Report of question 6 - CNN for CIFAR10

In this part of the exercise, we aim to train on 50,000 images from 10 classes. To implement the neural network, we use convolutional and pooling layers to reduce the number of parameters and make the model more manageable. Additionally, we will examine the effects of the number of blocks and hidden layers, and use dropout and early stopping methods to achieve higher accuracy. We will also display these changes on a graph.

First, we need to preprocess the data. One of the tasks we perform is one-hot encoding. Instead of representing each class with a single number, a one-hot array of length equal to the number of classes is created for the labels. In this array, the presence of each class is indicated: all elements are zero except for the index corresponding to the class of the image, which is one. Alternatively, all elements can be numerical values between 0 and 1, showing the probability of each class for the image. The sum of all numbers in the array must equal 1.



Part One: Building a Simple CNN Model

In this part, we implement a model consisting of three blocks, each consisting of just two convolutional layers and one max pooling layer. Finally, all these sections are flattened and produce output through a single fully connected layer.

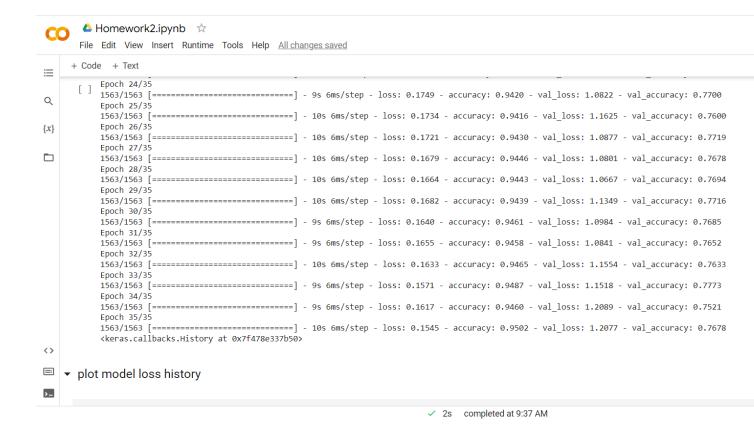
```
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Q
            input = Input(shape=(32, 32, 3))
            x = Conv2D(32, (3, 3), activation='relu', padding='same')(input)
\{x\}
            x = Conv2D(32, (3, 3), activation='relu', padding='same')(x)
            x = MaxPool2D((2, 2))(x)
x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
            x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
            x = MaxPool2D((2, 2))(x)
            x = Conv2D(128, (3, 3), activation='relu', padding='same')(x)
            x = Conv2D(128, (3, 3), activation='relu', padding='same')(x)
            x = MaxPool2D((2, 2))(x)
            x = Flatten()(x)
            x = Dropout(0.2)(x)
            x = Dense(units=128)(x)
            x = ReLU()(x)
            x = Dense(units=10)(x)
            predictions = Activation(activation='softmax')(x)
<>
\equiv
            our_CNN_model = Model(input, predictions)
>_
```

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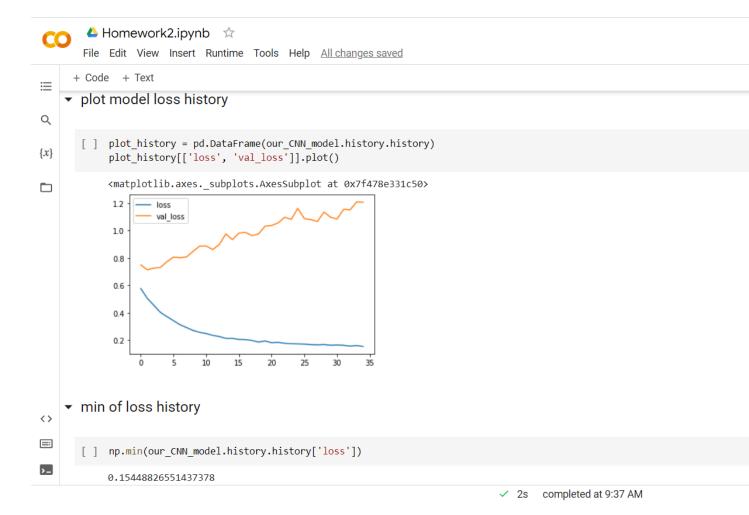
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```
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  our_CNN_model.fit(x=X_trainData, y=cat_y_trainData, epochs=35, batch_size=32,
          validation_data=(X_testData, cat_y_testData))
Q
    Epoch 8/35
\{x\}
    Epoch 9/35
    Epoch 10/35
    1563/1563 [=
              Epoch 11/35
    1563/1563 [==
             Epoch 12/35
    1563/1563 [==
             :==============] - 9s 6ms/step - loss: 0.2357 - accuracy: 0.9175 - val_loss: 0.8619 - val_accuracy: 0.7718
    Epoch 13/35
    Epoch 14/35
    1563/1563 [=========] - 10s 6ms/step - loss: 0.2138 - accuracy: 0.9248 - val_loss: 0.9761 - val_accuracy: 0.7628
    Epoch 15/35
    Epoch 16/35
    1563/1563 [==
             ==========] - 9s 6ms/step - loss: 0.2057 - accuracy: 0.9284 - val_loss: 0.9818 - val_accuracy: 0.7682
    Epoch 17/35
    1563/1563 [====
            Epoch 18/35
    <>
    Epoch 19/35
    1563/1563 [==
            ==================== ] - 10s 6ms/step - loss: 0.1869 - accuracy: 0.9361 - val_loss: 0.9758 - val_accuracy: 0.7687
\equiv
    Epoch 20/35
    >_
    Epoch 21/35
```

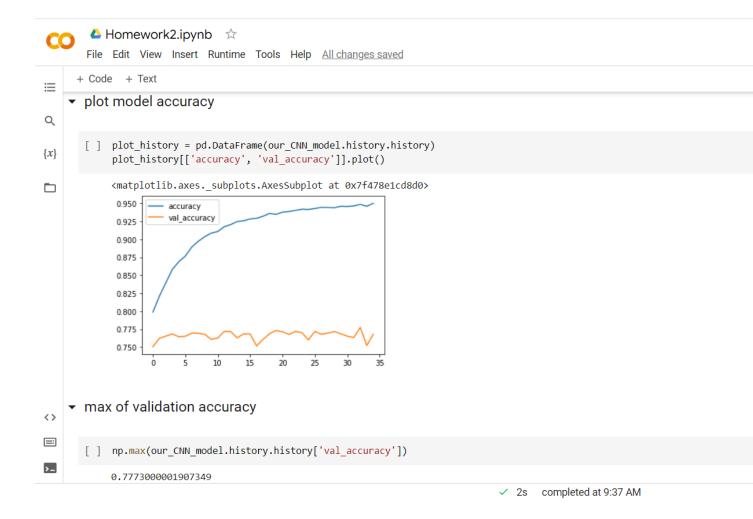
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As we can see, the model initially trains well but eventually slows down and suffers from overfitting. This indicates that the architecture can be optimized further. To clarify the status of the simple model, we will plot its performance graphs.



We observe that initially, the gap between training and validation data was decreasing, indicating that the model was performing well. However, due to overfitting, the gap between validation data and training data increased, which is undesirable. The same issue is evident with accuracy, where the performance on training data improves while the performance on validation data worsens.



Finally, we check to see how much the accuracy values of the data differ from the maximum accuracy achieved on the validation data.

Part Two: Implementing Hidden Layers with Greater Depth

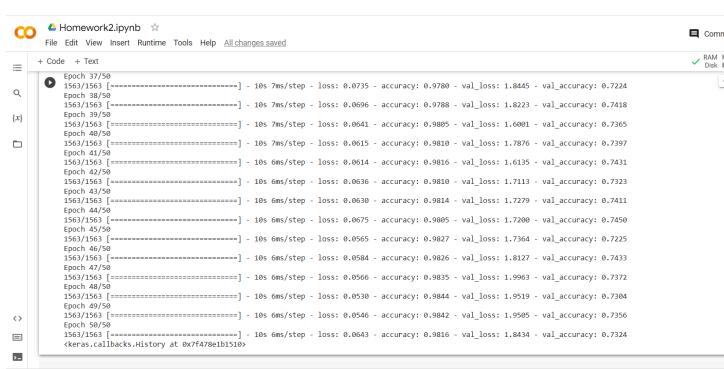
```
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∷
      [ ] input = Input(shape=(32, 32, 3))
Q
           x = Conv2D(filters=32, kernel_size=(3, 3), strides=1, padding='same')(input)
           x = ReLU()(x)
{x}
           x = MaxPool2D(pool size=(2, 2), strides=2, padding='same')(x)
           x = Conv2D(filters=64, kernel_size=(3, 3), strides=1, padding='same')(x)
x = ReLU()(x)
           x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)
           x = Conv2D(filters=128, kernel_size=(3, 3), strides=1, padding='same')(x)
           x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)
           x = Conv2D(filters=256, kernel_size=(3, 3), strides=1, padding='same')(x)
           x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)
           x = Conv2D(filters=512, kernel_size=(3, 3), strides=1, padding='same')(x)
           x = ReLU()(x)
           x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)
<>
           #globalaveragepooling
           x = GlobalAveragePooling2D()(x)
\equiv
           x = Dense(units=128)(x)
>_
            x = ReLU()(x)
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              x = Dense(units=32)(x)
              x = ReLU()(x)
              x = Dense(units=10)(x)
              predictions = Activation(activation='softmax')(x)
              our_CNN_model2 = Model(input, predictions)
```

In this layer, we increased the number of hidden layer blocks. Additionally, we also increased the number of fully connected layers to make the model deeper. We then retrained the model.

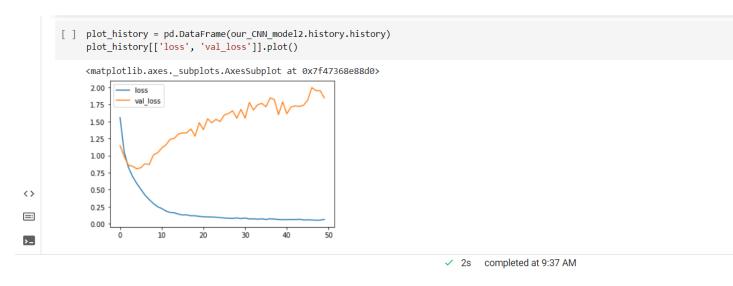
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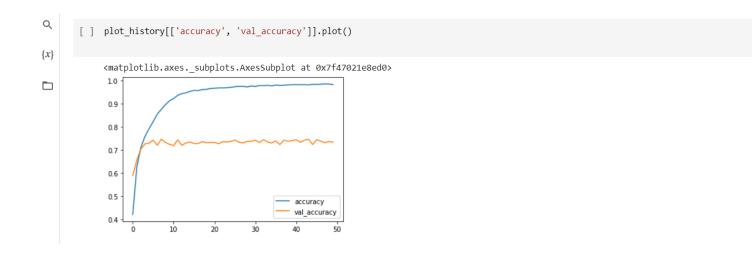
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```
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      our_cons_moderrectrix n_crainmodes, y cac_y_crainmodes, epocho po, bacch_pire pr, variaderon_dada (n_ecocodes)
      Epoch 1/50
Q
      1563/1563 [==
                Epoch 2/50
{x}
      1563/1563 [=
                  :=========] - 10s 7ms/step - loss: 1.0516 - accuracy: 0.6266 - val loss: 0.9858 - val accuracy: 0.6554
      Epoch 3/50
      Fnoch 4/50
      Epoch 5/50
      1563/1563 [=
                  :=========] - 10s 6ms/step - loss: 0.5932 - accuracy: 0.7913 - val_loss: 0.8069 - val_accuracy: 0.7285
      Epoch 6/50
      1563/1563 [=
                Epoch 7/50
      1563/1563 [=
                :==========] - 10s 6ms/step - loss: 0.4203 - accuracy: 0.8542 - val_loss: 0.8807 - val_accuracy: 0.7194
      Epoch 8/50
      Fnoch 9/50
      1563/1563 [=
                  ==============] - 10s 6ms/step - loss: 0.2976 - accuracy: 0.8946 - val_loss: 1.0104 - val_accuracy: 0.7312
      Epoch 10/50
      1563/1563 [=
                  ========] - 10s 6ms/step - loss: 0.2518 - accuracy: 0.9119 - val_loss: 1.0410 - val_accuracy: 0.7233
      Epoch 11/50
      Epoch 12/50
      1563/1563 [===
                <>
      Epoch 13/50
      1563/1563 [=====
                \equiv
      Epoch 14/50
      1563/1563 [=
                   :=========] - 10s 7ms/step - loss: 0.1623 - accuracy: 0.9460 - val_loss: 1.2518 - val_accuracy: 0.7293
>_
      Epoch 15/50
                           -- ] - 10c 6mc/ctan - locc: 0 1421 - accuracy: 0 0523 - val locc: 1 3186 - val accuracy: 0 7336
      1563/1563 [-
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```



As observed, although the model included more neurons and used global average pooling, there was no improvement in validation accuracy. In fact, the model even worsened.





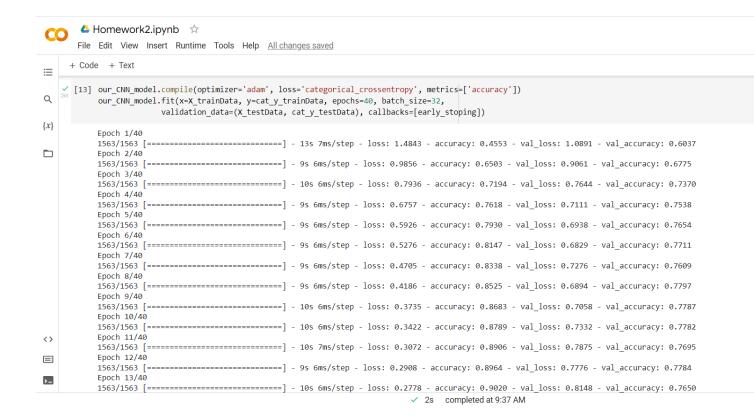
In this problem, since our number of samples is not very large, increasing the number of layers can lead to issues. Each convolutional layer extracts a portion of features, and as the layers increase, the features become more detailed. This can result in overfitting during training or even a decrease in accuracy if the model becomes too

complex. On the other hand, since the data is RGB, if the number of layers is too few, we may not extract meaningful features. Additionally, when flattening the model and adding more fully connected layers, the features obtained from the last convolutional layer might be insufficient, leading to inadequate updates during each epoch.

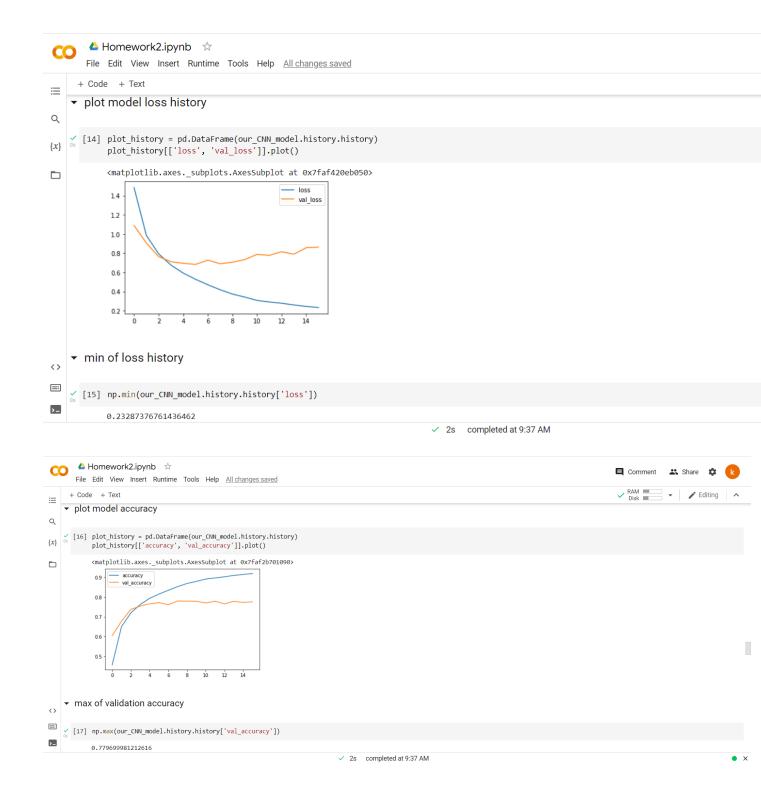


Part Three: Using Alternative Architectures to Optimize the Model

In this part, we use early stopping to prevent overfitting. We do this by monitoring either the maximum accuracy or the minimum loss. For example, we set a threshold for accuracy and stop training if the accuracy does not improve for a certain number of epochs (e.g., ten epochs). Alternatively, we can set a threshold for the minimum loss and halt training if the loss does not decrease beyond this point.

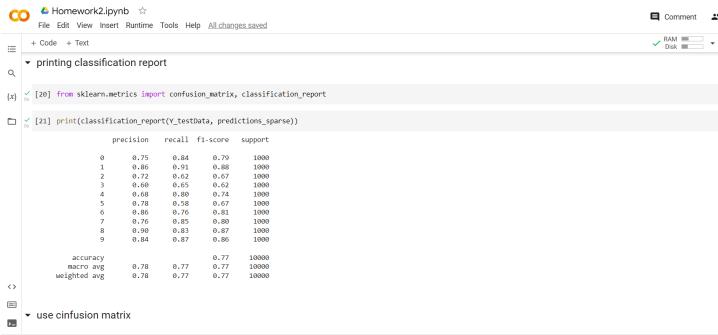


In the plots, we observe that training stopped just before overfitting occurred, and the data did not suffer from overfitting.



And ultimately, we will achieve one of the best validation accuracies.

We can make a confusion matrix for it:



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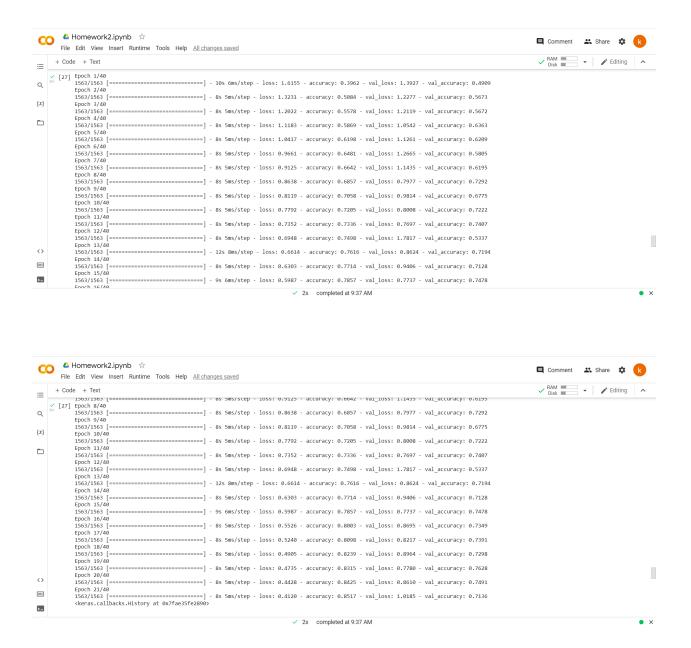
```
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Q
    ▼ use cinfusion matrix
\{x\}
    [22] confusion_matrix(Y_testData, predictions_sparse)
array([[843, 20, 27, 14, 19,
                  [ 10, 914, 1, 1, 2, 1, 5, 1, 15, 50],
                 [ 97, 5, 620, 50, 93, 37, 48, 31,
                 [ 25, 9, 49, 650, 77, 76, 34, 56,
                 [ 18, 1, 44, 44, 799, 11, 20, 54,
                  [ 14, 4, 46, 199, 54, 579, 10, 89,
                                                    8,
                 [ 11, 4, 38, 83, 74, 16, 756,
                       4, 22, 28, 46, 16, 1, 849,
                                                             17],
                 [ 15,
                 [ 68, 40, 11, 11, [ 27, 66, 4, 9,
                                     4, 1, 1, 5, 835, 24],
5, 4, 1, 8, 10, 866]]
                                                    8, 10, 866]])
```

This matrix is such that, except for the diagonal where the values are high, other numbers have significant deviations, indicating that the model did not perform well in those areas. For example, in this model, it struggled to distinguish between the dog and cat classes, represented as class 4 and class 6 (with values 199 and 83, respectively), leading to higher confusion in these categories.

Part Four: Using Batch Normalization and Dropout Techniques

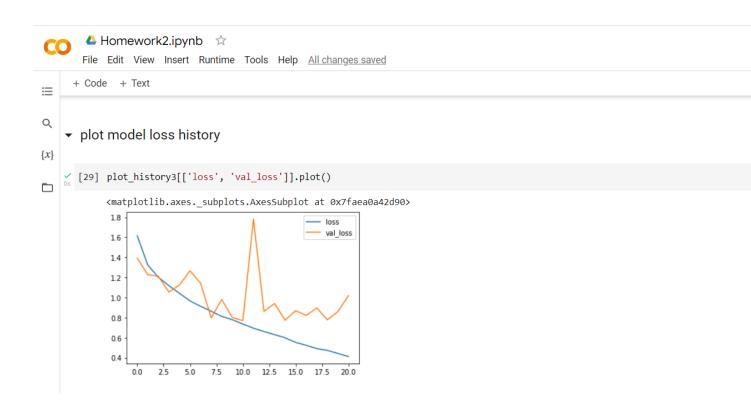
In batch normalization, the process works by normalizing the data to a specific range after each convolutional layer and then passing it through the ReLU activation function. This helps to prevent the production of excessive outlier data and ensures that the data remains well-distributed, preventing the loss of important information.

```
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\equiv
    [24] input = Input(shape=(32, 32, 3))
            x = Conv2D(filters=32, kernel_size=(5, 5), strides=1, padding='same')(input)
            x = BatchNormalization()(x)
{x}
           x = ReLU()(x)
           x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)
x = Conv2D(filters=64, kernel_size=(3, 3), strides=1, padding='same')(x)
            x = BatchNormalization()(x)
            x = ReLU()(x)
            x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)
            x = Conv2D(filters=128, kernel_size=(3, 3), strides=1, padding='same')(x)
            x = BatchNormalization()(x)
            x = ReLU()(x)
            x = MaxPool2D(pool size=(2, 2), strides=2, padding='same')(x)
            x = Flatten()(x)
            x = Dense(units=128)(x)
            x = ReLU()(x)
            x = Dropout(0.3)(x)
            x = Dense(units=10)(x)
<>
            predictions = Activation(activation='softmax')(x)
\equiv
            our_CNN_model3 = Model(input, predictions)
>_
```



As we can see, early stopping prevents overfitting, and on the other hand, we achieve good accuracy with minimal discrepancy between training and validation accuracy. This indicates that our model has become quite effective with these modifications.

```
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       File Edit View Insert Runtime Tools Help All changes saved
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\equiv
Q
    ▼ plot model loss history
{x}
    [29] plot_history3[['loss', 'val_loss']].plot()
<matplotlib.axes._subplots.AxesSubplot at 0x7faea0a42d90>
                                                    val_loss
             1.4
             1.2
             1.0
             0.8
             0.6
             0.4
                     2.5
                               7.5 10.0 12.5 15.0 17.5 20.0
                 0.0
                          5.0
```



Finally, if we calculate the validation accuracy, we will obtain a good result.



Part Five: Using a Subset of Data

In some cases, using a subset of the data can improve our accuracy, especially when the total amount of data is limited and training time is reduced. In this part of the code, we observe that even with a smaller portion of the data, we still achieve good accuracy. However, this subset cannot be too small because the initial data is grayscale, and it must be related to the type of data being used.

```
♣ Homework2.ipynb ☆
      File Edit View Insert Runtime Tools Help All changes saved
     + Code + Text
   [55] our_CNN_model3.fit(x=X_trainData, y=cat_y_trainData, epochs=40, batch_size=32,
                      validation_data=(X_testData, cat_y_testData), callbacks=[early_stoping])
Q
          Epoch 1/40
\{x\}
          313/313 [==========] - 3s 8ms/step - loss: 0.4471 - accuracy: 0.8349 - val loss: 0.8529 - val accuracy:
          Epoch 2/40
                        313/313 [===
Epoch 3/40
          313/313 [==========] - 3s 9ms/step - loss: 0.3825 - accuracy: 0.8603 - val_loss: 0.9930 - val_accuracy:
          Epoch 4/40
          313/313 [===
                              :=========] - 2s 7ms/step - loss: 0.3728 - accuracy: 0.8621 - val loss: 0.9829 - val accuracy:
          Epoch 5/40
          313/313 [==
                                 ========] - 3s 9ms/step - loss: 0.3307 - accuracy: 0.8800 - val loss: 1.1707 - val accuracy:
          Epoch 6/40
                              =========] - 2s 7ms/step - loss: 0.3248 - accuracy: 0.8806 - val_loss: 1.0778 - val_accuracy:
          313/313 [===
          Epoch 7/40
          313/313 [===
                              =========] - 2s 7ms/step - loss: 0.3042 - accuracy: 0.8882 - val_loss: 1.2034 - val_accuracy:
          Epoch 8/40
          313/313 [==
                             ======== ] - 3s 9ms/step - loss: 0.2952 - accuracy: 0.8923 - val loss: 1.1134 - val accuracy:
          Epoch 9/40
          313/313 [==========] - 2s 7ms/step - loss: 0.2991 - accuracy: 0.8890 - val loss: 1.0843 - val accuracy:
          Epoch 10/40
                             ==========] - 3s 9ms/step - loss: 0.2801 - accuracy: 0.9004 - val_loss: 1.0280 - val_accuracy:
          313/313 [===
          313/313 [==========] - 3s 9ms/step - loss: 0.2614 - accuracy: 0.9073 - val_loss: 1.1662 - val_accuracy:
<>
          <keras.callbacks.History at 0x7fae34465650>
\equiv
     loss function and accuracy metric
```

```
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    loss function and accuracy metric

Q

[56] plot_history3 = pd.DataFrame(our_CNN_model3.history.history)

{x}
            plot_history3[['accuracy', 'val_accuracy']].plot()
            <matplotlib.axes._subplots.AxesSubplot at 0x7fae34c2abd0>
accuracy
             0.90
                      val_accuracy
             0.85
             0.80
             0.75
             0.70
                  ó
                                                          10
```

