

CECS 456

Machine Learning

Adrian Seth
Kelly Duangrudeeswat
Luke Sunaoka
Matthew Quinn



Introduction and Dataset

We chose to do this project because we had an interest in classifying animals and love cute cat pictures.

Our dataset consists of 28,000 medium quality images of 10 different classifications of animals(dog, cat, horse, spyder, butterfly, chicken, sheep, cow, squirrel, elephant).

The different classifications have between 2-5 thousand images each.

There are intentionally some incorrectly classified data in the set, the intent is to simulate real like conditions.

We retrieved our data from

<https://www.kaggle.com/datasets/alessiocorrado99/animals10>

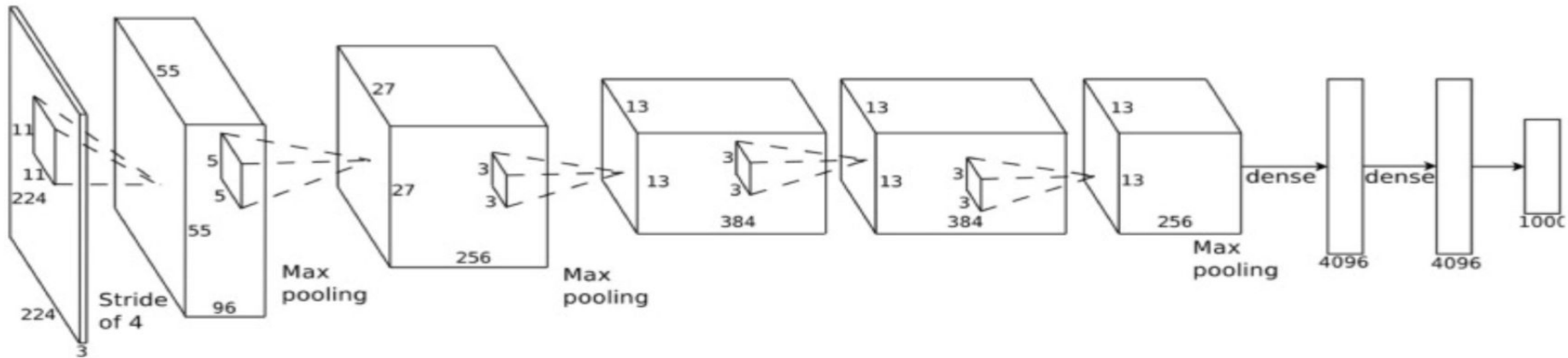
Description and Related Work

On Kaggle's web site there are a lot of related works that use convolutional neural networks as well as other neural network models in order to classify the animal data set. Some import, famous models such as VGG, AlexNet, and ResNet which are all used to classify their images while others build their models from the ground up.

For our project we decided to implement different variations of CNN and see how well they perform.

Definitions

- Convolution Layer
 - CONV2D:
 - Filter
 - Kernel size
 - Activation
 - padding:
- MaxPool2D
- Flattening
- Dense



Implementation Methodology

- My model was based on the CNN demo we did in class
- I added additional layers and tweaked parameters to see what would improve or worsen accuracy
- A big part of my methodology was testing many different combinations of inputs and layers.
- My model ended with 18 layers as well as 3 drop out layers
- A batch size of 100 and epochs of 5 seemed to be the most consistent. When increasing the epochs I ran into “out of resource errors” This was while the model on my own hardware.
- Activation function Relu
- Total params 1.8m

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 16)	448
max_pooling2d (MaxPooling2D)	(None, 111, 111, 16)	0
conv2d_1 (Conv2D)	(None, 109, 109, 32)	4640
conv2d_2 (Conv2D)	(None, 107, 107, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 53, 53, 32)	0
conv2d_3 (Conv2D)	(None, 51, 51, 64)	18496
conv2d_4 (Conv2D)	(None, 49, 49, 64)	36928
max_pooling2d_2 (MaxPooling2D)	(None, 24, 24, 64)	0
conv2d_5 (Conv2D)	(None, 22, 22, 128)	73856
conv2d_6 (Conv2D)	(None, 20, 20, 128)	147584
max_pooling2d_3 (MaxPooling2D)	(None, 10, 10, 128)	0
conv2d_7 (Conv2D)	(None, 8, 8, 256)	295168
conv2d_8 (Conv2D)	(None, 6, 6, 256)	590080
max_pooling2d_4 (MaxPooling2D)	(None, 3, 3, 256)	0
flatten (Flatten)	(None, 2304)	0
dense (Dense)	(None, 256)	590080
dense_1 (Dense)	(None, 128)	32896
dense_2 (Dense)	(None, 128)	16512
dense_3 (Dense)	(None, 10)	1290
Total params: 1,817,226		
Trainable params: 1,817,226		
Non-trainable params: 0		

Results

- Accuracy of 58%
- There is a lot of room for improvement.
- Total loss: 1.23
- Validation loss: 1.32
- Validation accuracy 0.5675

```
Epoch 1/5
655/655 [=====] - 111s 154ms/step - loss: 1.9750 - accuracy: 0.3131 - val_loss: 1.7947 - val_accuracy: 0.3802
Epoch 2/5
655/655 [=====] - 98s 149ms/step - loss: 1.6921 - accuracy: 0.4213 - val_loss: 1.5221 - val_accuracy: 0.4786
Epoch 3/5
655/655 [=====] - 98s 149ms/step - loss: 1.4872 - accuracy: 0.4997 - val_loss: 1.4437 - val_accuracy: 0.5166
Epoch 4/5
655/655 [=====] - 97s 148ms/step - loss: 1.3558 - accuracy: 0.5467 - val_loss: 1.3398 - val_accuracy: 0.5501
Epoch 5/5
655/655 [=====] - 97s 148ms/step - loss: 1.2381 - accuracy: 0.5853 - val_loss: 1.3258 - val_accuracy: 0.5675
```

Adrian's Model

Design

I followed the CNN Design as the foundation for my model. I used smaller strides and smaller kernel amounts and slowly

```
cnn = tf.keras.models.Sequential() #initialize model
cnn.add(tf.keras.layers.Conv2D(filters=16, kernel_size=(3,3), activation='relu', input_shape=(28, 28, 3)))
cnn.add(tf.keras.layers.Conv2D(filters=16, kernel_size=(3,3), activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=(2,2), activation='relu'))

cnn.add(tf.keras.layers.Conv2D(filters=32, kernel_size=(3,3), activation='relu'))
cnn.add(tf.keras.layers.Conv2D(filters=32, kernel_size=(3,3), activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=(2,2), activation='relu'))

cnn.add(tf.keras.layers.Conv2D(filters=64, kernel_size=(3,3), activation='relu'))
cnn.add(tf.keras.layers.Conv2D(filters=64, kernel_size=(3,3), activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=(2,2), activation='relu'))

cnn.add(tf.keras.layers.Conv2D(filters=128, kernel_size=(3,3), activation='relu'))
cnn.add(tf.keras.layers.Conv2D(filters=128, kernel_size=(3,3), activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=(2,2), activation='relu'))

cnn.add(tf.keras.layers.Flatten()) #Flatten the output
cnn.add(tf.keras.layers.Dense(units=128, activation='relu'))
cnn.add(tf.keras.layers.Dense(units=64, activation='relu'))
cnn.add(tf.keras.layers.Dense(units=32, activation='relu'))
cnn.add(tf.keras.layers.Dense(units= 10, activation='softmax'))
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_16 (Conv2D)	(None, 128, 128, 16)	448
conv2d_17 (Conv2D)	(None, 128, 128, 16)	2320
max_pooling2d_8 (MaxPooling2D)	(None, 64, 64, 16)	0
conv2d_18 (Conv2D)	(None, 64, 64, 32)	4640
conv2d_19 (Conv2D)	(None, 64, 64, 32)	9248
max_pooling2d_9 (MaxPooling2D)	(None, 32, 32, 32)	0
conv2d_20 (Conv2D)	(None, 32, 32, 64)	18496
conv2d_21 (Conv2D)	(None, 32, 32, 64)	36928
max_pooling2d_10 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_22 (Conv2D)	(None, 16, 16, 128)	73856
conv2d_23 (Conv2D)	(None, 16, 16, 128)	147584
max_pooling2d_11 (MaxPooling2D)	(None, 8, 8, 128)	0
flatten_2 (Flatten)	(None, 8192)	0
dense_7 (Dense)	(None, 128)	1048704
dense_8 (Dense)	(None, 64)	8256
dense_9 (Dense)	(None, 32)	2080
dense_10 (Dense)	(None, 10)	330

```
=====
Total params: 1,352,890
Trainable params: 1,352,890
Non-trainable params: 0
=====
```

The reason behind my decisions was to have my model slowly acquire parameters while avoiding having too many which I believed would reduce overfitting and decrease training time.

```
...t_shape=[128, 128, 3])) #Convolution 1
```

```
...onvolution 4
```

```
...onvolution 5
```

Adrian

Training accuracy - 81%

Testing accuracy - 66%

```
Epoch 1/10
84/84 [=====] - 9s 102ms/step - loss: 2.2487 - accuracy: 0.2200 - val_loss: 1.9873 - val_accuracy: 0.3435
Epoch 2/10
84/84 [=====] - 7s 88ms/step - loss: 1.8074 - accuracy: 0.3872 - val_loss: 1.6525 - val_accuracy: 0.4363
Epoch 3/10
84/84 [=====] - 7s 88ms/step - loss: 1.4918 - accuracy: 0.4911 - val_loss: 1.4768 - val_accuracy: 0.4956
Epoch 4/10
84/84 [=====] - 7s 89ms/step - loss: 1.3178 - accuracy: 0.5452 - val_loss: 1.3313 - val_accuracy: 0.5520
Epoch 5/10
84/84 [=====] - 7s 88ms/step - loss: 1.1573 - accuracy: 0.6023 - val_loss: 1.1898 - val_accuracy: 0.5999
Epoch 6/10
84/84 [=====] - 7s 88ms/step - loss: 1.0157 - accuracy: 0.6558 - val_loss: 1.2301 - val_accuracy: 0.5752
Epoch 7/10
84/84 [=====] - 7s 89ms/step - loss: 0.9153 - accuracy: 0.6903 - val_loss: 1.0807 - val_accuracy: 0.6417
Epoch 8/10
84/84 [=====] - 7s 89ms/step - loss: 0.7815 - accuracy: 0.7332 - val_loss: 1.1224 - val_accuracy: 0.6417
Epoch 9/10
84/84 [=====] - 7s 89ms/step - loss: 0.6776 - accuracy: 0.7685 - val_loss: 1.1660 - val_accuracy: 0.6393
Epoch 10/10
84/84 [=====] - 8s 90ms/step - loss: 0.5539 - accuracy: 0.8097 - val_loss: 1.1643 - val_accuracy: 0.6484
```

```
164/164 [=====] - 1s 8ms/step - loss: 1.1186 - accuracy: 0.6596
```

```
Total loss on Testing Set: 1.118599534034729
```

```
Accuracy of Testing Set: 0.6595866680145264
```


Implementation Methodology

- Based on VGG16
- Extracting data
- Splitting the dataset
- Creating the model
 - 16 layers
 - Activation = relu
 - Batch size = 100
 - Epoch = 20

References:

- <https://www.kaggle.com/code/bhupendrakumar/animal-10-vgg16-tf-lr>
- <https://www.kaggle.com/code/min4tozaki/animal-classification>

```
Epoch 7/20
#m: 210/210 [=====] - 62s 295ms/step - loss: 1.1827 - accuracy: 0.5935 - val_loss: 1.3071 - val_accuracy: 0.5
cnnr 634
Epoch 8/20
#ac: 210/210 [=====] - 62s 295ms/step - loss: 1.0739 - accuracy: 0.6317 - val_loss: 1.2404 - val_accuracy: 0.5
cnnr 865
Epoch 9/20
cnnr 210/210 [=====] - 62s 295ms/step - loss: 0.9798 - accuracy: 0.6666 - val_loss: 1.2192 - val_accuracy: 0.5
cnnr 949
Epoch 10/20
cnnr 210/210 [=====] - 62s 295ms/step - loss: 0.8736 - accuracy: 0.7010 - val_loss: 1.1783 - val_accuracy: 0.6
cnnr 073
Epoch 11/20
cnnr 210/210 [=====] - 62s 295ms/step - loss: 0.7601 - accuracy: 0.7421 - val_loss: 1.2424 - val_accuracy: 0.6
cnnr 138
Epoch 12/20
cnnr 210/210 [=====] - 62s 295ms/step - loss: 0.6562 - accuracy: 0.7766 - val_loss: 1.2684 - val_accuracy: 0.6
cnnr 062
Epoch 13/20
cnnr 210/210 [=====] - 62s 295ms/step - loss: 0.5590 - accuracy: 0.8083 - val_loss: 1.3899 - val_accuracy: 0.6
cnnr 199
Epoch 14/20
cnnr 210/210 [=====] - 62s 295ms/step - loss: 0.4690 - accuracy: 0.8392 - val_loss: 1.4044 - val_accuracy: 0.5
cnnr 942
Epoch 15/20
cnnr 210/210 [=====] - 62s 296ms/step - loss: 0.3773 - accuracy: 0.8698 - val_loss: 1.7056 - val_accuracy: 0.6
cnnr 117
Epoch 16/20
cnnr 210/210 [=====] - 62s 295ms/step - loss: 0.3313 - accuracy: 0.8865 - val_loss: 1.7279 - val_accuracy: 0.6
cnnr 018
Epoch 17/20
cnnr 210/210 [=====] - 62s 295ms/step - loss: 0.2756 - accuracy: 0.9064 - val_loss: 2.0465 - val_accuracy: 0.6
tf. 012
Epoch 18/20
cnnr 210/210 [=====] - 62s 296ms/step - loss: 0.2232 - accuracy: 0.9225 - val_loss: 2.2411 - val_accuracy: 0.5
tf. 942
Epoch 19/20
cnnr 210/210 [=====] - 62s 296ms/step - loss: 0.2104 - accuracy: 0.9269 - val_loss: 2.2097 - val_accuracy: 0.6
tf. 049
Epoch 20/20
cnnr 210/210 [=====] - 62s 296ms/step - loss: 0.1700 - accuracy: 0.9414 - val_loss: 2.0952 - val_accuracy: 0.6
cnnr 045
```

VGG16

Luke Sunaoka's Model

Results

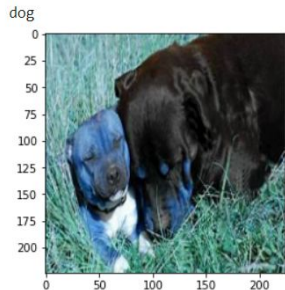
Luke Sunaoka's Model

- Total Loss on Testing Set: 0.533
- Accuracy of Testing Set: 0.883
- Did surprisingly well!
- May be due to implementation

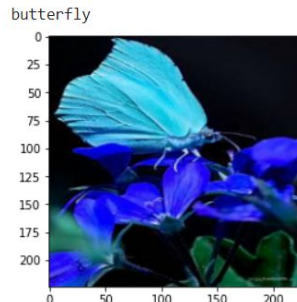
```
score = cnn.evaluate(x_test, y_test)
print('Total loss on Testing Set:', score[0])
print('Accuracy of Testing Set:', score[1])
```

164/164 [=====] - 5s 33ms/step - loss: 0.5330 - accuracy: 0.8831
Total loss on Testing Set: 0.5330036282539368
Accuracy of Testing Set: 0.8831169009208679

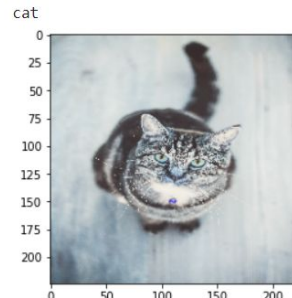
```
[ ] #prediction 1
plt.imshow(x_new[0]/255.) #displays the image
print(names[y_pred[0]])
```



```
[ ] #prediction 2
plt.imshow(x_new[1]/255.) #displays the image
print(names[y_pred[1]])
```



```
[ ] #prediction 3
plt.imshow(x_new[2]/255.) #displays the image
print(names[y_pred[2]])
```

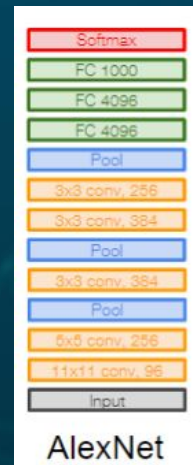


Model: AlexNet

Reasoning

Achieves better results for image classification

- Relu activation function is used
$$f(x) = \max(0, x)$$
- Standardization
 - Dropout method prevents overfitting
- Data Enhancement
 - Dropout method: randomly setting output of some neurons = 0



Implementation Methodology

```
# Layer 1
alexnet.add(Conv2D(96, (11, 11), input_shape=(100, 100, 3), padding='same', kernel_regularizer=l2(0)))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))
alexnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 2
alexnet.add(Conv2D(256, (5, 5), padding='same'))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))
alexnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 3
alexnet.add(ZeroPadding2D((1, 1)))
alexnet.add(Conv2D(512, (3, 3), padding='same'))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))
alexnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 4
alexnet.add(ZeroPadding2D((1, 1)))
alexnet.add(Conv2D(1024, (3, 3), padding='same'))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))

# Layer 5
alexnet.add(ZeroPadding2D((1, 1)))
alexnet.add(Conv2D(1024, (3, 3), padding='same'))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))
alexnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 6
alexnet.add(Flatten())
alexnet.add(Dense(3872))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))
alexnet.add(Dropout(0.5))

# Layer 7
alexnet.add(Dense(4896))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))
alexnet.add(Dropout(0.5))

# Layer 8
alexnet.add(Dense(10))
alexnet.add(BatchNormalization())
alexnet.add(Activation('softmax'))
```

Design

- Based on AlexNet
- Data extraction
- Split data into Training and Testing datasets
 - Training: 20,858
 - Testing: 5,320
- Training parameters:
 - 8 layers (5 convolutional, 3 fully connected)
 - Activation func = relu
 - Batch size = 53
 - Epoch = 69

Total params: 229,985,586

Trainable params: 229,965,406

Non-trainable params: 20,180

Results

```
Epoch 1/69
53/53 [=====] - 31s 375ms/step - loss: 2.2115 - accuracy: 0.2360 - val_loss: 4.9016 - val_accuracy: 0.1205
Epoch 2/69
53/53 [=====] - 14s 270ms/step - loss: 1.8616 - accuracy: 0.3528 - val_loss: 3.0363 - val_accuracy: 0.2145
Epoch 3/69
53/53 [=====] - 14s 271ms/step - loss: 1.7204 - accuracy: 0.4087 - val_loss: 2.3990 - val_accuracy: 0.2472
Epoch 4/69
53/53 [=====] - 14s 270ms/step - loss: 1.5958 - accuracy: 0.4564 - val_loss: 1.9446 - val_accuracy: 0.3402
Epoch 5/69
53/53 [=====] - 14s 270ms/step - loss: 1.5386 - accuracy: 0.4817 - val_loss: 3.6854 - val_accuracy: 0.2083
Epoch 6/69
53/53 [=====] - 14s 269ms/step - loss: 1.4388 - accuracy: 0.5173 - val_loss: 2.8521 - val_accuracy: 0.1889
```

```
Epoch 64/69
53/53 [=====] - 16s 295ms/step - loss: 0.4615 - accuracy: 0.9306 - val_loss: 1.0443 - val_accuracy: 0.7256
Epoch 65/69
53/53 [=====] - 16s 295ms/step - loss: 0.4727 - accuracy: 0.9206 - val_loss: 1.0382 - val_accuracy: 0.7310
Epoch 66/69
53/53 [=====] - 16s 295ms/step - loss: 0.4807 - accuracy: 0.9206 - val_loss: 1.1581 - val_accuracy: 0.6562
Epoch 67/69
53/53 [=====] - 15s 294ms/step - loss: 0.4648 - accuracy: 0.9228 - val_loss: 1.2414 - val_accuracy: 0.6188
Epoch 68/69
53/53 [=====] - 16s 295ms/step - loss: 0.4468 - accuracy: 0.9292 - val_loss: 1.0275 - val_accuracy: 0.7261
Epoch 69/69
53/53 [=====] - 16s 296ms/step - loss: 0.4307 - accuracy: 0.9349 - val_loss: 1.0156 - val_accuracy: 0.7530
```

Epoch 69/69

- Accuracy: 0.9349
- Loss: 0.4307
- Validation accuracy: 0.7530
- Validation loss: 1.0156

```
max_pooling2d_10 (MaxPoolin (None, 13, 13, 512) 0
g2D)
zero_padding2d_7 (ZeroPaddi (None, 15, 15, 512) 0
ng2D)
conv2d_13 (Conv2D) (None, 15, 15, 1024) 4719616
batch_normalization_19 (Bat (None, 15, 15, 1024) 4096
chNormalization)
activation_19 (Activation) (None, 15, 15, 1024) 0
zero_padding2d_8 (ZeroPaddi (None, 17, 17, 1024) 0
ng2D)
conv2d_14 (Conv2D) (None, 17, 17, 1024) 9438208
batch_normalization_20 (Bat (None, 17, 17, 1024) 4096
chNormalization)
activation_20 (Activation) (None, 17, 17, 1024) 0
max_pooling2d_11 (MaxPoolin (None, 8, 8, 1024) 0
g2D)
flatten_2 (Flatten) (None, 65536) 0
dense_6 (Dense) (None, 3072) 201329664
batch_normalization_21 (Bat (None, 3072) 12288
chNormalization)
activation_21 (Activation) (None, 3072) 0
dropout_4 (Dropout) (None, 3072) 0
dense_7 (Dense) (None, 4096) 12587008
batch_normalization_22 (Bat (None, 4096) 16384
chNormalization)
activation_22 (Activation) (None, 4096) 0
dropout_5 (Dropout) (None, 4096) 0
dense_8 (Dense) (None, 10) 40970
batch_normalization_23 (Bat (None, 10) 40
chNormalization)
activation_23 (Activation) (None, 10) 0
=====
Total params: 229,985,586
Trainable params: 229,965,406
Non-trainable params: 20,180
```

Kelly Duangrudeeswat

Results, Analysis, and Conclusion

- Kelly (69) and Luke(20) used a higher number of epoch while Matt(5) and Adrian(10) used a lower number of epochs
- Accuracy scores were as follows:
Matthew : 0.58
Adrian:0.65
Luke: 0.88
Kelly: 0.93
- Although VGG should be having a higher accuracy, because Kelly had higher number of epochs with her AlexNet model, her accuracy had the highest
- Furthermore, Matt and Adrian implemented their own CNN which maybe why its performance is limited in accuracy and results.
- The project was overall an accumulation of everything we've learned and it was great to see it being applied.

The background is a dark teal color with a subtle, abstract pattern of thin, light teal lines forming a network or mesh. Scattered throughout are several small, glowing circular nodes in shades of teal and light blue. The overall aesthetic is modern and technological.

Thank you