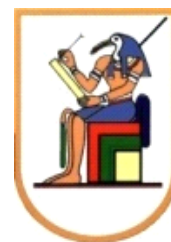




Credit Hours System
HEMN451: Medical Pattern
Recognition



Cairo University
Faculty of Engineering

Final Project

Submitted to: Eng. Peter Farag

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Problem Definition

The problem is that we have to classify different cell organelles which is important when characterizing newly discovered genes or genes with an unknown function.

Solution

We will build a Convolutional Neural Network (CNN) to build an image classifier.

Dataset

We used the dataset from (<https://ome.grc.nia.nih.gov/iicbu2008/hela/index.html>).

The images include 10 organelles, we divided them manually to be 70% for training, 15% for validation, and 15% for testing. We classified them as following:

Classes	Labels	Number of Training Images	Number of Testing Images	Number of Validation Images
actin	0	70	15	14
dna	1	62	13	13
endosome	2	64	14	13
er	3	60	13	13
golgia	4	61	13	13
golgpp	5	60	13	12
lysosome	6	60	13	12
microtubules	7	64	14	13
mitochondria	8	52	11	10
nucleolus	9	56	12	12

Methods and Algorithms

Attempted Models

First Model

```
cnn_model = ks.models.Sequential()
cnn_model.add(ks.layers.Conv2D(96, (3,3), activation= 'relu', padding= 'same', input_shape= (32, 32, 3)))
cnn_model.add(ks.layers.Dropout(0.2))

cnn_model.add(ks.layers.Conv2D(96, (3,3), activation= 'relu', padding= 'same'))
cnn_model.add(ks.layers.Conv2D(96, (3,3), activation= 'relu', padding= 'same', strides= 2))
cnn_model.add(ks.layers.Dropout(0.5))

cnn_model.add(ks.layers.Conv2D(192, (3,3), activation= 'relu', padding= 'same'))
cnn_model.add(ks.layers.Conv2D(192, (3,3), activation= 'relu', padding= 'same'))
cnn_model.add(ks.layers.Conv2D(192, (3,3), activation= 'relu', padding= 'same', strides= 2))
cnn_model.add(ks.layers.Dropout(0.5))

cnn_model.add(ks.layers.Conv2D(192, (3,3), padding= 'same'))
cnn_model.add(ks.layers.Activation('relu'))
cnn_model.add(ks.layers.Conv2D(192, (1,1), padding= 'valid'))
cnn_model.add(ks.layers.Activation('relu'))
cnn_model.add(ks.layers.Conv2D(10, (1,1), padding= 'valid'))

cnn_model.add(ks.layers.GlobalAveragePooling2D())
cnn_model.add(ks.layers.Activation('softmax'))
```

Input size of image: 32x32x3

- Layer 1: Convolution with 96 filters 3x3
- Layer 2: Dropout layer with rate 0.2
- Layers 3 and 4: Convolution with 96 filters 3x3
- Layer 5: Dropout layer with rate 0.5
- Layers 6, 7, 8: Convolution with 192 filters 3x3
- Layer 9: Dropout layer with rate 0.5
- Layers 10, 12: Convolution with 192 filters
- Layers 11, 13: Activation relu
- Layer 14: Convolution with 10 filters
- Layer 15: Global Average Pooling
- Layer 16: Activation function Softmax

This model has accuracy of range 60% and takes long time

Second Model

Input size of image: 28x28x1

```
cnn_model = ks.models.Sequential()
cnn_model.add(ks.layers.Conv2D(32, (5,5), activation= 'relu', input_shape= (28, 28, 1), kernel_initializer='he_uniform',
                                name='Convolutional_layer_1', kernel_regularizer=l2(0.0005)))
cnn_model.add(ks.layers.Conv2D(32, (5,5), activation= 'relu', kernel_initializer='he_uniform',
                                name='Convolutional_layer_2', kernel_regularizer=l2(0.0005)))
cnn_model.add(ks.layers.MaxPooling2D((2,2), name= 'Maxpooling_2D_2'))
cnn_model.add(ks.layers.Dropout(0.2))

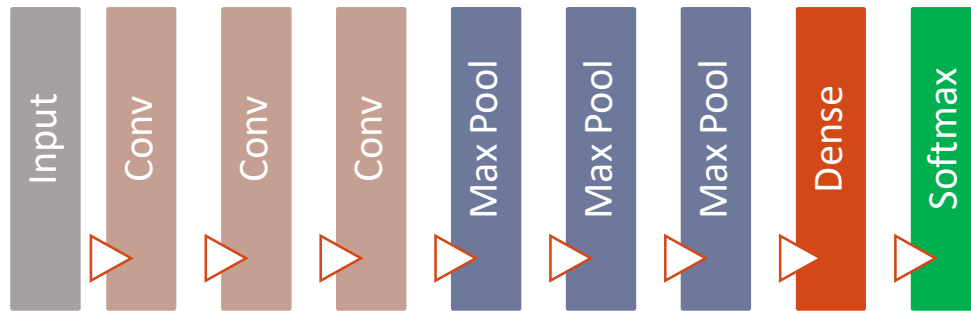
cnn_model.add(ks.layers.Conv2D(64, (3,3), activation= 'relu', kernel_initializer='he_uniform',
                                name='Convolutional_layer_3', kernel_regularizer=l2(0.0005)))
cnn_model.add(ks.layers.Conv2D(64, (3,3), activation= 'relu', kernel_initializer='he_uniform',
                                name='Convolutional_layer_4', kernel_regularizer=l2(0.0005)))
cnn_model.add(ks.layers.MaxPooling2D((2,2), name= 'Maxpooling_2D_3'))
cnn_model.add(ks.layers.Dropout(0.3))

cnn_model.add(ks.layers.Flatten(name= 'Flatten'))
cnn_model.add(ks.layers.Dense(128, activation='relu', kernel_initializer='he_uniform', name='Hidden_layer'))
cnn_model.add(ks.layers.Dropout(0.4))
cnn_model.add(ks.layers.Dense(10, activation='softmax', name='Output_layer'))
```

- Layers 1 and 2: Convolution with 32 filters 5x5, updating weights using l2
- Layer 3: Max Pooling with size 2x2
- Layer 4: Dropout layer with rate 0.2
- Layers 5 and 6: Convolution with 64 filters 3x3, updating weights using l2
- Layer 7: Max Pooling with size 2x2
- Layer 8: Dropout layer with rate 0.3
- Layer 9: Flatten
- Layer 10: Dense with activation function relu 128
- Layer 11: Dropout layer with rate 0.4
- Layer 12: Activation function Softmax

At first it was about 76% accuracy with small time period, around 2 seconds per epochs, but then it started to decrease significantly

Final Layers Used



Input size of image: 28x28x1

- Layers 1 and 2: Convolution with 64 filters 5x5
- Layer 3: Convolution with 128 filters 3x3
- Layers 4, 5 and 6: Max Pooling with size 2x2
- Layer 7: Flattening
- Layer 8: Dense with activation function relu 128
- Layer 9: Dense with activation function Softmax with 10 categories

Implementation

1. Imports:

- PyQt5
- PIL
- tensorflow
- numpy
- sys
- cv2
- os

2. Reading images in grayscale and labelling them
3. Data augmentation: Flipping and Rotation
4. Normalization of images, divided by 255
5. Training the CNN with training dataset
6. Optimizing learning rate using "Adam" algorithm
7. Model Fitting
 - Number of epochs is 40
8. Prediction

Results

Maximum results:

Type	Accuracy
Training	99%
Validation	75%
Testing	78%

```
train_loss, train_accuracy = cnn_model.evaluate(train_images, train_labels)
print('Train Accuracy{}'.format(round(float(train_accuracy), 2)))
57/57 [=====] - 1s 26ms/step - loss: 0.0333 - accuracy: 0.9923
Train Accuracy0.99

validation_loss, validation_accuracy = cnn_model.evaluate(validation_images, validation_labels)
print('Validation Accuracy{}'.format(round(float(validation_accuracy), 2)))
12/12 [=====] - 0s 24ms/step - loss: 1.7048 - accuracy: 0.7547
Validation Accuracy0.75

test_loss, test_accuracy = cnn_model.evaluate(test_images, test_labels)
print('Test Accuracy {}'.format(round(float(test_accuracy), 2)))
5/5 [=====] - 0s 18ms/step - loss: 1.4708 - accuracy: 0.7786
Test Accuracy 0.78
```

Random Results

Result 1

```
In [89]: train_loss, train_accuracy = cnn_model.evaluate(train_images, train_labels)
print('Train Accuracy{} '.format(round(float(train_accuracy), 2)))

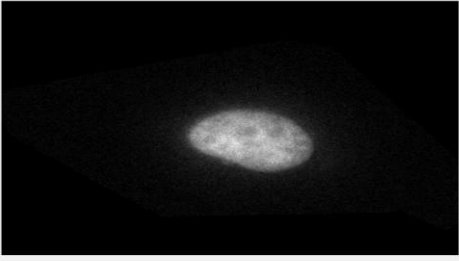

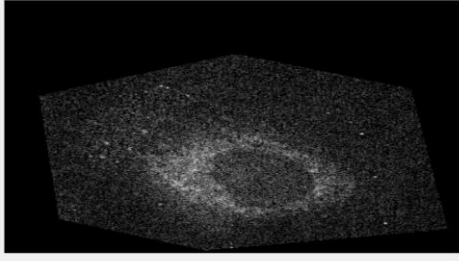
57/57 [=====] - 1s 14ms/step - loss: 3.8088e-04 - accuracy: 1.0000
Train Accuracy1.0

In [90]: validation_loss, validation_accuracy = cnn_model.evaluate(validation_images, validation_labels)
print('Validation Accuracy{} '.format(round(float(validation_accuracy), 2)))

12/12 [=====] - 0s 12ms/step - loss: 2.5908 - accuracy: 0.7360
Validation Accuracy0.74

In [91]: test_loss, test_accuracy = cnn_model.evaluate(test_images, test_labels)
print('Test Accuracy {} '.format(round(float(test_accuracy), 2)))

5/5 [=====] - 0s 10ms/step - loss: 2.0543 - accuracy: 0.7634
Test Accuracy 0.76
```

True Classification	False Classifications
<div data-bbox="315 785 781 1161"><p>Image Classification</p><p>Browse</p><p>This image most likely belongs to dna Test Accuracy: 76.34 %</p></div>	<div data-bbox="816 785 1282 1161"><p>Image Classification</p><p>Browse</p><p>This image most likely belongs to dna Test Accuracy: 76.34 %</p></div>
<div data-bbox="315 1176 781 1547"><p>Image Classification</p><p>Browse</p><p>This image most likely belongs to mitochondria Test Accuracy: 76.34 %</p></div>	

Result 2

```
In [89]: train_loss, train_accuracy = cnn_model.evaluate(train_images, train_labels)
print('Train Accuracy {} '.format(round(float(train_accuracy), 2)))

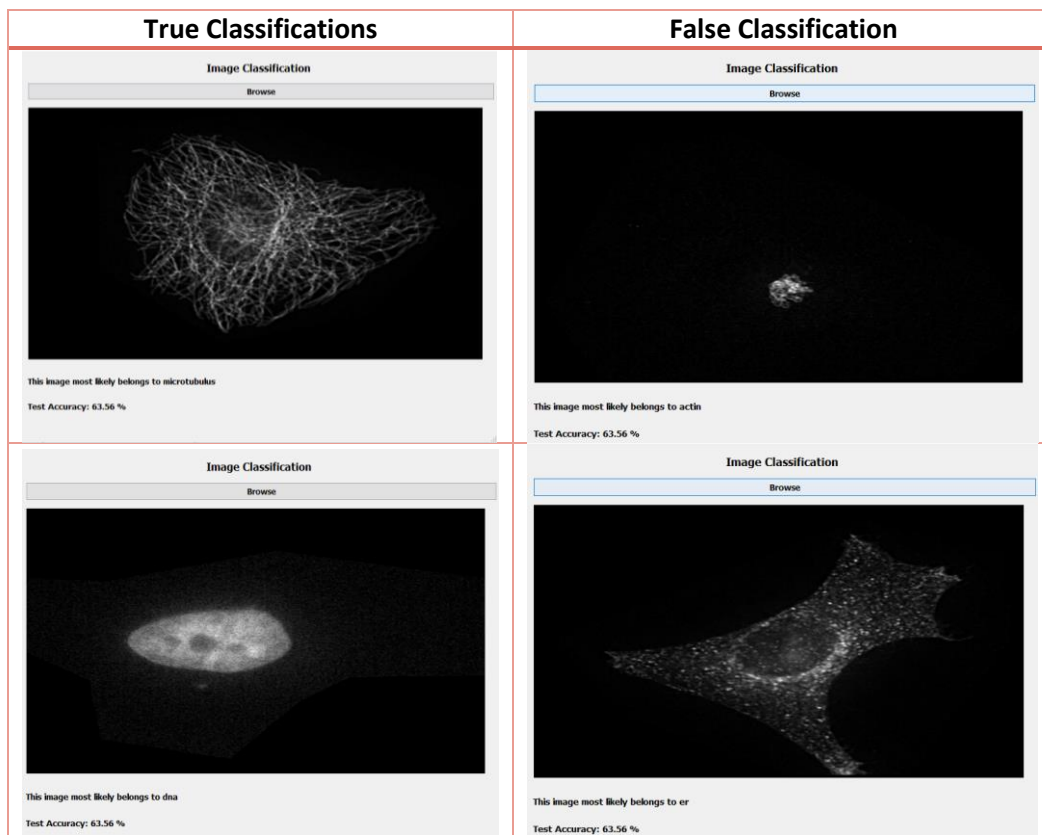
57/57 [=====] - 1s 14ms/step - loss: 3.8088e-04 - accuracy: 1.0000
Train Accuracy1.0

In [90]: validation_loss, validation_accuracy = cnn_model.evaluate(validation_images, validation_labels)
print('Validation Accuracy {} '.format(round(float(validation_accuracy), 2)))

12/12 [=====] - 0s 12ms/step - loss: 2.5908 - accuracy: 0.7360
Validation Accuracy0.74

In [91]: test_loss, test_accuracy = cnn_model.evaluate(test_images, test_labels)
print('Test Accuracy {} '.format(round(float(test_accuracy), 2)))

5/5 [=====] - 0s 10ms/step - loss: 2.0543 - accuracy: 0.7634
Test Accuracy 0.76
```



Result 3

```
train_loss, train_accuracy = cnn_model.evaluate(train_images, train_labels)
print('Train Accuracy{} '.format(round(float(train_accuracy), 2)))

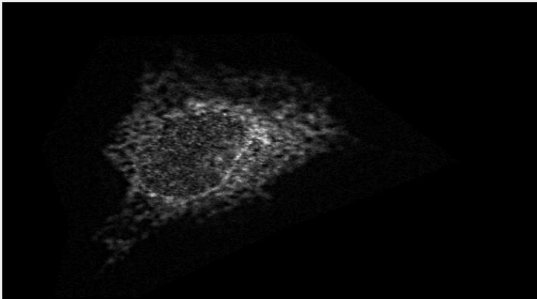
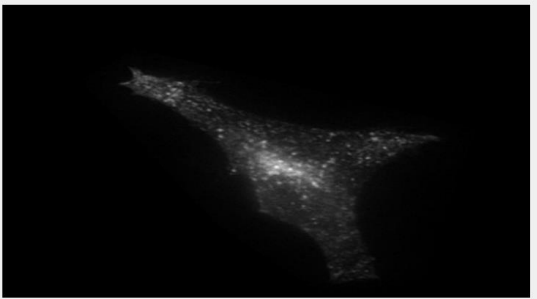
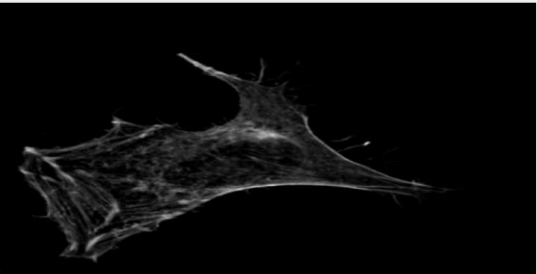
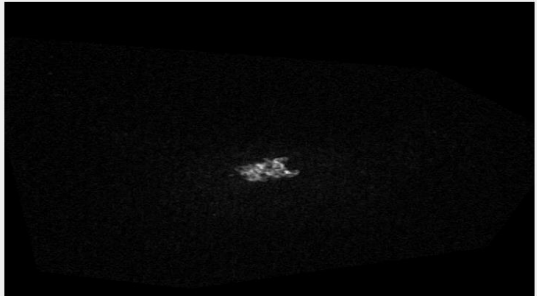
57/57 [=====] - 1s 25ms/step - loss: 0.0377 - accuracy: 0.9917
Train Accuracy0.99

validation_loss, validation_accuracy = cnn_model.evaluate(validation_images, validation_labels)
print('Validation Accuracy{} '.format(round(float(validation_accuracy), 2)))

12/12 [=====] - 0s 24ms/step - loss: 1.4314 - accuracy: 0.7280
Validation Accuracy0.73

test_loss, test_accuracy = cnn_model.evaluate(test_images, test_labels)
print('Test Accuracy {} '.format(round(float(test_accuracy), 2)))

5/5 [=====] - 0s 17ms/step - loss: 1.6092 - accuracy: 0.7099
Test Accuracy 0.71
```

True Classifications	False Classification
<div><div>Image Classification</div><div>Browse</div><div></div><div>This image most likely belongs to er</div><div>Test Accuracy: 70.99 %</div></div>	<div><div>Image Classification</div><div>Browse</div><div></div><div>This image most likely belongs to dna</div><div>Test Accuracy: 70.99 %</div></div>
<div><div>Image Classification</div><div>Browse</div><div></div><div>This image most likely belongs to actin</div><div>Test Accuracy: 70.99 %</div></div>	
<div><div>Image Classification</div><div>Browse</div><div></div><div>This image most likely belongs to golgia</div><div>Test Accuracy: 70.99 %</div></div>	

Time

Each epochs takes from 6 to 7 seconds. The whole training takes about 4 minutes

Open Source Model

Used tensorflow_hub

Input size of image: 224x224x3

```
feature_extractor_model = "https://tfhub.dev/google/tf2-preview/mobilenet_v2/feature_vector/4"
pretrained_model_without_top_layer = hub.KerasLayer(
    feature_extractor_model, input_shape=(224, 224, 3), trainable=False)

model = tf.keras.Sequential([pretrained_model_without_top_layer, tf.keras.layers.Dense(10)])
model.summary()

Model: "sequential_7"
Layer (type)                Output Shape                Param #
-----
keras_layer_5 (KerasLayer)   (None, 1280)                2257984
dense_7 (Dense)              (None, 10)                  12810
-----
Total params: 2,270,794
Trainable params: 12,810
Non-trainable params: 2,257,984

model.compile(optimizer="adam", loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True), metrics=['acc'])
model.fit(train_images, train_labels, epochs=5)
```

Random Results

```
model.evaluate(train_images, train_labels)
57/57 [=====] - 29s 511ms/step - loss: 0.1212 - acc: 0.9692
[0.12119679898023605, 0.9691969156265259]

model.evaluate(test_images, test_labels)
5/5 [=====] - 2s 320ms/step - loss: 0.6530 - acc: 0.8244
[0.6529501676559448, 0.8244274854660034]
```

```
model.evaluate(train_images, train_labels)
57/57 [=====] - 52s 914ms/step - loss: 0.1212 - acc: 0.9736
[0.1211928129196167, 0.9735973477363586]

model.evaluate(test_images, test_labels)
5/5 [=====] - 2s 309ms/step - loss: 0.6889 - acc: 0.7863
[0.688930094242096, 0.7862595319747925]
```

Time

Each epochs takes about 30 seconds. Using 5 epochs, takes about 2.5 minutes.

Comparison

The maximum accuracy of the open source model is 84%, which is higher than ours, 78%. However, the time of each epoch in open source model is higher than ours.

The open source reaches higher accuracy using less number of epochs.