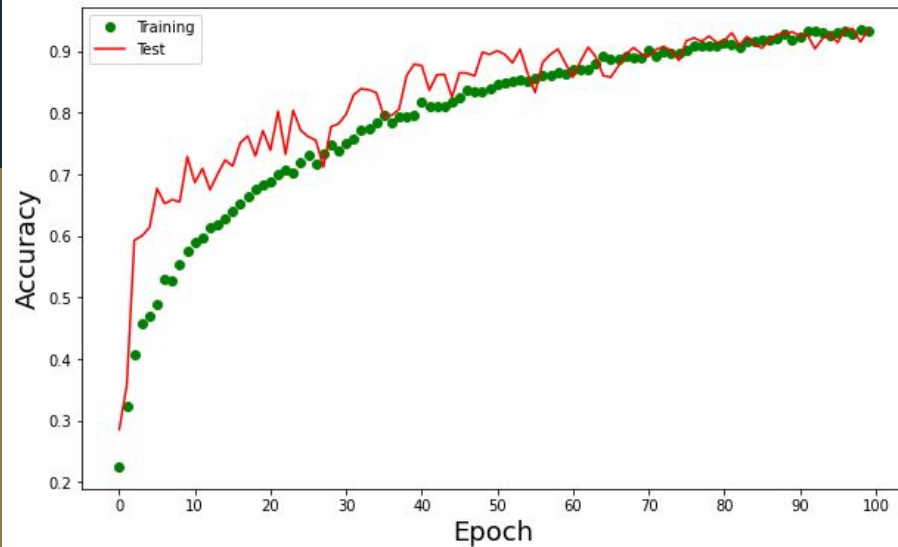


-7 shapes: cube, cow, dodecahedron, icosahedron, torus, cylinder, human

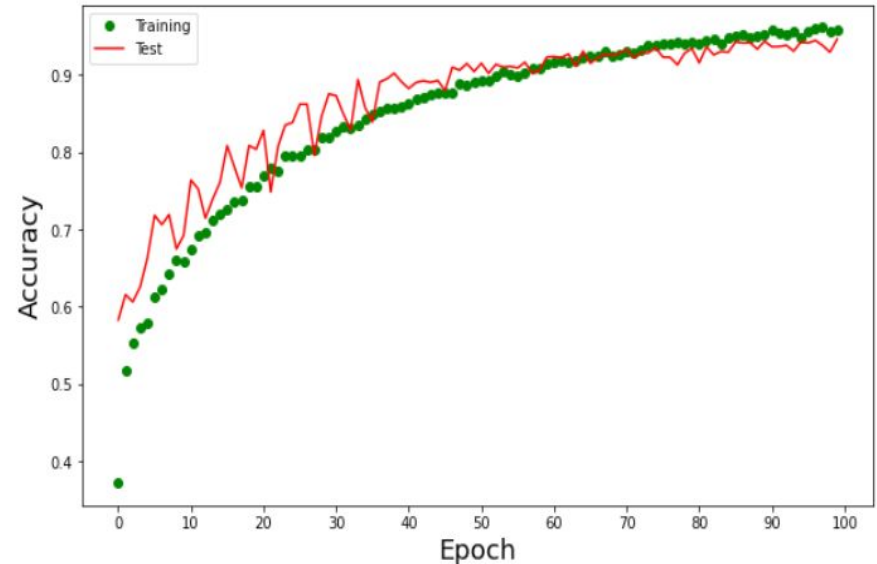
-Less ambiguity than for 10 shapes: cube, diamond, tetrahedron and pyramid are problematic

-Results:

Edges



Full shapes



Classification reports

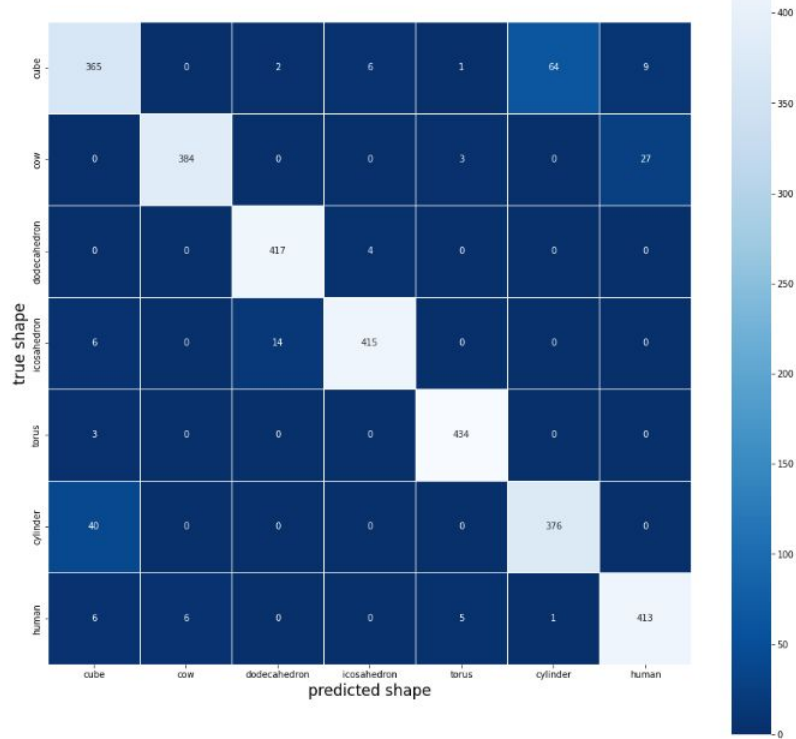
Edges

	precision	recall	f1-score	support
cube	0.87	0.82	0.84	447
cow	0.98	0.93	0.96	414
dodecahedron	0.96	0.99	0.98	421
icosahedron	0.98	0.95	0.97	435
torus	0.98	0.99	0.99	437
cylinder	0.85	0.90	0.88	416
human	0.92	0.96	0.94	431
accuracy			0.93	3001
macro avg	0.94	0.93	0.93	3001
weighted avg	0.93	0.93	0.93	3001

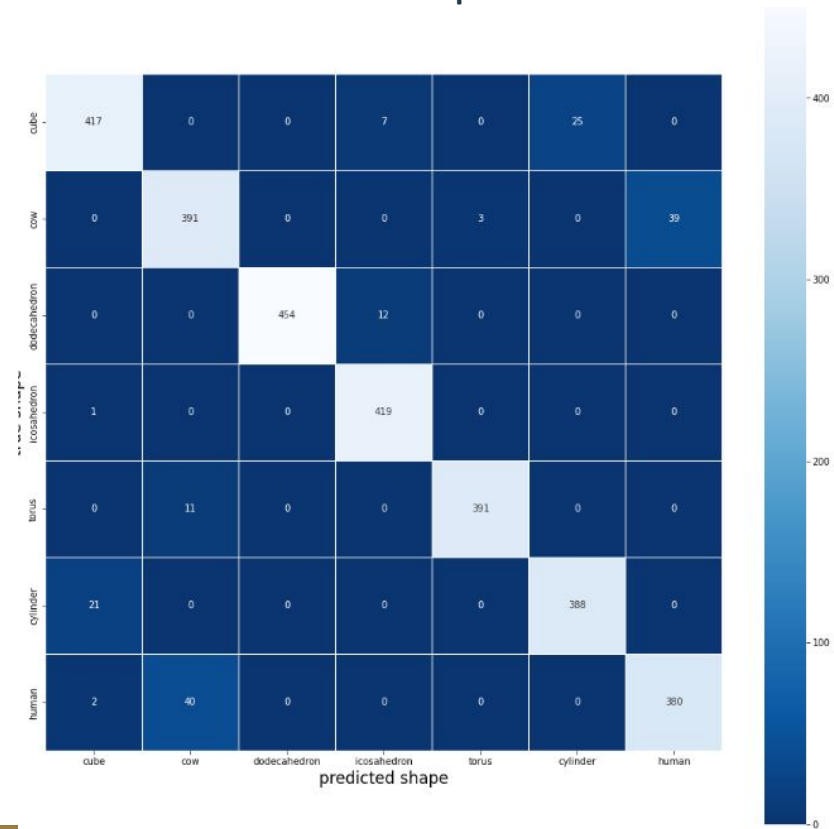
Full shapes

	precision	recall	f1-score	support
cube	0.95	0.93	0.94	449
cow	0.88	0.90	0.89	433
dodecahedron	1.00	0.97	0.99	466
icosahedron	0.96	1.00	0.98	420
torus	0.99	0.97	0.98	402
cylinder	0.94	0.95	0.94	409
human	0.91	0.90	0.90	422
accuracy			0.95	3001
macro avg	0.95	0.95	0.95	3001
weighted avg	0.95	0.95	0.95	3001

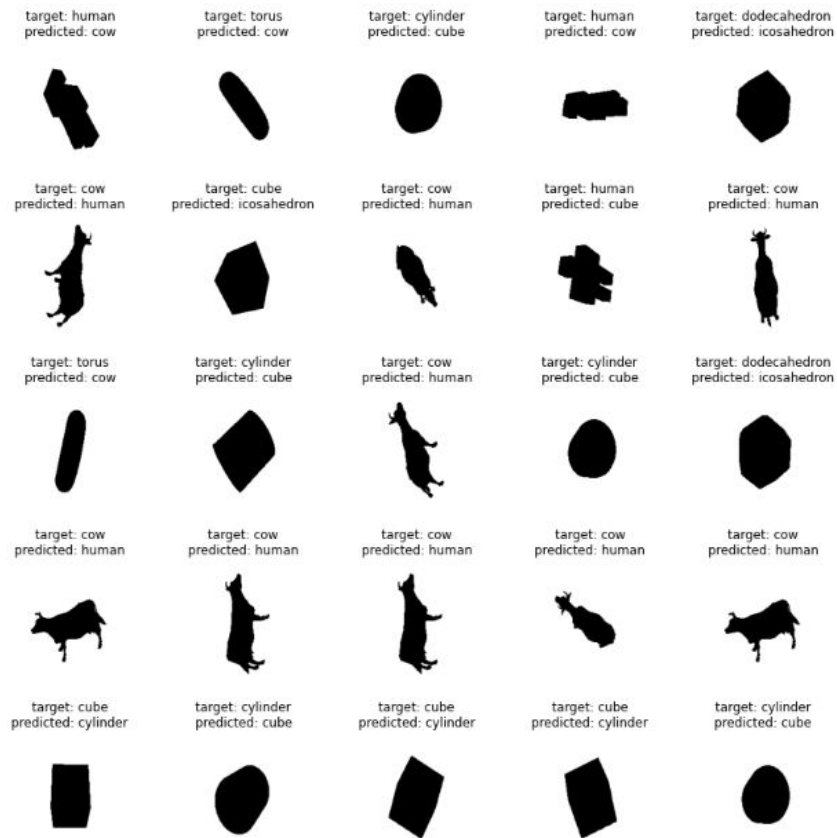
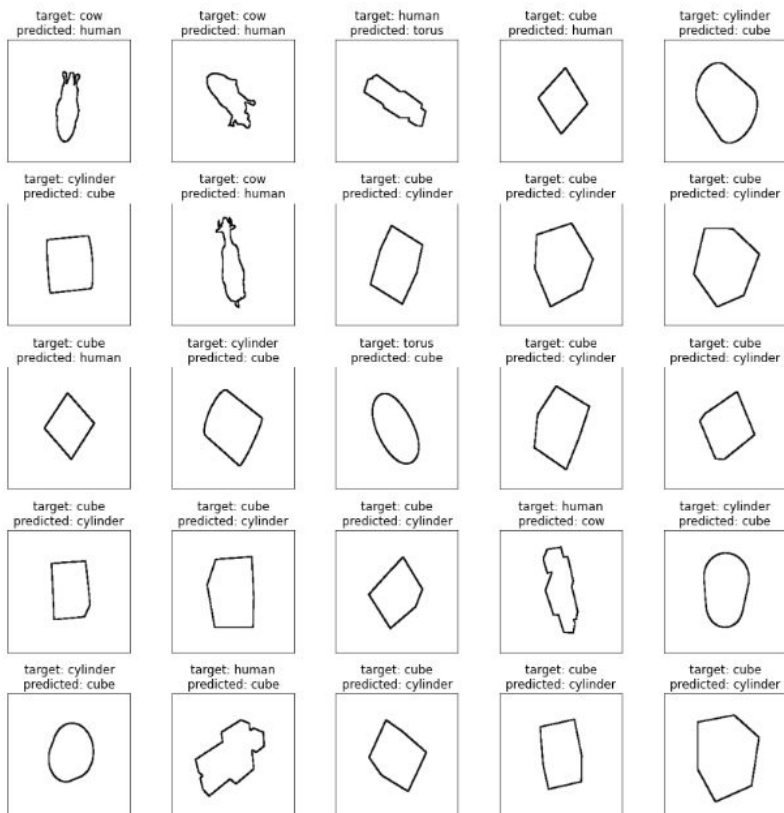
Edges



Full shapes

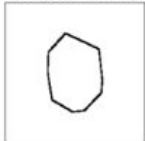


Wrong predictions

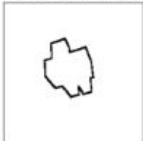


Correct predictions

target: dodecahedron
predicted: dodecahedron



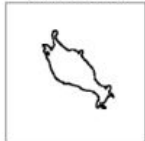
target: human
predicted: human



target: torus
predicted: torus



target: cow
predicted: cow



target: cow
predicted: cow



target: icosahedron
predicted: icosahedron



target: tetrahedron
predicted: tetrahedron



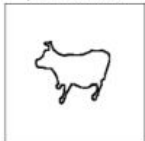
target: cube
predicted: cube



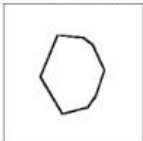
target: torus
predicted: torus



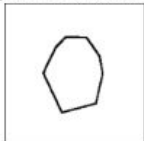
target: cow
predicted: cow



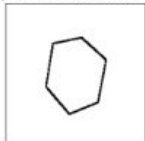
target: icosahedron
predicted: icosahedron



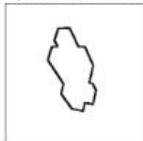
target: icosahedron
predicted: icosahedron



target: icosahedron
predicted: icosahedron



target: human
predicted: human



target: tetrahedron
predicted: icosahedron



target: torus
predicted: torus



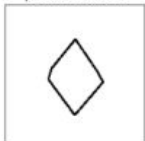
target: dodecahedron
predicted: dodecahedron



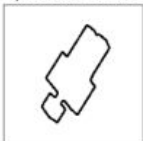
target: tetrahedron
predicted: tetrahedron



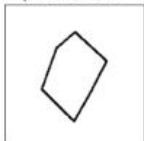
target: cube
predicted: cube



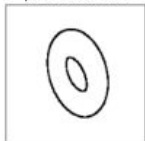
target: human
predicted: human



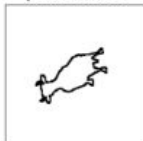
target: cube
predicted: cube



target: torus
predicted: torus



target: cow
predicted: cow



target: cow
predicted: cow



target: diamond
predicted: diamond



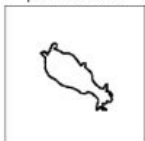
target: tetrahedron
predicted: tetrahedron



target: dodecahedron
predicted: dodecahedron



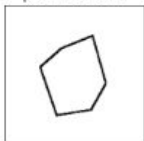
target: cow
predicted: cow



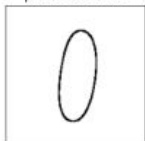
target: cow
predicted: cow



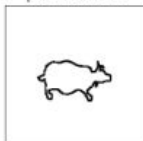
target: cube
predicted: cube



target: torus
predicted: torus



target: cow
predicted: cow



target: human
predicted: human



target: pyramid
predicted: pyramid



target: dodecahedron
predicted: dodecahedron



target: human
predicted: human



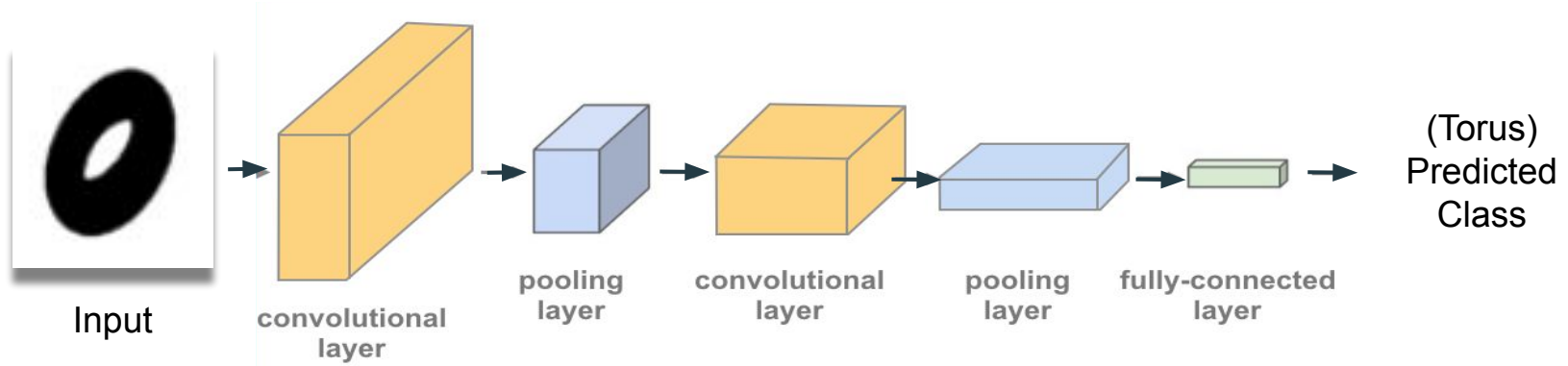
Conclusion for DNN

- full shapes perform better than edges
- good results for 7 shapes

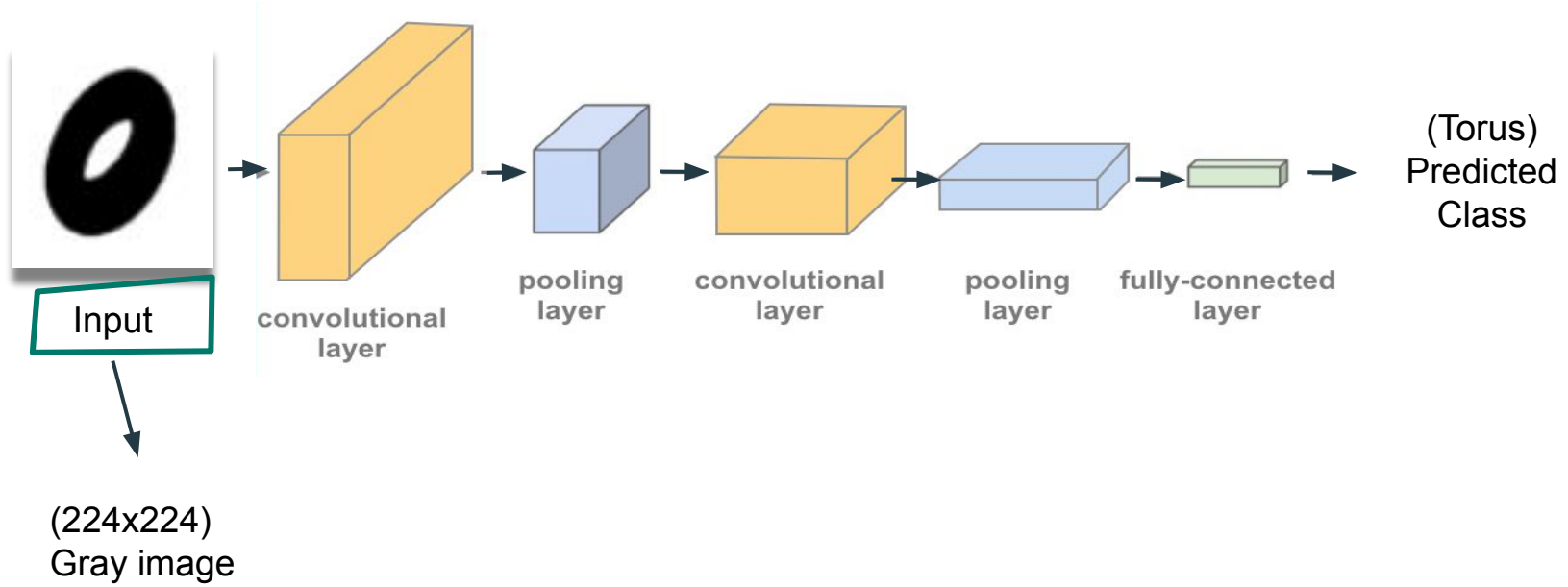


Convolutional Neural Network

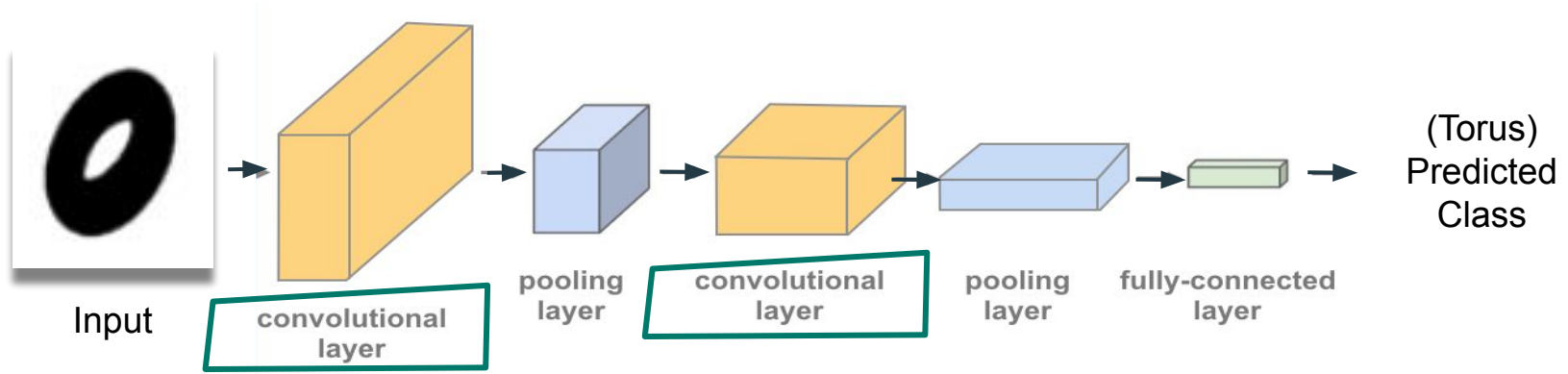
CNN



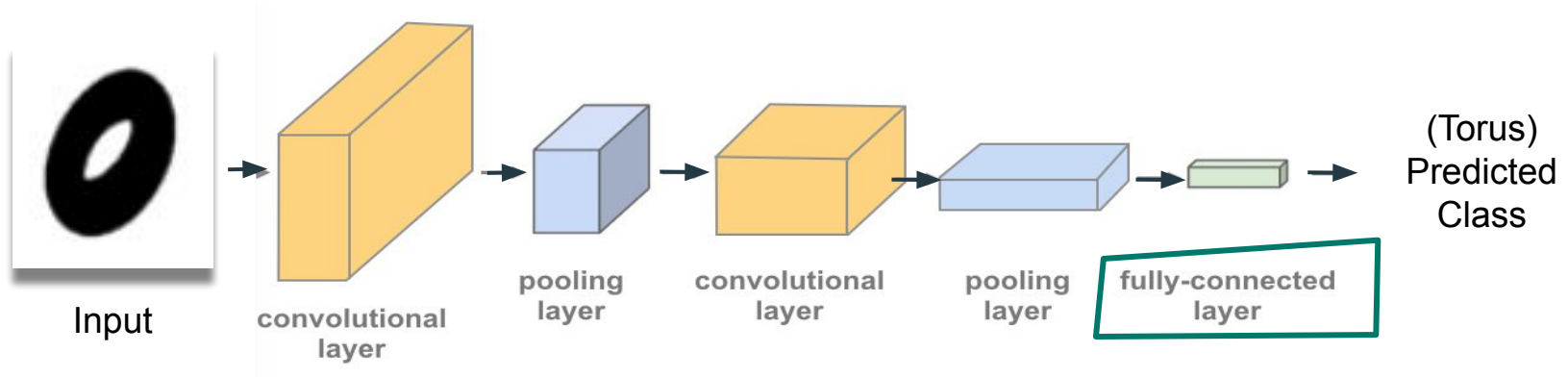
CNN



CNN

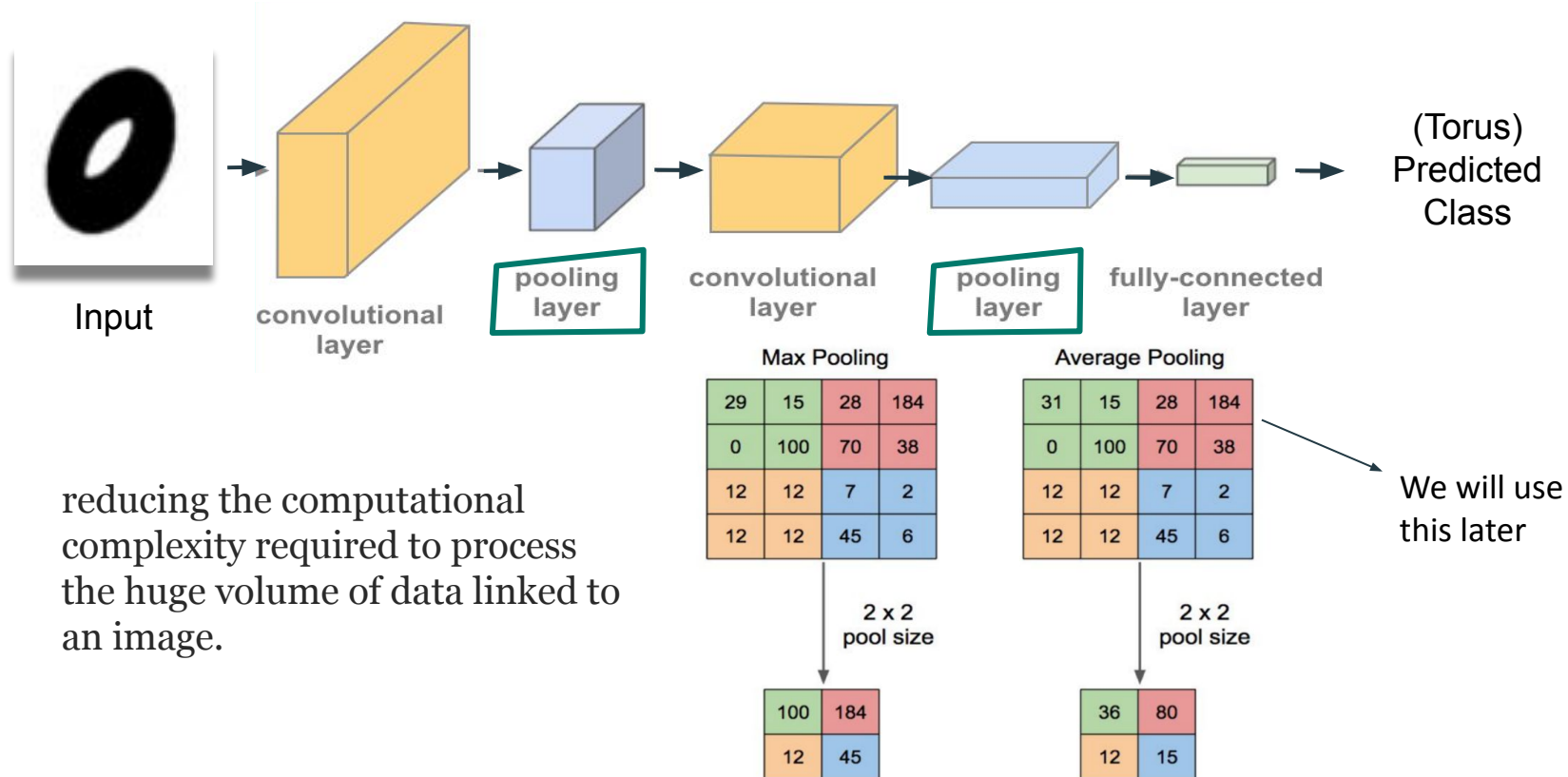


CNN



using Softmax layer (in the last layer of CNN, FC) for our multi-classification

CNN



Source:

<https://towardsdatascience.com/convolution-neural-network-for-image-processing-using-keras-dc3429056306>

CNN Results

We used various Architectures (VGG, LeNet,..) with different channels trends before any regularization.

```
model.compile(optimizer = tf.optimizers.Adam(), loss=keras.losses.categorical_crossentropy, metrics = ['accuracy'])
```

Learning_rate=0.01 batch_size = 32 epochs=20

CNN Results

VGG-like

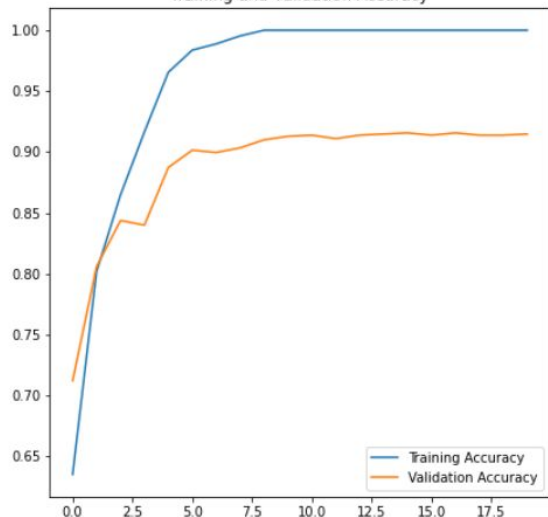
Train loss: 3.516e-05

Train accuracy: 1.0

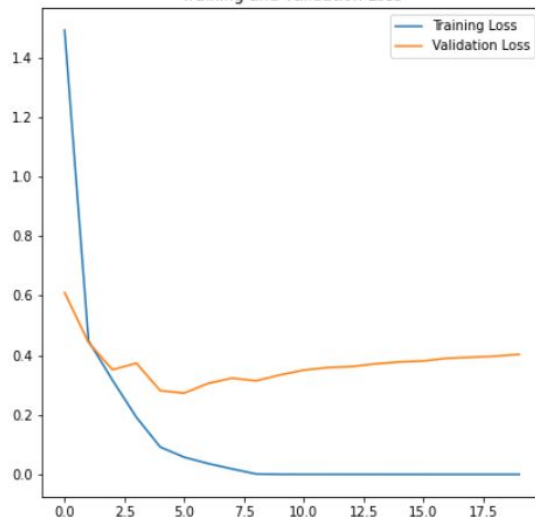
Test loss: 0.4031

Test accuracy: 0.9148

Training and Validation Accuracy



Training and Validation Loss



Layer (type)	Output Shape	Param #
conv2d_18 (Conv2D)	(None, 200, 200, 16)	160
conv2d_19 (Conv2D)	(None, 200, 200, 16)	2320
max_pooling2d_13 (MaxPooling)	(None, 100, 100, 16)	0
conv2d_20 (Conv2D)	(None, 98, 98, 32)	4640
conv2d_21 (Conv2D)	(None, 96, 96, 32)	9248
max_pooling2d_14 (MaxPooling)	(None, 48, 48, 32)	0
flatten_4 (Flatten)	(None, 73728)	0
dense_8 (Dense)	(None, 512)	37749248
dense_9 (Dense)	(None, 4)	2052
Total params: 37,767,668		
Trainable params: 37,767,668		
Non-trainable params: 0		

CNN Results

Train loss: 0.0003416

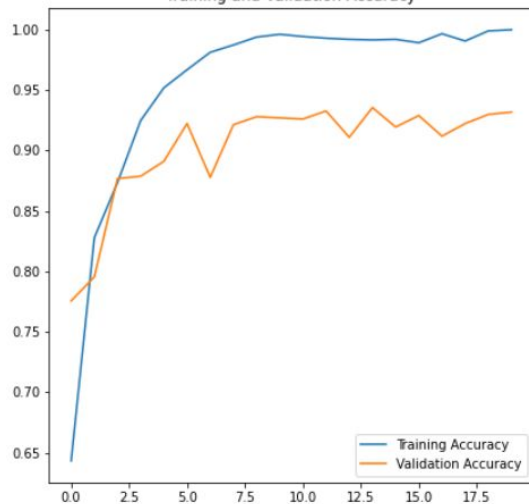
Train accuracy: 1.0

Test loss: 0.2841

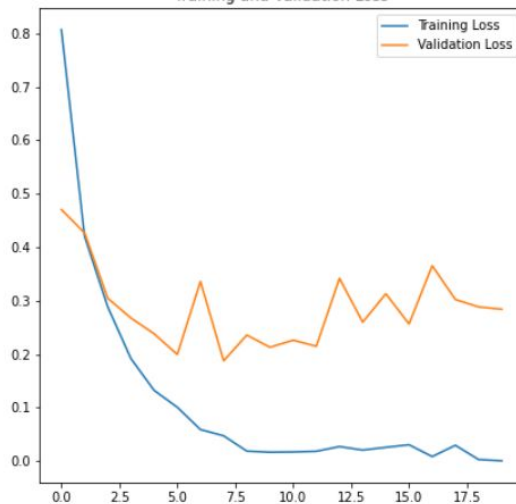
Test accuracy: 0.9318

LeNet

Training and Validation Accuracy



Training and Validation Loss

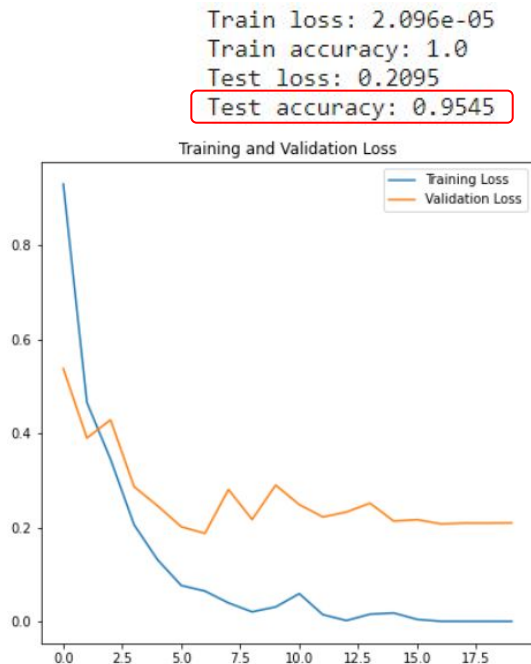
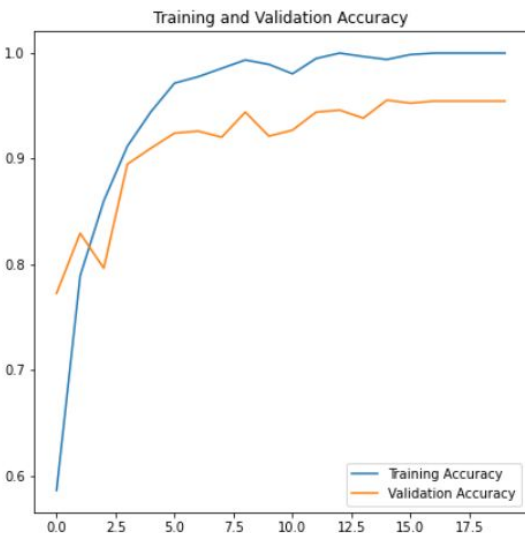


Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv2d_22 (Conv2D)	(None, 196, 196, 6)	156
max_pooling2d_15 (MaxPooling)	(None, 98, 98, 6)	0
conv2d_23 (Conv2D)	(None, 94, 94, 16)	2416
max_pooling2d_16 (MaxPooling)	(None, 47, 47, 16)	0
flatten_5 (Flatten)	(None, 35344)	0
dense_10 (Dense)	(None, 120)	4241400
dense_11 (Dense)	(None, 84)	10164
dense_12 (Dense)	(None, 4)	340
Total params: 4,254,476		
Trainable params: 4,254,476		
Non-trainable params: 0		

CNN Results

Conv-Conv-Pool / 32-64-64
(highest Accuracy)



Train loss: 2.096e-05

Train accuracy: 1.0

Test loss: 0.2095

Test accuracy: 0.9545

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 200, 200, 32)	320
conv2d_1 (Conv2D)	(None, 198, 198, 32)	9248
max_pooling2d (MaxPooling2D)	(None, 99, 99, 32)	0
conv2d_2 (Conv2D)	(None, 99, 99, 64)	18496
conv2d_3 (Conv2D)	(None, 97, 97, 64)	36928
max_pooling2d_1 (MaxPooling2D)	(None, 48, 48, 64)	0
conv2d_4 (Conv2D)	(None, 48, 48, 64)	36928
conv2d_5 (Conv2D)	(None, 46, 46, 64)	36928
max_pooling2d_2 (MaxPooling2D)	(None, 23, 23, 64)	0
flatten (Flatten)	(None, 33856)	0
dense (Dense)	(None, 512)	17334784
dense_1 (Dense)	(None, 10)	5130

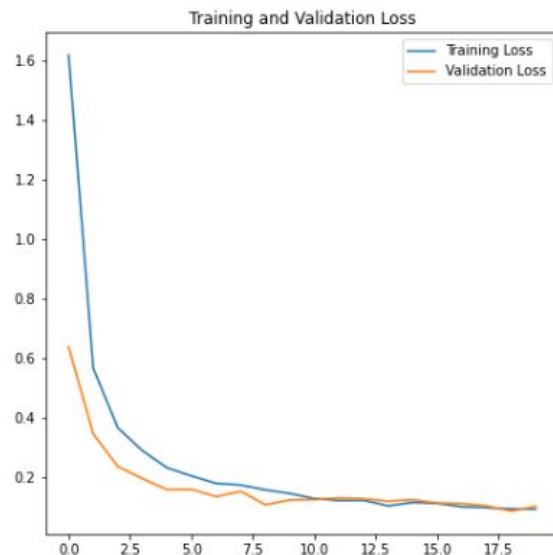
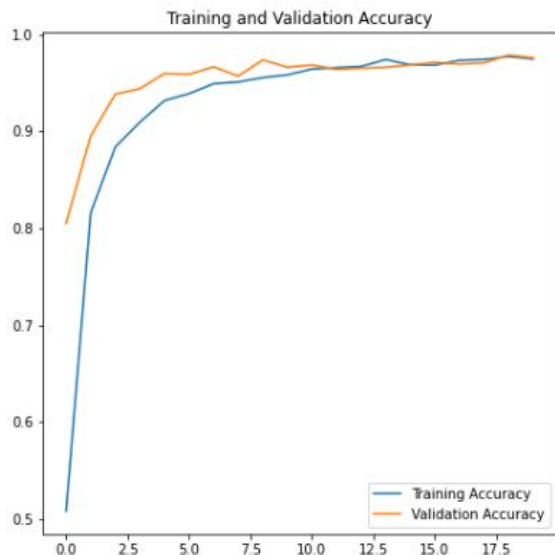
=====

Total params: 17,478,762
Trainable params: 17,478,762
Non-trainable params: 0

CNN Results

Conv-Conv-Pool-Conv-Conv-Pool /
32-64-64 (highest Accuracy)

Train loss: 0.03076
Train accuracy: 0.9987
Test loss: 0.1034
Test accuracy: 0.9758



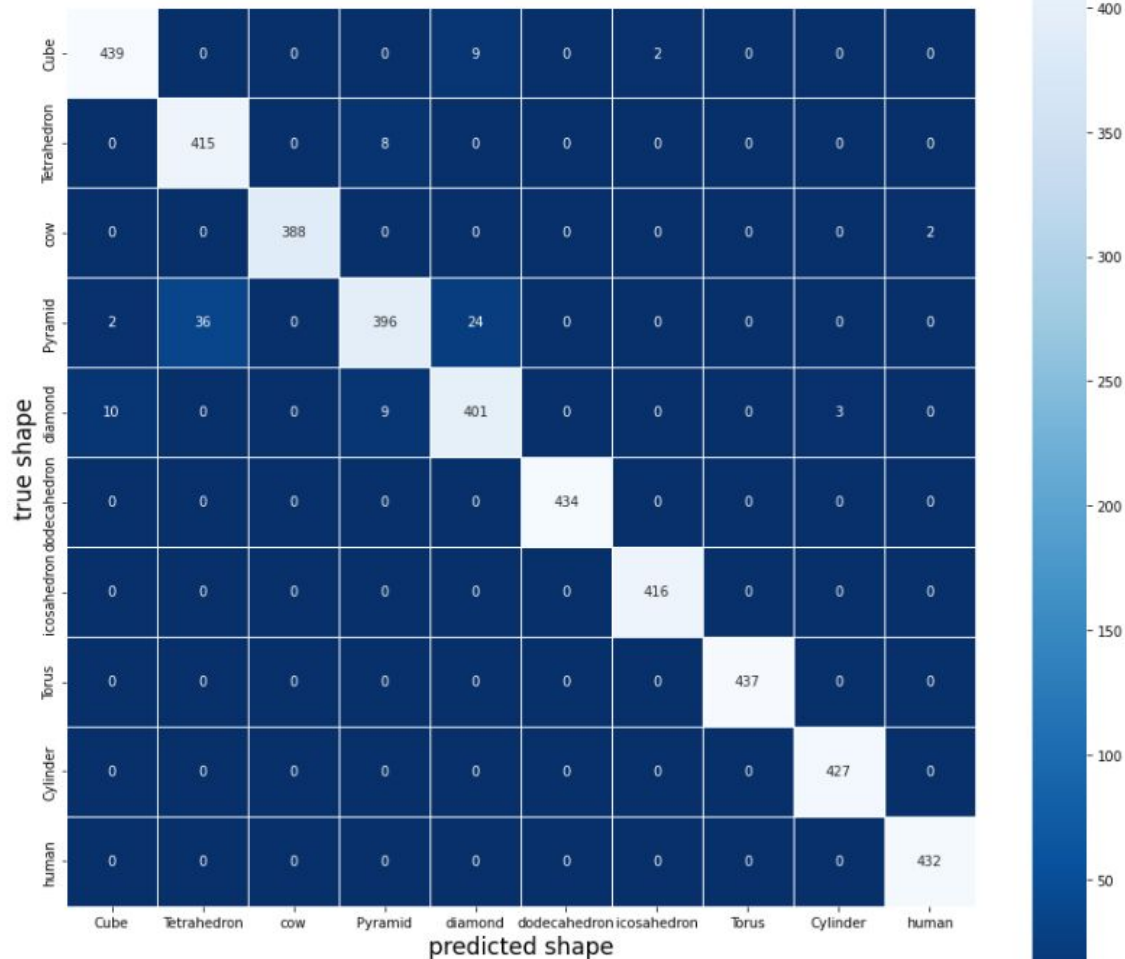
Now using regularization
(dropout, L2)

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 200, 200, 32)	320
conv2d_1 (Conv2D)	(None, 198, 198, 32)	9248
max_pooling2d (MaxPooling2D)	(None, 99, 99, 32)	0
dropout (Dropout)	(None, 99, 99, 32)	0
conv2d_2 (Conv2D)	(None, 99, 99, 64)	18496
conv2d_3 (Conv2D)	(None, 97, 97, 64)	36928
max_pooling2d_1 (MaxPooling2D)	(None, 48, 48, 64)	0
dropout_1 (Dropout)	(None, 48, 48, 64)	0
conv2d_4 (Conv2D)	(None, 48, 48, 64)	36928
conv2d_5 (Conv2D)	(None, 46, 46, 64)	36928
max_pooling2d_2 (MaxPooling2D)	(None, 23, 23, 64)	0
dropout_2 (Dropout)	(None, 23, 23, 64)	0
flatten (Flatten)	(None, 33856)	0
dense (Dense)	(None, 512)	17334784
dropout_3 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 10)	5130
Total params: 17,478,762		
Trainable params: 17,478,762		
Non-trainable params: 0		

CNN Results

Test accuracy: 0.9758

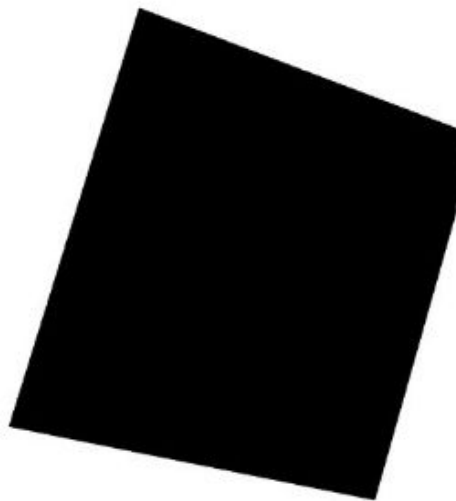
	precision	recall	f1-score	support
Pyramid	0.94	0.86	0.90	433
Tetrahedron	0.94	0.95	0.95	406
cow	1.00	0.99	1.00	450
Cube	0.98	0.99	0.98	415
Torus	1.00	1.00	1.00	436
diamond	0.92	0.98	0.95	412
dodecahedron	1.00	1.00	1.00	400
human	0.99	1.00	1.00	446
Cylinder	1.00	1.00	1.00	469
icosahedron	1.00	1.00	1.00	423
accuracy			0.98	4290
macro avg	0.98	0.98	0.98	4290
weighted avg	0.98	0.98	0.98	4290



Challenge



what is the shape?



tinyurl.com/MLHO22

Diamond



Conv-Conv-Pool-Conv-Conv-Pool / 32-64-64 (highest Accuracy)

target: Cube
predicted: Cube



target: Tetrahedron
predicted: Tetrahedron



target: diamond
predicted: diamond



target: Tetrahedron
predicted: Tetrahedron

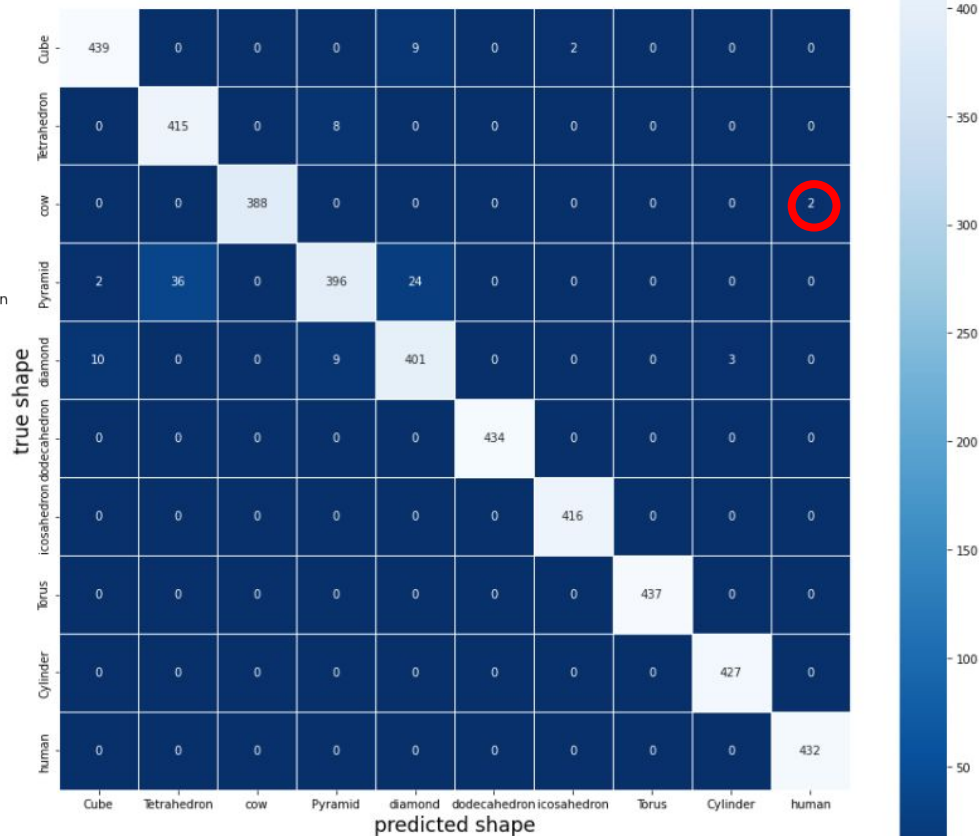


Some errors

target: cow
predicted: human



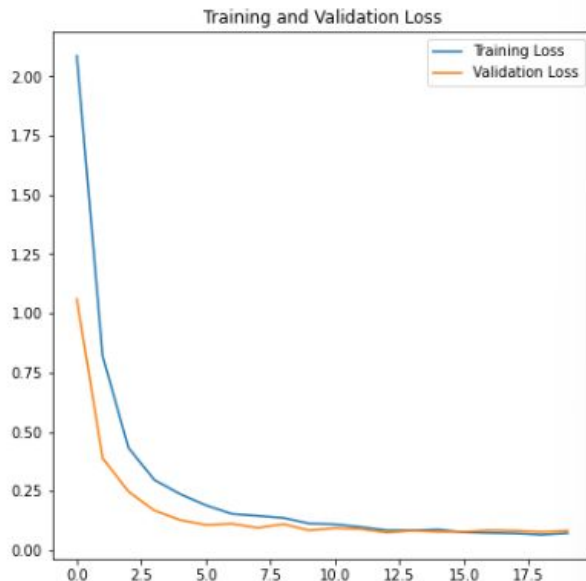
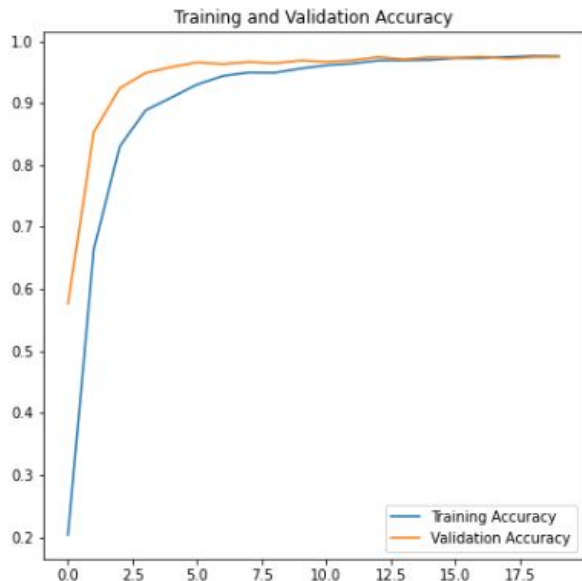
target: Pyramid
predicted: diamond



CNN Results (Edges)

Conv-Conv-Pool / 16-32-64

Train loss: 0.004168
Train accuracy: 0.9994
Test loss: 0.0821
Test accuracy: 0.9744

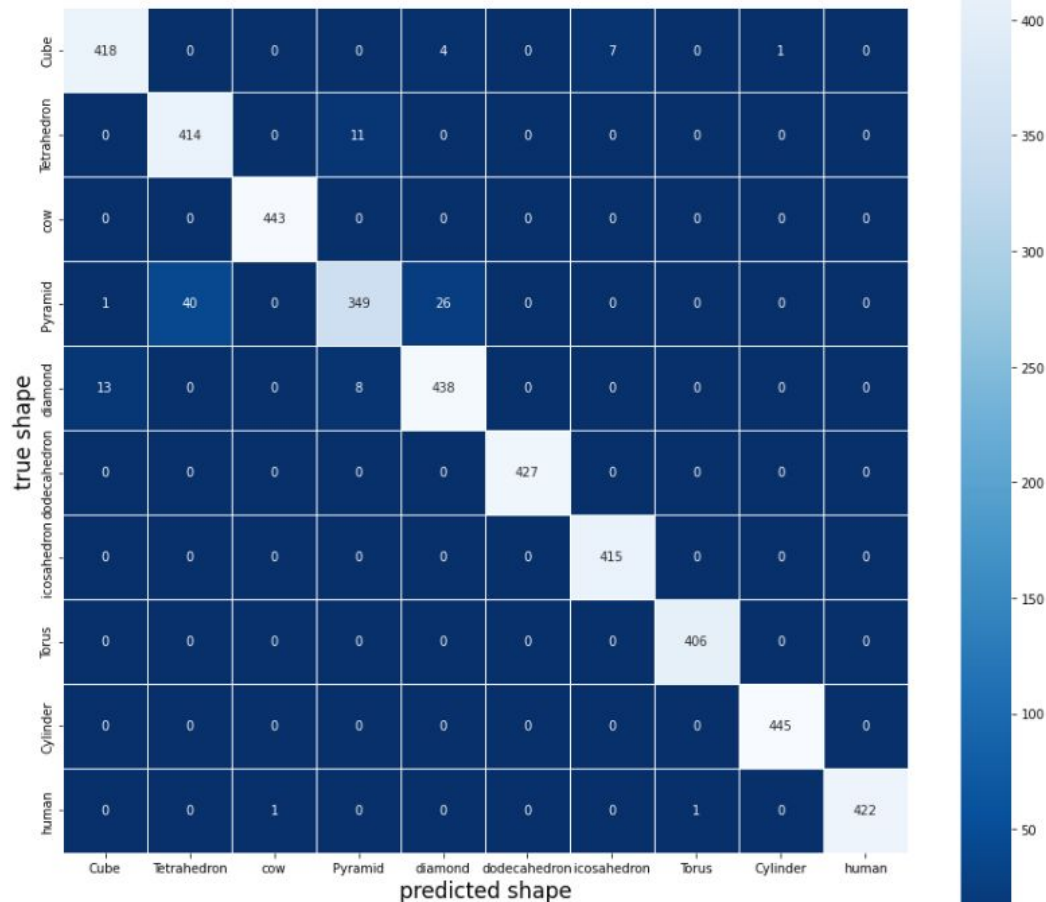


Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 200, 200, 16)	160
conv2d_7 (Conv2D)	(None, 198, 198, 16)	2320
max_pooling2d_3 (MaxPooling2)	(None, 99, 99, 16)	0
dropout_4 (Dropout)	(None, 99, 99, 16)	0
conv2d_8 (Conv2D)	(None, 99, 99, 32)	4640
conv2d_9 (Conv2D)	(None, 97, 97, 32)	9248
max_pooling2d_4 (MaxPooling2)	(None, 48, 48, 32)	0
dropout_5 (Dropout)	(None, 48, 48, 32)	0
conv2d_10 (Conv2D)	(None, 48, 48, 64)	18496
conv2d_11 (Conv2D)	(None, 46, 46, 64)	36928
max_pooling2d_5 (MaxPooling2)	(None, 23, 23, 64)	0
dropout_6 (Dropout)	(None, 23, 23, 64)	0
flatten_1 (Flatten)	(None, 33856)	0
dense_2 (Dense)	(None, 512)	17334784
dropout_7 (Dropout)	(None, 512)	0
dense_3 (Dense)	(None, 10)	5130
Total params: 17,411,706		
Trainable params: 17,411,706		
Non-trainable params: 0		

CNN Results (Edges)

	precision	recall	f1-score	support
Cube	0.97	0.97	0.97	420
Tetrahedron	0.97	0.95	0.96	444
cow	0.97	1.00	0.99	440
Pyramid	0.92	0.92	0.92	406
diamond	0.94	0.95	0.94	425
dodecahedron	1.00	1.00	1.00	411
icosahedron	0.99	1.00	1.00	461
Torus	0.99	1.00	0.99	426
Cylinder	1.00	1.00	1.00	417
human	1.00	0.96	0.98	440
accuracy			0.97	4290
macro avg	0.97	0.97	0.97	4290
weighted avg	0.97	0.97	0.97	4290

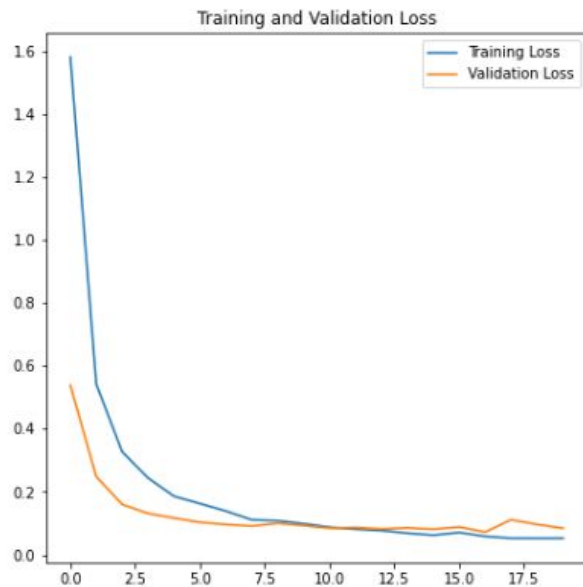
Train loss: 0.004168
 Train accuracy: 0.9994
 Test loss: 0.0821
 Test accuracy: 0.9744



CNN Results (Solid shadows again)

Conv-Conv-Pool-Conv-Conv-Pool /
16-32-64 (drop out only) ALL
shapes(msh far2a kteer)

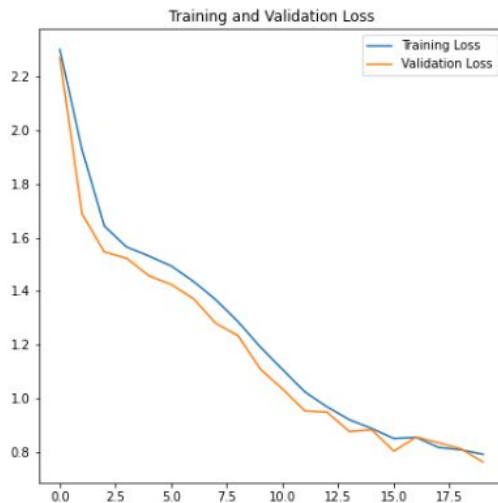
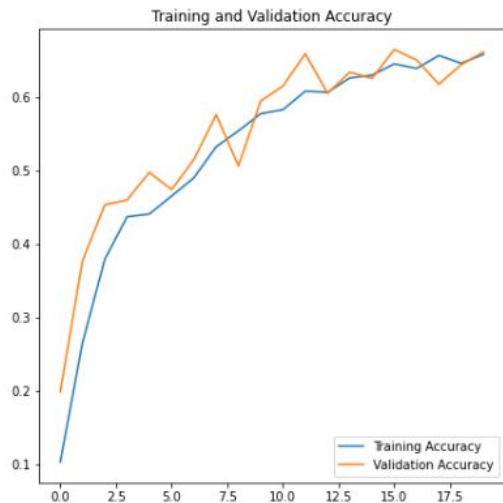
Train loss: 0.00195
Train accuracy: 0.9998
Test loss: 0.09294
Test accuracy: 0.9755



Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 200, 200, 16)	160
conv2d_7 (Conv2D)	(None, 198, 198, 16)	2320
max_pooling2d_3 (MaxPooling2D)	(None, 99, 99, 16)	0
dropout_4 (Dropout)	(None, 99, 99, 16)	0
conv2d_8 (Conv2D)	(None, 99, 99, 32)	4640
conv2d_9 (Conv2D)	(None, 97, 97, 32)	9248
max_pooling2d_4 (MaxPooling2D)	(None, 48, 48, 32)	0
dropout_5 (Dropout)	(None, 48, 48, 32)	0
conv2d_10 (Conv2D)	(None, 48, 48, 64)	18496
conv2d_11 (Conv2D)	(None, 46, 46, 64)	36928
max_pooling2d_5 (MaxPooling2D)	(None, 23, 23, 64)	0
dropout_6 (Dropout)	(None, 23, 23, 64)	0
flatten_1 (Flatten)	(None, 33856)	0
dense_2 (Dense)	(None, 512)	17334784
dropout_7 (Dropout)	(None, 512)	0
dense_3 (Dense)	(None, 10)	5130
Total params: 17,411,706		
Trainable params: 17,411,706		
Non-trainable params: 0		

CAM

```
model = Sequential()  
model.add(Conv2D(16, input_shape=input_shape, kernel_size=(3, 3), activation='relu', padding='same'))  
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', padding='same'))  
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu', padding='same'))  
model.add(Conv2D(128, kernel_size=(3, 3), activation='relu', padding='same'))  
model.add(GlobalAveragePooling2D())  
model.add(Dense(len(labels), activation='softmax'))
```



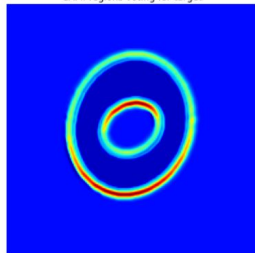
Train loss: 0.7704
Train accuracy: 0.6635
Test loss: 0.764
Test accuracy: 0.6613

CAM

Predicted class= Torus
ture class=Torus, Probability = 0.638



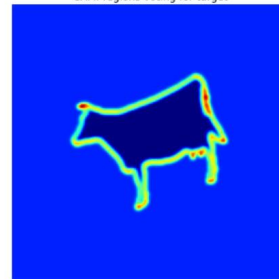
CAM: regions voting for target



Predicted class= cow
ture class=cow, Probability = 0.996



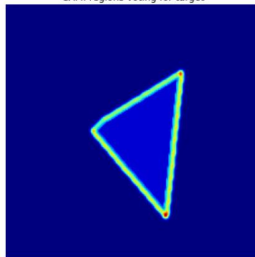
CAM: regions voting for target



Predicted class= Tetrahedron
ture class=Tetrahedron, Probability = 0.760



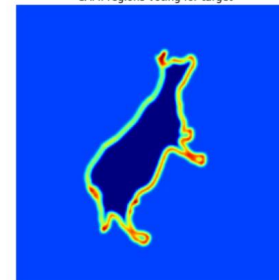
CAM: regions voting for target



Predicted Class = 2, Probability = 0.999



CAM: regions voting for target

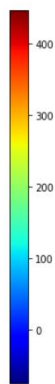
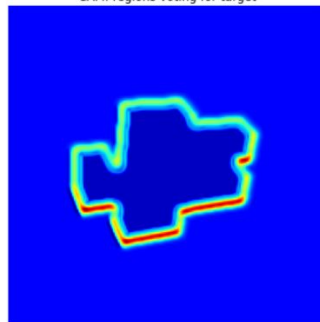


CAM

Predicted class= Torus
ture class=human, Probability = 0.611



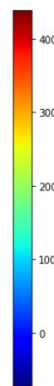
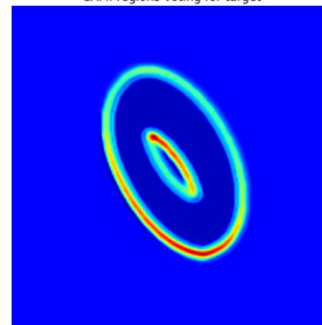
CAM: regions voting for target



Predicted class= Torus
ture class=Torus, Probability = 0.622



CAM: regions voting for target



Conclusion and Outlook

- CNN proved itself capable of better image classifications than DNN
- The problem is underdetermined because some shadows of different shapes are the same for different orientations
- Complicated shapes are easier to distinguish
- The project can be extended to cover more shapes and other lighting conditions



Thank you for
your attention

Questions?

