Date: 09/27/2021

### 1. What you learned in the ICP:

In this ICP I learned how to build an image classification using Convolutional neural network model for the cifar10 dataset. Also, I worked on the data augmentation to prevent the overfitting.

## 2. ICP description what was the task you were performing:

I performed image classification in the Cifar10 dataset using CNN model. I changed 4 hyper parameters in the model and will explain what are that in the following section. Also, I have uploaded 5 different images (out of the dataset) to validate the model.

## 3. Challenges that you faced:

I could not use GPU runtime in light of I have reached the limit of usage. I got the following message from Google Colab (You cannot currently connect to a GPU due to usage limits in Colab). However, I solved this issue by using another Google account.

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4. <u>Screen shots that shows the successful execution of each required step of your code:</u>

## **Hyper-parameter #1: (Changing the activation layer = Softmax):**

I changed the activation function in output layer to "softmax" instead of "relu", and I found that the model accuracy has decreased (Accuracy: 51.32%) and the loss was still high (1.3591). Also, I noticed that the model can't predict correctly as already did while I was using "relu" activation function.

```
♣ ICP5_BDAA.ipynb ☆
    File Edit View Insert Runtime Tools Help All changes saved
   + Code + Text
  [155] model = Sequential([
Q
         data_augmentation,
        layers.experimental.preprocessing.Rescaling(1./255),
        layers.Conv2D(16, 3, padding='same', activation='relu'),
         layers.MaxPooling2D(),
layers.Conv2D(32, 3, padding='same', activation='relu'),
        layers.MaxPooling2D(),
        layers.Conv2D(64, 3, padding='same', activation='relu'),
        layers.MaxPooling2D(),
        layers.Dropout(0.2),
        layers.Flatten(),
         layers.Dense(128, activation='softmax'),
         layers.Dense(class num)
    compile and train the model
   [156] model.compile(optimizer='adam',
                 loss=tf.keras.losses.SparseCategoricalCrossentropy(from logits=True),
                 metrics=['accuracy'])
CO LCP5_BDAA.ipynb 🚓
    File Edit View Insert Runtime Tools Help All changes saved
:=
   epochs = 10
Q
      history = model.fit(
X_train,
        y_train,
        validation_data=(X_test, y_test),
epochs=epochs,
       batch_size=64,
    Epoch 1/10
782/782 [===
Epoch 2/10
782/782 [===
Epoch 3/10
782/782 [===
Epoch 4/10
                   =========] - 11s 12ms/step - loss: 2.1524 - accuracy: 0.2049 - val_loss: 2.0111 - val_accuracy: 0.2644
              782/782 [====
      782/782 [====
Epoch 8/10
                     782/782 [===
   [159] #model as given has reached = Accuracy: 65.71%
# Accuracy: 51.32% with softmax
      model_eval = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (model_eval[1]*100))
\equiv
      Accuracy: 51.32%
```

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# Hyper-parameter #2: (Conv2D filter 32, output dense layer activiation function = relu with 256):

I have increased the convolutional layer on 32 input channels and 256 output which means that every 32 channels was traversed by 256 3x3 kernels in result of 8,192 feature maps. In this change, I noticed that the model has performed much better than other changes. The accuracy is 73.02%.



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```
▲ ICP5_BDAA.ipynb ☆
     File Edit View Insert Runtime Tools Help All changes saved
   [182] epochs = 10
Q
         history = model.fit(
          X train,
<>
          validation_data=(X_test, y_test),
          epochs=epochs,
batch_size=64,
         Epoch 1/10
                           ========= ] - 15s 17ms/step - loss: 1.6194 - accuracy: 0.4104 - val loss: 1.3020 - val accuracy: 0.5303
         782/782 [==:
                         782/782 [===
                                   :=====] - 12s 16ms/step - loss: 1.1638 - accuracy: 0.5873 - val loss: 1.0741 - val accuracy: 0.6251
         782/782 [==
         Epoch 4/10
                           =========] - 12s 16ms/step - loss: 1.0909 - accuracy: 0.6163 - val_loss: 0.9704 - val_accuracy: 0.6626
         Epoch 5/10
782/782 [==:
                            ==========] - 13s 16ms/step - loss: 1.0302 - accuracy: 0.6346 - val_loss: 1.0373 - val_accuracy: 0.6438
         Epoch 6/10
782/782 [==
                        Epoch 7/10
                       Epoch 8/10
                        =========] - 13s 16ms/step - loss: 0.9108 - accuracy: 0.6805 - val_loss: 0.8443 - val_accuracy: 0.7040
         Epoch 9/10
                             :=======] - 13s 16ms/step - loss: 0.8844 - accuracy: 0.6892 - val_loss: 0.8492 - val_accuracy: 0.7026
         Epoch 10/10
         782/782 [===
                          =========] - 13s 16ms/step - loss: 0.8604 - accuracy: 0.6970 - val_loss: 0.7971 - val_accuracy: 0.7302
     #model as given has reached = Accuracy: 65.71%
         # Accuracy: 51.32% with softmax
# Accuracy: 73.02% with relu activiation layer and conv2d start 32
         model_eval = model.evaluate(X_test, y_test, verbose=0)
        print("Accuracy: %.2f%%" % (model eval[1]*100))
\equiv
     Accuracy: 73.02%
>_
```

## **Hyper-parameter #3: (Dropout = 0.7):**

I have played with the Dropout many times in order to see what is going to happen to the model. In the first time, I have added the (Dropout 0.2) before the data augmentation, but I could not see any big different on the model performance nor the training loss. However, I removed the one before the data augmentation and increase the one after to be (0.7) and I found that the model is underfitted. The good thing is that I've prevent the model to be overfitting, but the model has underfitted. Therefore, the dropout layer rate should be a 0.2 to fit the model.

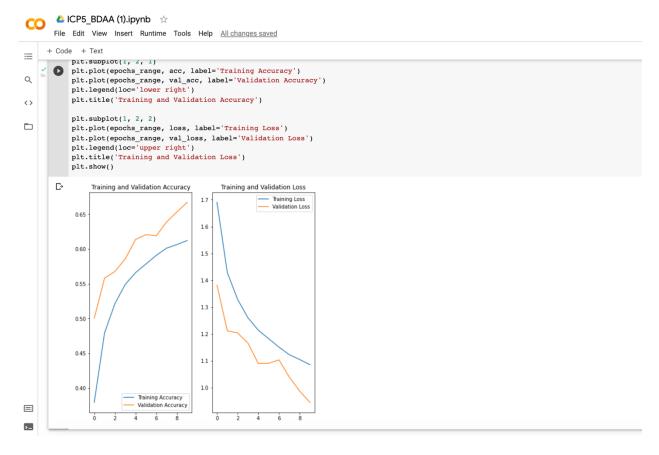
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```
△ ICP5_BDAA (1).ipynb ☆
      File Edit View Insert Runtime Tools Help All changes saved
\equiv
      randomny morn the applied layer
Q
    / [49] model = Sequential([
            data_augmentation,
()
            layers.experimental.preprocessing.Rescaling(1./255),
            layers.Conv2D(32, 3, padding='same', activation='relu'),
            layers.MaxPooling2D(),
layers.Conv2D(64, 3, padding='same', activation='relu'),
            layers.MaxPooling2D(),
            layers.Conv2D(128, 3, padding='same', activation='relu'),
            layers.MaxPooling2D(),
            layers.Dropout(0.7),
            layers.Flatten(),
            layers.Dense(256, activation='relu'),
            layers.Dense(class_num)
          1)
      compile and train the model
    model.compile(optimizer='adam',
                        loss=tf.keras.losses.SparseCategoricalCrossentropy(from logits=True),
                        metrics=['accuracy'])
    / [46] model.summary()
          Model: "sequential_8"
                                     Output Shape
                                                              Param #
          sequential_7 (Sequential) (None, 32, 32, 3)
                                                              0
          rescaling_5 (Rescaling)
                                  (None, 32, 32, 3)
          conv2d 15 (Conv2D)
                                     (None, 32, 32, 32)
                                                              896
=
          max_pooling2d_15 (MaxPooling (None, 16, 16, 32)
                                                              0
>_
          conv2d 16 (Conv2D)
                                     (None 16 16 64)
                                                              18496
      📤 ICP5_BDAA (1).ipynb 🔯
      File Edit View Insert Runtime Tools Help All changes saved
     + Code + Text
    (51) epochs = 10
          history = model.fit(
<>
            y_train,
            validation data=(X test, y test),
epochs=epochs,
            batch_size=64,
          Epoch 1/10
                              =========] - 11s 13ms/step - loss: 1.6901 - accuracy: 0.3793 - val_loss: 1.3816 - val_accuracy: 0.5005
          782/782 [==
          Epoch 2/10
                                    782/782 [=:
          Epoch 3/10
                             ============== | - 10s 13ms/step - loss: 1.3286 - accuracy: 0.5214 - val loss: 1.2037 - val accuracy: 0.5677
          782/782 [==
                                    ======== ] - 10s 12ms/step - loss: 1.2602 - accuracy: 0.5491 - val loss: 1.1659 - val accuracy: 0.5857
          782/782 [==
                                  ========= | - 10s 13ms/step - loss: 1.2139 - accuracy: 0.5660 - val loss: 1.0898 - val accuracy: 0.6138
          782/782 [==
                                ========= - 10s 13ms/step - loss: 1.1827 - accuracy: 0.5784 - val loss: 1.0909 - val accuracy: 0.6207
          782/782 [==
          Epoch 7/10
          782/782 [==
                                    ========] - 10s 13ms/step - loss: 1.1510 - accuracy: 0.5909 - val loss: 1.1035 - val accuracy: 0.6190
          Epoch 8/10
                                ======== ] - 10s 13ms/step - loss: 1.1228 - accuracy: 0.6012 - val loss: 1.0395 - val accuracy: 0.6389
          782/782 [==
                                ========= ] - 10s 12ms/step - loss: 1.1049 - accuracy: 0.6065 - val loss: 0.9875 - val accuracy: 0.6534
          782/782 [=:
          Epoch 10/10
                             ========== ] - 10s 13ms/step - loss: 1.0857 - accuracy: 0.6122 - val_loss: 0.9452 - val_accuracy: 0.6672
          782/782 [==
    #model as given has reached = Accuracy: 65.71%
           # Accuracy: 51.32% with softmax
          # Accuracy: 73.02% with relu activiation layer and conv2d start 32
          model eval = model.evaluate(X test, y test, verbose=0)
          print("Accuracy: %.2f%%" % (model_eval[1]*100))
\equiv

→ Accuracy: 66.72%

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#### **Hyper-parameter #4:**

# ( Data Augmentation – preprocessing.RandomFlip("horizontal\_and\_vertical")

This time I changed the data augmentation in order to help the model to be more aspects of the data and generalize better as well as to help in preventing the overfit. In the randomly flip, I changed the mode to "horizontally and vertically" which mean to flip the images left-tight (horizontal), and top-bottom (vertical). In the end this would not help and the model was still overfitting.

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```
♣ ICP5_BDAA (1).ipynb ☆
       File Edit View Insert Runtime Tools Help All changes saved
∷
       the fill implement data augmentation using experimental neral reprocessing Eagers. These can be included inside your moder like other
       layers, and run on the GPU.
Q
    [12] data_augmentation = keras.Sequential(
                layers.experimental.preprocessing.RandomFlip("horizontal_and_vertical",
input_shape=(img_height,
                                                                               img_width,
                                                                                3)),
                 {\tt layers.experimental.preprocessing.RandomRotation(0.1),}
                 {\tt layers.experimental.preprocessing.RandomZoom(0.1),}
       Dropout
       Another technique to reduce overfitting is to introduce Dropout to the network, a form of regularization. When you apply Dropout to a layer it
       randomly drops out (by setting the activation to zero) a number of output units from the layer during the training process. Dropout takes a
       fractional number as its input value, in the form such as 0.1, 0.2, 0.4, etc. This means dropping out 10%, 20% or 40% of the output units
       randomly from the applied layer
                                                                                                      + Code — + Text
    [13] model = Sequential([
              data_augmentation,
              layers.experimental.preprocessing.Rescaling(1./255),
              layers.Conv2D(32, 3, padding='same', activation='relu'),
              layers.MaxPooling2D(),
              layers.Conv2D(64, 3, padding='same', activation='relu'),
              layers.MaxPooling2D(),
              layers.Conv2D(128, 3, padding='same', activation='relu'),
              layers.MaxPooling2D(),
              layers.Dropout(0.2),
              layers.Flatten(),
layers.Dense(256, activation='relu'),
\equiv
              layers.Dense(class_num)
>_
```

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```
♣ ICP5_BDAA (1).ipynb ☆
       File Edit View Insert Runtime Tools Help All changes saved
∷
    / [16] epochs = 10
Q
           history = model.fit(
             X_train,
             y_train,
<>
             validation_data=(X_test, y_test),
             epochs=epochs,
batch_size=64,
           Epoch 1/10
                                         =======] - 13s 15ms/step - loss: 1.6988 - accuracy: 0.3732 - val loss: 1.3912 - val_accuracy: 0.4909
           782/782 [==
           Epoch 2/10
                                                 ===1 - 11s 15ms/step - loss: 1.4275 - accuracy: 0.4815 - val loss: 1.3097 - val accuracy: 0.5317
           782/782 [==
                                       ========= ] - 11s 15ms/step - loss: 1.3255 - accuracy: 0.5248 - val loss: 1.1903 - val accuracy: 0.5796
           782/782 [==
           Epoch 4/10
                                                 ===] - 11s 15ms/step - loss: 1.2443 - accuracy: 0.5545 - val loss: 1.1928 - val accuracy: 0.5778
           782/782 [==
                                         =======] - 11s 14ms/step - loss: 1.1878 - accuracy: 0.5777 - val loss: 1.0925 - val accuracy: 0.6058
           782/782 [==
                                         ======== ] - 11s 15ms/step - loss: 1.1414 - accuracy: 0.5950 - val loss: 1.0907 - val accuracy: 0.6172
           782/782 [==
                                                 ===] - 11s 14ms/step - loss: 1.1050 - accuracy: 0.6068 - val loss: 1.0149 - val accuracy: 0.6419
           782/782 [=:
           Epoch 8/10
                                      ========] - 11s 15ms/step - loss: 1.0728 - accuracy: 0.6184 - val_loss: 0.9684 - val_accuracy: 0.6548
           782/782 [==
           Epoch 9/10
                                        =======] - 11s 14ms/step - loss: 1.0444 - accuracy: 0.6251 - val_loss: 0.9777 - val_accuracy: 0.6563
           Epoch 10/10
782/782 [===
                                     ========] - 11s 14ms/step - loss: 1.0271 - accuracy: 0.6352 - val_loss: 0.9421 - val_accuracy: 0.6692
       #model as given has reached = Accuracy: 65.71%
           # Accuracy: 51.32% with softmax
           # Accuracy: 73.02% with relu activiation layer and conv2d start 32
           # Accuracy: 66.92% : with data augmentation mode (horizontal_and_vertical)
           model eval = model.evaluate(X test, y test, verbose=0)
           print("Accuracy: %.2f%%" % (model_eval[1]*100))
=
       Accuracy: 66.92%
>_
       ▲ ICP5_BDAA (1).ipynb ☆
       File Edit View Insert Runtime Tools Help All changes saved
∷
     [18] plt.legend(loc='lower right')
           plt.title('Training and Validation Accuracy')
Q
           plt.subplot(1, 2, 2)
<>
           plt.plot(epochs_range, loss, label='Training Loss')
           plt.plot(epochs_range, val_loss, label='Validation Loss')
           plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
           plt.show()
                Training and Validation Accuracy
                                                Training and Validation Loss
                                                          — Training Loss
                                                        Validation Loss
            0.65
                                          1.6
            0.60
                                          1.5
                                          1.4
            0.55
                                          1.3
            0.50
                                          1.2
            0.45
                                          1.1
            0.40
                                          1.0
                           Training Accuracy
Predict on new data
5_
```

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# 5. Video link:

https://drive.google.com/file/d/1bKdPBeNvON77XFZudalbUp7ISlHcyqME/view?usp=sharing