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In [ ]: #import keras libraries
        from keras.models import Sequential
        from keras.layers import Dense
        from keras.layers import Convolution2D
        from keras.layers import MaxPooling2D
        from keras.layers import Flatten

In [ ]: #image preprocessing(or) image augmentation
        from keras.preprocessing.image import ImageDataGenerator

In [ ]: train_datagen = ImageDataGenerator(rescale=1./255,shear_range=0.2,zoom_range=0.2,horizontal_flip=True
        #rescale => rescaling pixel value from 0 to 255 to 0 to 1
        #shear_range=> counter clock wise rotation(anti clock)

In [ ]: test_datagen = ImageDataGenerator(rescale=1./255)

In [ ]: x_train = train_datagen.flow_from_directory("/content/drive/MyDrive/ibm project/TRAIN_SET",target_size=
Found 4118 images belonging to 5 classes.

In [ ]: x_test = test_datagen.flow_from_directory("/content/drive/MyDrive/ibm project/TEST_SET",target_size=(
Found 929 images belonging to 3 classes.

In [ ]: x_train.class_indices

Out[ ]: {'APPLES': 0, 'BANANA': 1, 'ORANGE': 2, 'PINEAPPLE': 3, 'WATERMELON': 4}

In [ ]: #checking the number of classes
        print(x_test.class_indices)

{'APPLES': 0, 'BANANA': 1, 'ORANGE': 2}

In [ ]: from collections import Counter as c
        c(x_train.labels)

Out[ ]: Counter({0: 995, 1: 1354, 2: 1019, 3: 275, 4: 475})

In [ ]: #Initializing the model
        model = Sequential()

In [ ]: # add First convolution layer

In [ ]: model.add(Convolution2D(32,(3,3),input_shape=(64,64,3),activation="relu"))
        # 32 indicates => no of feature detectors
        #(3,3)=> kernel size (feature detector size)

In [ ]: # add Maxpooling layer

In [ ]: model.add(MaxPooling2D(pool_size=(2,2)))

In [ ]: #Second convolution layer and pooling
        model.add(Convolution2D(32,(3,3),activation="relu"))

In [ ]: model.add(MaxPooling2D(pool_size=(2,2)))

In [ ]: #Flattening the layers
        model.add(Flatten())

In [ ]: model.add(Dense(units=128,activation="relu"))

In [ ]: model.add(Dense(units=5,activation="softmax"))

In [ ]: # add flatten layer => input to your ANN

In [ ]: model.add(Flatten())

In [ ]: model.summary()

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Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 62, 62, 32)	896
max_pooling2d (MaxPooling2D)	(None, 31, 31, 32)	0
conv2d_1 (Conv2D)	(None, 29, 29, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 32)	0
flatten (Flatten)	(None, 6272)	0
dense (Dense)	(None, 128)	802944
dense_1 (Dense)	(None, 5)	645
flatten_1 (Flatten)	(None, 5)	0

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conv2d (Conv2D)	(None, 62, 62, 32)	896
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conv2d_1 (Conv2D)	(None, 29, 29, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 32)	0
flatten (Flatten)	(None, 6272)	0
dense (Dense)	(None, 128)	802944
dense_1 (Dense)	(None, 5)	645
flatten_1 (Flatten)	(None, 5)	0

=====  
 Total params: 813,733  
 Trainable params: 813,733  
 Non-trainable params: 0

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In [ ]: # adding dense layer

In [ ]: #hidden layer

In [ ]: model.add(Dense(units=300, kernel_initializer="random_uniform", activation="relu"))

In [ ]: model.add(Dense(units=200, kernel_initializer="random_uniform", activation="relu"))

In [ ]: #output layer

In [ ]: model.add(Dense(units=4, kernel_initializer="random_uniform", activation="softmax"))
        len(x_train)

Out[ ]: 129

In [ ]: #Ann starts so need to add dense layers

In [ ]: model.add(Dense(units=128, activation="relu", kernel_initializer="random_uniform"))

In [ ]: model.add(Dense(units=1, activation="sigmoid", kernel_initializer="random_uniform"))

In [ ]: #Compile the model
        model.compile(loss="binary_crossentropy", optimizer="adam", metrics=['accuracy'])

In [ ]: #Train the model

In [ ]: model.fit_generator(x_train, steps_per_epoch=len(x_train), validation_data=x_test, validation_steps=1e

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/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: UserWarning: 'Model.fit_generator' is
deprecated and will be removed in a future version. Please use 'Model.fit', which supports generator
s.
"""Entry point for launching an IPython kernel.
Epoch 1/20
129/129 [=====] - 2459s 19s/step - loss: -0.0526 - accuracy: 0.3273 - val_lo
ss: 0.1126 - val_accuracy: 0.4467
Epoch 2/20
129/129 [=====] - 36s 277ms/step - loss: -3.0746 - accuracy: 0.3288 - val_lo
ss: 0.2155 - val_accuracy: 0.4467
Epoch 3/20
129/129 [=====] - 35s 268ms/step - loss: -8.7866 - accuracy: 0.3288 - val_lo
ss: 0.5095 - val_accuracy: 0.4467
Epoch 4/20
129/129 [=====] - 36s 281ms/step - loss: -17.7107 - accuracy: 0.3288 - val_l
oss: 0.9337 - val_accuracy: 0.4467
Epoch 5/20
129/129 [=====] - 36s 282ms/step - loss: -29.8704 - accuracy: 0.3288 - val_l
oss: 1.4811 - val_accuracy: 0.4467
Epoch 6/20
129/129 [=====] - 36s 277ms/step - loss: -45.0273 - accuracy: 0.3288 - val_l
oss: 2.1422 - val_accuracy: 0.4467
Epoch 7/20
129/129 [=====] - 35s 269ms/step - loss: -62.9152 - accuracy: 0.3288 - val_l
oss: 2.9106 - val_accuracy: 0.4467
Epoch 8/20
129/129 [=====] - 40s 309ms/step - loss: -83.5868 - accuracy: 0.3288 - val_l
oss: 3.7855 - val_accuracy: 0.4467
Epoch 9/20
129/129 [=====] - 36s 281ms/step - loss: -106.7443 - accuracy: 0.3288 - val_
loss: 4.7640 - val_accuracy: 0.4467
Epoch 10/20
129/129 [=====] - 36s 278ms/step - loss: -132.3641 - accuracy: 0.3288 - val_
loss: 5.8398 - val_accuracy: 0.4467
Epoch 11/20
129/129 [=====] - 35s 271ms/step - loss: -160.3758 - accuracy: 0.3288 - val_
loss: 7.0081 - val_accuracy: 0.4467
Epoch 12/20
129/129 [=====] - 35s 269ms/step - loss: -190.6966 - accuracy: 0.3288 - val_
loss: 8.2454 - val_accuracy: 0.4467
Epoch 13/20
129/129 [=====] - 36s 279ms/step - loss: -223.1146 - accuracy: 0.3288 - val_
loss: 9.6145 - val_accuracy: 0.4467
Epoch 14/20
129/129 [=====] - 36s 280ms/step - loss: -257.9082 - accuracy: 0.3288 - val_
loss: 11.0088 - val_accuracy: 0.4467
Epoch 15/20
129/129 [=====] - 37s 290ms/step - loss: -294.5687 - accuracy: 0.3288 - val_
loss: 12.5175 - val_accuracy: 0.4467
Epoch 16/20
129/129 [=====] - 34s 266ms/step - loss: -333.2441 - accuracy: 0.3288 - val_
loss: 14.1130 - val_accuracy: 0.4467
Epoch 17/20
129/129 [=====] - 36s 279ms/step - loss: -374.0325 - accuracy: 0.3288 - val_
loss: 15.7641 - val_accuracy: 0.4467
Epoch 18/20
129/129 [=====] - 36s 278ms/step - loss: -416.7053 - accuracy: 0.3288 - val_
loss: 17.5287 - val_accuracy: 0.4467
Epoch 19/20

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129/129 [=====] - 35s 267ms/step - loss: -461.2285 - accuracy: 0.3288 - val_
loss: 19.3238 - val_accuracy: 0.4467
Epoch 20/20
129/129 [=====] - 34s 265ms/step - loss: -507.5266 - accuracy: 0.3288 - val_
loss: 21.2192 - val_accuracy: 0.4467
```

Out[ ]:

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In [ ]: model.save("nutrition.h5")
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In [ ]: #Prediction the result
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In [ ]: from tensorflow.keras.models import load_model
from keras.preprocessing import image
model = load_model("nutrition.h5")
```

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In [ ]: import numpy as np
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```
In [ ]: from tensorflow.keras.utils import load_img
from tensorflow.keras.utils import img_to_array
#loading of the image
img = load_img(r'/content/drive/MyDrive/ibm project/Sample_Images-20221102T071233Z-001/Sample_Images/
#image to array
x = img_to_array(img)
#changing the shape
x = np.expand_dims(x,axis = 0)
predict_x=model.predict(x)
classes_x=np.argmax(predict_x,axis = -1)
classes_x
```

```
1/1 [=====] - 0s 166ms/step
```

Out[ ]: array([0])

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In [ ]: index=['APPLES', 'BANANA', 'ORANGE', 'PINEAPPLE', 'WATERMELON']
result=str(index[classes_x[0]])
result
```

Out[ ]: 'APPLES'