

Fundamentals of Statistical Learning and Pattern Recognition
CSE 569

Project Report on Deep Learning with CNN

Submitted To
Prof. Dr. Baoxin Li

Submitted By
Sai Vikhyath Kudhroli
ASU Id: 1225432689

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INTRODUCTION

Problem Statement: To perform hyperparameter tuning in a Convolutional Neural Network used to classify CIFAR-10 dataset. Convolutional Neural Network is used to classify the CIFAR-10 dataset into appropriate classes.

Dataset Description: The dataset used is the CIFAR-10 dataset which is included in the Keras framework's datasets. It consists of 60000 colored images, each of the size 32 x 32 which implies the size of the dataset when read into NumPy array would be of the shape 32 x 32 x 3, where 3 represents the RGB channel of each image. The dataset consists of 10 classes. Out of the 60000 images in the dataset, 50000 are training images and the rest of the 10000 are testing images.

PARAMETER DESCRIPTION

Learning Rate: Learning Rate is a parameter that can be tuned in an optimization algorithm that determines the amount by which the weights of the neural network must be varied with respect to the minimum loss function.

If the learning rate of the algorithm is extremely low, the algorithm takes an extremely long time to converge to the global optimum. Whereas if the learning rate is too big, then the algorithm may overshoot the global optimum and may converge at some other point other than global optimum. So, a learning rate must be carefully defined for the algorithm to converge at global optimum within reasonable time.

Kernel Size: Kernel size is a two-dimensional matrix with each cell containing some value, which is used to perform convolution operation with the image. Kernel size specifies the window size for the convolution operation.

Optimizer: An optimizer is an algorithm that modifies the attributes of the neural network. Typically, an optimizer reduces the overall loss resulting in enhancing the accuracy of the neural network. Optimizer modifies the parameters such as weights to improve the accuracy of the model. Some of the prominent optimizers used are Adam, RMSprop (Root Mean Square propagation), SGD (Stochastic Gradient Descent).

Batch Normalization: Batch Normalization is a technique used to expedite the training process of the network by normalizing the layers' inputs by using some normalization technique. Batch Normalization in general, re-centers and re-scales the data which ensures faster computation and faster training. Some of the popular normalization techniques are Min-Max Normalization, Log Scaling, Decimal Scaling, Feature Clipping, Z-Score.

Dropout: Dropout is a regularization technique that nullifies the contribution of some nodes that have least contribution to learning process. A percent of the nodes that contributes least to the training are cut off from the network by removing the forward and backward edges that pass through those nodes. Dropout is used to avoid overfitting of the model. When the model over fits, it performs well on training data and performs poorly on test data and when some of the least contributing nodes are removed from the network, it generates a more regularized function that fits well to the test data.

Batch Size: Batch size defines the number of training samples that will be propagated through the network. Once the samples of one batch are propagated through the network, the model is updated, hence controlling the accuracy of the error of the gradient when training the neural network.

RESULTS AND OBSERVATIONS

Results with out any modifications: Without any modifications to the network, the model performs well both during training and on test data. During training, it can be observed that the training accuracy, training loss, validation accuracy and validation loss are improving with each epoch. The following are the test accuracy and test loss obtained:

Test Accuracy: 85.49%

Test Loss: 0.5943

```
[38] # https://keras.io/optimizers/
model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.01), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.05), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.0001), metrics=['accuracy'])

[39] model.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, verbose=1, validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

Epoch 23/50
782/782 [=====] - 8s 10ms/step - loss: 0.3107 - accuracy: 0.8956 - val_loss: 0.5582 - val_accuracy: 0.8502
Epoch 24/50
782/782 [=====] - 8s 10ms/step - loss: 0.2755 - accuracy: 0.9064 - val_loss: 0.5652 - val_accuracy: 0.8551
Epoch 25/50
782/782 [=====] - 8s 10ms/step - loss: 0.2674 - accuracy: 0.9108 - val_loss: 0.5550 - val_accuracy: 0.8474
Epoch 26/50
782/782 [=====] - 8s 10ms/step - loss: 0.2710 - accuracy: 0.9101 - val_loss: 0.5704 - val_accuracy: 0.8491
Epoch 27/50
782/782 [=====] - 8s 10ms/step - loss: 0.2590 - accuracy: 0.9153 - val_loss: 0.6748 - val_accuracy: 0.8285
Epoch 28/50
782/782 [=====] - 8s 10ms/step - loss: 0.2665 - accuracy: 0.9117 - val_loss: 0.6163 - val_accuracy: 0.8441
Epoch 29/50
782/782 [=====] - 8s 10ms/step - loss: 0.2678 - accuracy: 0.9109 - val_loss: 0.6090 - val_accuracy: 0.8533
Epoch 30/50
782/782 [=====] - 8s 10ms/step - loss: 0.2720 - accuracy: 0.9109 - val_loss: 0.6389 - val_accuracy: 0.8403
Epoch 31/50
782/782 [=====] - 8s 10ms/step - loss: 0.2677 - accuracy: 0.9112 - val_loss: 0.5691 - val_accuracy: 0.8509
Epoch 32/50
782/782 [=====] - 8s 10ms/step - loss: 0.2667 - accuracy: 0.9110 - val_loss: 0.5453 - val_accuracy: 0.8544
Epoch 33/50
782/782 [=====] - 8s 10ms/step - loss: 0.2626 - accuracy: 0.9126 - val_loss: 0.5644 - val_accuracy: 0.8475
Epoch 34/50
782/782 [=====] - 8s 11ms/step - loss: 0.2675 - accuracy: 0.9116 - val_loss: 0.6220 - val_accuracy: 0.8491
Epoch 35/50
782/782 [=====] - 8s 10ms/step - loss: 0.2597 - accuracy: 0.9137 - val_loss: 0.6041 - val_accuracy: 0.8494
Epoch 36/50
782/782 [=====] - 8s 10ms/step - loss: 0.2593 - accuracy: 0.9142 - val_loss: 0.5739 - val_accuracy: 0.8440
Epoch 37/50
782/782 [=====] - 8s 10ms/step - loss: 0.2567 - accuracy: 0.9141 - val_loss: 0.5735 - val_accuracy: 0.8478
Epoch 38/50
782/782 [=====] - 8s 10ms/step - loss: 0.2561 - accuracy: 0.9150 - val_loss: 0.5929 - val_accuracy: 0.8506
Epoch 39/50
782/782 [=====] - 8s 10ms/step - loss: 0.2667 - accuracy: 0.9124 - val_loss: 0.5745 - val_accuracy: 0.8533
Epoch 40/50
782/782 [=====] - 8s 10ms/step - loss: 0.2545 - accuracy: 0.9158 - val_loss: 0.6850 - val_accuracy: 0.8428
Epoch 41/50
782/782 [=====] - 8s 10ms/step - loss: 0.2536 - accuracy: 0.9158 - val_loss: 0.6095 - val_accuracy: 0.8521
Epoch 42/50
782/782 [=====] - 8s 10ms/step - loss: 0.2569 - accuracy: 0.9137 - val_loss: 0.6140 - val_accuracy: 0.8498
Epoch 43/50
782/782 [=====] - 8s 10ms/step - loss: 0.2496 - accuracy: 0.9174 - val_loss: 0.5964 - val_accuracy: 0.8553
Epoch 44/50
782/782 [=====] - 8s 10ms/step - loss: 0.2568 - accuracy: 0.9150 - val_loss: 0.5597 - val_accuracy: 0.8488
Epoch 45/50
782/782 [=====] - 8s 10ms/step - loss: 0.3242 - accuracy: 0.8934 - val_loss: 0.5525 - val_accuracy: 0.8456
Epoch 46/50
782/782 [=====] - 8s 10ms/step - loss: 0.2659 - accuracy: 0.9110 - val_loss: 0.5679 - val_accuracy: 0.8509
Epoch 47/50
782/782 [=====] - 8s 10ms/step - loss: 0.2473 - accuracy: 0.9175 - val_loss: 0.5799 - val_accuracy: 0.8515
Epoch 48/50
782/782 [=====] - 8s 10ms/step - loss: 0.2404 - accuracy: 0.9212 - val_loss: 0.5976 - val_accuracy: 0.8541
Epoch 49/50
782/782 [=====] - 8s 10ms/step - loss: 0.2458 - accuracy: 0.9197 - val_loss: 0.5881 - val_accuracy: 0.8548
Epoch 50/50
782/782 [=====] - 8s 10ms/step - loss: 0.2356 - accuracy: 0.9224 - val_loss: 0.5943 - val_accuracy: 0.8549
Test loss: 0.5942748188972473
Test accuracy: 0.8549000024795532
```

Results with 0.05 learning rate: The model performs decently with 0.05 as the learning rate but the accuracy reported is less than that of with 0.01 learning rate. When the learning rate is increased to 0.05, the algorithm takes bigger steps to update weights to reach global optimum, but with high learning rate there is always a possibility that the algorithm may overshoot the global optima which could have happened in this case. The following are results reported:

Test Accuracy: 83.29%

Test Loss: 1.5227

```
[40] # https://keras.io/optimizers/
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.01), metrics=['accuracy'])
model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.05), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.0001), metrics=['accuracy'])

/usr/local/lib/python3.8/dist-packages/keras/optimizers/optimizer_v2/adam.py:110: UserWarning: The `lr` argument is deprecated, use `learning_rate` instead.
  super(Adam, self).__init__(name, **kwargs)

[41] model.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, verbose=1, validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

Epoch 23/50
782/782 [=====] - 8s 10ms/step - loss: 1.0472 - accuracy: 0.8072 - val_loss: 1.0519 - val_accuracy: 0.7999
Epoch 24/50
782/782 [=====] - 8s 10ms/step - loss: 1.1367 - accuracy: 0.8007 - val_loss: 1.9035 - val_accuracy: 0.7385
Epoch 25/50
782/782 [=====] - 8s 10ms/step - loss: 1.1848 - accuracy: 0.8048 - val_loss: 1.4002 - val_accuracy: 0.8007
Epoch 26/50
782/782 [=====] - 8s 10ms/step - loss: 1.0403 - accuracy: 0.8149 - val_loss: 1.2354 - val_accuracy: 0.7991
Epoch 27/50
782/782 [=====] - 8s 10ms/step - loss: 1.1002 - accuracy: 0.8129 - val_loss: 1.3263 - val_accuracy: 0.7923
Epoch 28/50
782/782 [=====] - 8s 10ms/step - loss: 1.1040 - accuracy: 0.8147 - val_loss: 1.2042 - val_accuracy: 0.8044
Epoch 29/50
782/782 [=====] - 8s 10ms/step - loss: 1.1924 - accuracy: 0.8123 - val_loss: 1.0428 - val_accuracy: 0.8261
Epoch 30/50
782/782 [=====] - 8s 10ms/step - loss: 1.0132 - accuracy: 0.8255 - val_loss: 1.2017 - val_accuracy: 0.8050
Epoch 31/50
782/782 [=====] - 8s 10ms/step - loss: 1.0579 - accuracy: 0.8244 - val_loss: 1.8948 - val_accuracy: 0.7846
Epoch 32/50
782/782 [=====] - 8s 10ms/step - loss: 1.0885 - accuracy: 0.8232 - val_loss: 1.8146 - val_accuracy: 0.7796
Epoch 33/50
782/782 [=====] - 8s 10ms/step - loss: 1.1400 - accuracy: 0.8238 - val_loss: 2.1018 - val_accuracy: 0.7618
Epoch 34/50
782/782 [=====] - 8s 10ms/step - loss: 1.0662 - accuracy: 0.8277 - val_loss: 1.4394 - val_accuracy: 0.7903
Epoch 35/50
782/782 [=====] - 8s 10ms/step - loss: 1.1429 - accuracy: 0.8272 - val_loss: 1.4326 - val_accuracy: 0.8102
Epoch 36/50
782/782 [=====] - 8s 10ms/step - loss: 1.1227 - accuracy: 0.8296 - val_loss: 1.4159 - val_accuracy: 0.8109
Epoch 37/50
782/782 [=====] - 8s 10ms/step - loss: 1.0883 - accuracy: 0.8351 - val_loss: 1.3297 - val_accuracy: 0.8138
Epoch 38/50
782/782 [=====] - 8s 10ms/step - loss: 1.1016 - accuracy: 0.8341 - val_loss: 1.2145 - val_accuracy: 0.8278
Epoch 39/50
782/782 [=====] - 8s 10ms/step - loss: 1.1653 - accuracy: 0.8321 - val_loss: 1.3809 - val_accuracy: 0.8074
Epoch 40/50
782/782 [=====] - 8s 10ms/step - loss: 1.1084 - accuracy: 0.8366 - val_loss: 1.4029 - val_accuracy: 0.8097
Epoch 41/50
782/782 [=====] - 8s 10ms/step - loss: 1.1258 - accuracy: 0.8369 - val_loss: 2.1614 - val_accuracy: 0.7875
Epoch 42/50
782/782 [=====] - 8s 10ms/step - loss: 1.2022 - accuracy: 0.8362 - val_loss: 1.5389 - val_accuracy: 0.7990
Epoch 43/50
782/782 [=====] - 8s 10ms/step - loss: 1.0821 - accuracy: 0.8420 - val_loss: 2.0380 - val_accuracy: 0.7634
Epoch 44/50
782/782 [=====] - 8s 10ms/step - loss: 1.1520 - accuracy: 0.8395 - val_loss: 1.6068 - val_accuracy: 0.8026
Epoch 45/50
782/782 [=====] - 8s 10ms/step - loss: 1.1772 - accuracy: 0.8431 - val_loss: 1.6018 - val_accuracy: 0.8018
Epoch 46/50
782/782 [=====] - 8s 10ms/step - loss: 1.1259 - accuracy: 0.8443 - val_loss: 1.4089 - val_accuracy: 0.8196
Epoch 47/50
782/782 [=====] - 8s 10ms/step - loss: 1.1429 - accuracy: 0.8445 - val_loss: 1.4067 - val_accuracy: 0.8342
Epoch 48/50
782/782 [=====] - 8s 10ms/step - loss: 1.1894 - accuracy: 0.8461 - val_loss: 1.5194 - val_accuracy: 0.8177
Epoch 49/50
782/782 [=====] - 8s 10ms/step - loss: 1.2173 - accuracy: 0.8445 - val_loss: 1.5041 - val_accuracy: 0.8278
Epoch 50/50
782/782 [=====] - 8s 10ms/step - loss: 1.1817 - accuracy: 0.8483 - val_loss: 1.5228 - val_accuracy: 0.8329
Test loss: 1.5227998495101929
Test accuracy: 0.8328999876976013
```

Results with 0.0001 learning rate: The model performs better when the learning rate is set to 0.0001 than when set to 0.01 and 0.05. When the learning rate is set to a lower value, the algorithm takes smaller steps in updating weights to reach the global optima. Thus, reducing the learning rate to 0.0001 may have reduced the step size of reaching global optima and may have appropriately reached global optima. However, setting the learning rate to a low value may not always be a good approach because the algorithm would take a lot of time to converge to global optimum. The following are the results obtained:

Test Accuracy: 86.74%

Test Loss: 0.6290

```
[42] # https://keras.io/optimizers/
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.01), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.05), metrics=['accuracy'])
model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.0001), metrics=['accuracy'])

[43] model.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, verbose=1, validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

Epoch 23/50
782/782 [=====] - 8s 10ms/step - loss: 0.3760 - accuracy: 0.9108 - val_loss: 0.8262 - val_accuracy: 0.8645
Epoch 24/50
782/782 [=====] - 8s 10ms/step - loss: 0.3991 - accuracy: 0.9135 - val_loss: 0.8179 - val_accuracy: 0.8654
Epoch 25/50
782/782 [=====] - 8s 10ms/step - loss: 0.3692 - accuracy: 0.9131 - val_loss: 0.8050 - val_accuracy: 0.8649
Epoch 26/50
782/782 [=====] - 8s 10ms/step - loss: 0.3653 - accuracy: 0.9117 - val_loss: 0.7998 - val_accuracy: 0.8658
Epoch 27/50
782/782 [=====] - 8s 10ms/step - loss: 0.3568 - accuracy: 0.9130 - val_loss: 0.7893 - val_accuracy: 0.8650
Epoch 28/50
782/782 [=====] - 8s 10ms/step - loss: 0.3519 - accuracy: 0.9134 - val_loss: 0.7793 - val_accuracy: 0.8655
Epoch 29/50
782/782 [=====] - 8s 10ms/step - loss: 0.3498 - accuracy: 0.9119 - val_loss: 0.7680 - val_accuracy: 0.8664
Epoch 30/50
782/782 [=====] - 8s 10ms/step - loss: 0.3489 - accuracy: 0.9125 - val_loss: 0.7597 - val_accuracy: 0.8652
Epoch 31/50
782/782 [=====] - 8s 10ms/step - loss: 0.3409 - accuracy: 0.9140 - val_loss: 0.7549 - val_accuracy: 0.8655
Epoch 32/50
782/782 [=====] - 8s 10ms/step - loss: 0.3361 - accuracy: 0.9127 - val_loss: 0.7440 - val_accuracy: 0.8658
Epoch 33/50
782/782 [=====] - 8s 10ms/step - loss: 0.3397 - accuracy: 0.9122 - val_loss: 0.7369 - val_accuracy: 0.8662
Epoch 34/50
782/782 [=====] - 8s 10ms/step - loss: 0.3224 - accuracy: 0.9168 - val_loss: 0.7317 - val_accuracy: 0.8667
Epoch 35/50
782/782 [=====] - 8s 10ms/step - loss: 0.3202 - accuracy: 0.9164 - val_loss: 0.7227 - val_accuracy: 0.8676
Epoch 36/50
782/782 [=====] - 8s 10ms/step - loss: 0.3487 - accuracy: 0.9151 - val_loss: 0.7170 - val_accuracy: 0.8662
Epoch 37/50
782/782 [=====] - 8s 10ms/step - loss: 0.3193 - accuracy: 0.9154 - val_loss: 0.7101 - val_accuracy: 0.8671
Epoch 38/50
782/782 [=====] - 8s 10ms/step - loss: 0.3215 - accuracy: 0.9139 - val_loss: 0.7027 - val_accuracy: 0.8655
Epoch 39/50
782/782 [=====] - 8s 10ms/step - loss: 0.3062 - accuracy: 0.9167 - val_loss: 0.6951 - val_accuracy: 0.8666
Epoch 40/50
782/782 [=====] - 8s 10ms/step - loss: 0.3388 - accuracy: 0.9159 - val_loss: 0.6925 - val_accuracy: 0.8662
Epoch 41/50
782/782 [=====] - 8s 10ms/step - loss: 0.2990 - accuracy: 0.9178 - val_loss: 0.6863 - val_accuracy: 0.8669
Epoch 42/50
782/782 [=====] - 8s 10ms/step - loss: 0.3027 - accuracy: 0.9159 - val_loss: 0.6783 - val_accuracy: 0.8668
Epoch 43/50
782/782 [=====] - 8s 10ms/step - loss: 0.3011 - accuracy: 0.9167 - val_loss: 0.6715 - val_accuracy: 0.8673
Epoch 44/50
782/782 [=====] - 8s 10ms/step - loss: 0.3078 - accuracy: 0.9154 - val_loss: 0.6653 - val_accuracy: 0.8671
Epoch 45/50
782/782 [=====] - 8s 10ms/step - loss: 0.2916 - accuracy: 0.9172 - val_loss: 0.6579 - val_accuracy: 0.8667
Epoch 46/50
782/782 [=====] - 8s 10ms/step - loss: 0.2938 - accuracy: 0.9171 - val_loss: 0.6506 - val_accuracy: 0.8669
Epoch 47/50
782/782 [=====] - 8s 10ms/step - loss: 0.2868 - accuracy: 0.9176 - val_loss: 0.6463 - val_accuracy: 0.8675
Epoch 48/50
782/782 [=====] - 8s 10ms/step - loss: 0.2896 - accuracy: 0.9175 - val_loss: 0.6433 - val_accuracy: 0.8667
Epoch 49/50
782/782 [=====] - 8s 10ms/step - loss: 0.2906 - accuracy: 0.9166 - val_loss: 0.6356 - val_accuracy: 0.8669
Epoch 50/50
782/782 [=====] - 8s 10ms/step - loss: 0.3185 - accuracy: 0.9155 - val_loss: 0.6291 - val_accuracy: 0.8674
Test loss: 0.6290989518165588
Test accuracy: 0.8673999905586243
```

Results with 7x7 kernel size: Model's accuracy dropped when a kernel of 7x7 size was used. Increasing the kernel size increases the window of the convolution operation. Increasing the kernel size can increase the complexity of the model, however, with a large kernel size, more area of the image is convolved at once leading to important and unimportant features of the image to be convolved at the same time which can dampen the efficiency of the model. With a lower kernel size, small area of the image is convolved leading to important features to be convolved to a single cell in next layer. The following results were obtained:

Test Accuracy: 80.54%

Test Loss: 0.6462

```
[44] model = Sequential()
# model.add(Conv2D(filters = 32, kernel_size = (3,3), padding='same', input_shape = input_shape))
model.add(Conv2D(filters = 32, kernel_size = (7,7), padding='same', input_shape = input_shape))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 32, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 64, kernel_size = (4,4), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D((2,2)))
model.add(Dropout(0.2))

model.add(Conv2D(filters = 64, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 64, kernel_size = (4,4), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D((2,2)))
model.add(Dropout(0.3))

model.add(Conv2D(filters = 128, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 128, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D((2,2)))
model.add(Dropout(0.4))

model.add(Flatten())
model.add(Dense(units = 10, activation = 'softmax'))

[45] # https://keras.io/optimizers/
model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.01), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.005), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.0001), metrics=['accuracy'])

[46] model.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, verbose=1, validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('test loss:', score[0])
print('test accuracy:', score[1])
```

Epoch 23/50	782/782	10ms/step	loss: 0.4688	accuracy: 0.8384	val_loss: 0.5886	val_accuracy: 0.8127
Epoch 24/50	782/782	10ms/step	loss: 0.4626	accuracy: 0.8407	val_loss: 0.6294	val_accuracy: 0.8012
Epoch 25/50	782/782	10ms/step	loss: 0.4539	accuracy: 0.8446	val_loss: 0.6098	val_accuracy: 0.8137
Epoch 26/50	782/782	11ms/step	loss: 0.4436	accuracy: 0.8476	val_loss: 0.6084	val_accuracy: 0.8186
Epoch 27/50	782/782	10ms/step	loss: 0.4361	accuracy: 0.8516	val_loss: 0.6394	val_accuracy: 0.7948
Epoch 28/50	782/782	10ms/step	loss: 0.4309	accuracy: 0.8544	val_loss: 0.5882	val_accuracy: 0.8177
Epoch 29/50	782/782	10ms/step	loss: 0.4299	accuracy: 0.8523	val_loss: 0.6413	val_accuracy: 0.8094
Epoch 30/50	782/782	10ms/step	loss: 0.4184	accuracy: 0.8557	val_loss: 0.6215	val_accuracy: 0.8114
Epoch 31/50	782/782	10ms/step	loss: 0.4141	accuracy: 0.8589	val_loss: 0.5558	val_accuracy: 0.8253
Epoch 32/50	782/782	10ms/step	loss: 0.4074	accuracy: 0.8602	val_loss: 0.5924	val_accuracy: 0.8217
Epoch 33/50	782/782	10ms/step	loss: 0.3980	accuracy: 0.8632	val_loss: 0.5415	val_accuracy: 0.8325
Epoch 34/50	782/782	10ms/step	loss: 0.3985	accuracy: 0.8644	val_loss: 0.5865	val_accuracy: 0.8241
Epoch 35/50	782/782	10ms/step	loss: 0.3909	accuracy: 0.8663	val_loss: 0.5681	val_accuracy: 0.8245
Epoch 36/50	782/782	11ms/step	loss: 0.4848	accuracy: 0.8685	val_loss: 0.6096	val_accuracy: 0.8096
Epoch 37/50	782/782	10ms/step	loss: 0.3823	accuracy: 0.8689	val_loss: 0.5648	val_accuracy: 0.8263
Epoch 38/50	782/782	10ms/step	loss: 0.3742	accuracy: 0.8706	val_loss: 0.5889	val_accuracy: 0.8279
Epoch 39/50	782/782	10ms/step	loss: 0.3723	accuracy: 0.8736	val_loss: 0.6134	val_accuracy: 0.8242
Epoch 40/50	782/782	11ms/step	loss: 0.4708	accuracy: 0.8743	val_loss: 0.5740	val_accuracy: 0.8317
Epoch 41/50	782/782	10ms/step	loss: 0.3657	accuracy: 0.8754	val_loss: 0.5686	val_accuracy: 0.8293
Epoch 42/50	782/782	10ms/step	loss: 0.3584	accuracy: 0.8772	val_loss: 0.5594	val_accuracy: 0.8351
Epoch 43/50	782/782	10ms/step	loss: 0.4562	accuracy: 0.8782	val_loss: 0.6078	val_accuracy: 0.8270
Epoch 44/50	782/782	12ms/step	loss: 0.3553	accuracy: 0.8784	val_loss: 0.6077	val_accuracy: 0.8321
Epoch 45/50	782/782	11ms/step	loss: 0.3488	accuracy: 0.8801	val_loss: 0.6296	val_accuracy: 0.8157
Epoch 46/50	782/782	10ms/step	loss: 0.3483	accuracy: 0.8817	val_loss: 0.5808	val_accuracy: 0.8264
Epoch 47/50	782/782	10ms/step	loss: 0.3463	accuracy: 0.8807	val_loss: 0.5798	val_accuracy: 0.8268
Epoch 48/50	782/782	10ms/step	loss: 0.3450	accuracy: 0.8814	val_loss: 0.5802	val_accuracy: 0.8280
Epoch 49/50	782/782	10ms/step	loss: 0.3353	accuracy: 0.8848	val_loss: 0.6019	val_accuracy: 0.8324
Epoch 50/50	782/782	11ms/step	loss: 0.4464	accuracy: 0.8849	val_loss: 0.6462	val_accuracy: 0.8054
test loss: 0.64616328478095						
test accuracy: 0.805400013923645						

Results with RMSprop optimizer: The results obtained with Root Mean Square propagation optimizer are close to the results obtained with Adam's optimizer with a minimal loss of accuracy. Both Adam and RMSprop are adaptive optimizers. However, RMSprop uses a decaying average of partial gradients to update the parameters, which simply is a way to update weights by considering some history of the gradient descent. While Adam adapts the parameters based on the mean and the variance of the past few gradients. So, Adam in most cases performs better than other optimizers. The following results were obtained:

Test Accuracy: 84.62%

Test Loss: 0.5240

```
[47] model = Sequential()
model.add(Conv2D(filters = 32, kernel_size = (3,3), padding='same', input_shape = input_shape))
# model.add(Conv2D(filters = 32, kernel_size = (7,7), padding='same', input_shape = input_shape))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 64, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 64, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.5))

model.add(Conv2D(filters = 64, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 64, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.5))

model.add(Conv2D(filters = 128, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 128, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.5))

model.add(Flatten())
model.add(Dense(units = 10, activation = 'softmax'))

[48] # https://keras.io/optimizers/
model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.RMSprop(lr=0.01), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.05), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.0001), metrics=['accuracy'])

/user/local/lib/python3.8/dist-packages/keras/optimizers/optimizer_v2/rmsprop.py:135: UserWarning: The "lr" argument is deprecated, use "learning_rate" instead.
super(RMSprop, self).__init__(name, "rmsprop")

[49] model.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, verbose=1, validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

Epoch 24/50
782/782 [-----] - 8s 10ms/step - loss: 0.4379 - accuracy: 0.8499 - val_loss: 0.6437 - val_accuracy: 0.8065
Epoch 24/50
782/782 [-----] - 8s 10ms/step - loss: 0.4274 - accuracy: 0.8531 - val_loss: 0.6363 - val_accuracy: 0.8005
Epoch 25/50
782/782 [-----] - 8s 10ms/step - loss: 0.4187 - accuracy: 0.8583 - val_loss: 0.7447 - val_accuracy: 0.7789
Epoch 26/50
782/782 [-----] - 8s 10ms/step - loss: 0.4165 - accuracy: 0.8570 - val_loss: 0.5744 - val_accuracy: 0.8151
Epoch 27/50
782/782 [-----] - 9s 12ms/step - loss: 0.4101 - accuracy: 0.8595 - val_loss: 0.5500 - val_accuracy: 0.8189
Epoch 28/50
782/782 [-----] - 8s 10ms/step - loss: 0.4043 - accuracy: 0.8628 - val_loss: 0.6114 - val_accuracy: 0.8092
Epoch 29/50
782/782 [-----] - 8s 10ms/step - loss: 0.3969 - accuracy: 0.8640 - val_loss: 0.6804 - val_accuracy: 0.7969
Epoch 30/50
782/782 [-----] - 8s 10ms/step - loss: 0.3974 - accuracy: 0.8654 - val_loss: 0.6897 - val_accuracy: 0.8021
Epoch 31/50
782/782 [-----] - 8s 10ms/step - loss: 0.3858 - accuracy: 0.8682 - val_loss: 0.4953 - val_accuracy: 0.8433
Epoch 32/50
782/782 [-----] - 8s 10ms/step - loss: 0.3860 - accuracy: 0.8668 - val_loss: 0.5910 - val_accuracy: 0.8135
Epoch 33/50
782/782 [-----] - 8s 10ms/step - loss: 0.3753 - accuracy: 0.8710 - val_loss: 0.7235 - val_accuracy: 0.7972
Epoch 34/50
782/782 [-----] - 8s 10ms/step - loss: 0.4771 - accuracy: 0.8707 - val_loss: 0.6098 - val_accuracy: 0.7925
Epoch 35/50
782/782 [-----] - 8s 10ms/step - loss: 0.3652 - accuracy: 0.8748 - val_loss: 0.6250 - val_accuracy: 0.8114
Epoch 36/50
782/782 [-----] - 8s 10ms/step - loss: 0.3602 - accuracy: 0.8778 - val_loss: 0.6758 - val_accuracy: 0.7970
Epoch 37/50
782/782 [-----] - 8s 10ms/step - loss: 0.3562 - accuracy: 0.8791 - val_loss: 0.6457 - val_accuracy: 0.8132
Epoch 38/50
782/782 [-----] - 8s 10ms/step - loss: 0.3542 - accuracy: 0.8798 - val_loss: 0.5811 - val_accuracy: 0.8246
Epoch 39/50
782/782 [-----] - 8s 10ms/step - loss: 0.3525 - accuracy: 0.8791 - val_loss: 0.7227 - val_accuracy: 0.8003
Epoch 40/50
782/782 [-----] - 8s 10ms/step - loss: 0.3510 - accuracy: 0.8786 - val_loss: 0.5805 - val_accuracy: 0.8330
Epoch 41/50
782/782 [-----] - 8s 10ms/step - loss: 0.3474 - accuracy: 0.8814 - val_loss: 0.5285 - val_accuracy: 0.8377
Epoch 42/50
782/782 [-----] - 8s 10ms/step - loss: 0.3412 - accuracy: 0.8840 - val_loss: 0.7034 - val_accuracy: 0.8036
Epoch 43/50
782/782 [-----] - 8s 10ms/step - loss: 0.3365 - accuracy: 0.8856 - val_loss: 0.5493 - val_accuracy: 0.8334
Epoch 44/50
782/782 [-----] - 8s 10ms/step - loss: 0.3312 - accuracy: 0.8879 - val_loss: 0.5573 - val_accuracy: 0.8471
Epoch 45/50
782/782 [-----] - 8s 10ms/step - loss: 0.3447 - accuracy: 0.8872 - val_loss: 0.6096 - val_accuracy: 0.8059
Epoch 46/50
782/782 [-----] - 8s 10ms/step - loss: 0.4424 - accuracy: 0.8869 - val_loss: 0.5910 - val_accuracy: 0.8422
Epoch 47/50
782/782 [-----] - 8s 11ms/step - loss: 0.3241 - accuracy: 0.8904 - val_loss: 0.6440 - val_accuracy: 0.8183
Epoch 48/50
782/782 [-----] - 8s 10ms/step - loss: 0.3214 - accuracy: 0.8910 - val_loss: 0.5392 - val_accuracy: 0.8389
Epoch 49/50
782/782 [-----] - 8s 10ms/step - loss: 0.3182 - accuracy: 0.8911 - val_loss: 0.7017 - val_accuracy: 0.7934
Epoch 50/50
782/782 [-----] - 8s 10ms/step - loss: 0.3198 - accuracy: 0.8902 - val_loss: 0.5240 - val_accuracy: 0.8462
Test loss: 0.5240421891212464
Test accuracy: 0.8461999893188477
```


Results with batch normalization removed: The results obtained after removing batch normalization are extremely poor. Removing batch normalization will not normalize the inputs at each layer resulting in the inputs being of very large values and would require an extremely low learning rate to converge to global optimum. Because the inputs are not normalized and the learning rate not modified, the model performs poorly. The following results are obtained:

Test Accuracy: 10%

Test Loss: 2.3034

```
[50] model = Sequential()
model.add(Conv2D(filters = 32, kernel_size = (3,3), padding='same', input_shape = input_shape))
# model.add(Conv2D(filters = 32, kernel_size = (7,7), padding='same', input_shape = input_shape))
model.add(Activation('relu'))
# model.add(BatchNormalization())
model.add(Conv2D(filters = 32, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
# model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.2))

model.add(Conv2D(filters = 64, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
# model.add(BatchNormalization())
model.add(Conv2D(filters = 64, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
# model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.2))

model.add(Conv2D(filters = 128, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
# model.add(BatchNormalization())
model.add(Conv2D(filters = 128, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
# model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.4))

model.add(Flatten())

model.add(Dense(units = 10, activation = 'softmax'))

[51] # https://keras.io/optimizers/
model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.01), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.01), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.05), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.0001), metrics=['accuracy'])

/usr/local/lib/python3.8/dist-packages/keras/optimizers/optimizer_v2/adam.py:110: UserWarning: The 'lr' argument is deprecated, use 'learning_rate' instead.
super(Adam, self).init_(name, **kwargs)

[52] model.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, verbose=1, validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('test loss:', score[0])
print('test accuracy:', score[1])

Epoch 23/50 ----- 7s 8ms/step - loss: 2.3036 - accuracy: 0.0978 - val_loss: 2.3032 - val_accuracy: 0.1000
Epoch 24/50 ----- 7s 8ms/step - loss: 2.3035 - accuracy: 0.0988 - val_loss: 2.3031 - val_accuracy: 0.1000
Epoch 25/50 ----- 7s 8ms/step - loss: 2.3037 - accuracy: 0.0979 - val_loss: 2.3033 - val_accuracy: 0.1000
Epoch 26/50 ----- 7s 8ms/step - loss: 2.3036 - accuracy: 0.0981 - val_loss: 2.3035 - val_accuracy: 0.1000
Epoch 27/50 ----- 7s 9ms/step - loss: 2.3037 - accuracy: 0.0977 - val_loss: 2.3033 - val_accuracy: 0.1000
Epoch 28/50 ----- 7s 8ms/step - loss: 2.3036 - accuracy: 0.1023 - val_loss: 2.3032 - val_accuracy: 0.1000
Epoch 29/50 ----- 7s 8ms/step - loss: 2.3037 - accuracy: 0.0981 - val_loss: 2.3032 - val_accuracy: 0.1000
Epoch 30/50 ----- 7s 8ms/step - loss: 2.3038 - accuracy: 0.0976 - val_loss: 2.3037 - val_accuracy: 0.1000
Epoch 31/50 ----- 7s 9ms/step - loss: 2.3037 - accuracy: 0.0973 - val_loss: 2.3038 - val_accuracy: 0.1000
Epoch 32/50 ----- 7s 9ms/step - loss: 2.3035 - accuracy: 0.1017 - val_loss: 2.3032 - val_accuracy: 0.1000
Epoch 33/50 ----- 7s 8ms/step - loss: 2.3036 - accuracy: 0.0980 - val_loss: 2.3034 - val_accuracy: 0.1000
Epoch 34/50 ----- 6s 8ms/step - loss: 2.3036 - accuracy: 0.1003 - val_loss: 2.3034 - val_accuracy: 0.1000
Epoch 35/50 ----- 6s 8ms/step - loss: 2.3035 - accuracy: 0.1015 - val_loss: 2.3038 - val_accuracy: 0.1000
Epoch 36/50 ----- 7s 8ms/step - loss: 2.3035 - accuracy: 0.1007 - val_loss: 2.3033 - val_accuracy: 0.1000
Epoch 37/50 ----- 7s 9ms/step - loss: 2.3036 - accuracy: 0.0980 - val_loss: 2.3037 - val_accuracy: 0.1000
Epoch 38/50 ----- 7s 8ms/step - loss: 2.3037 - accuracy: 0.1004 - val_loss: 2.3031 - val_accuracy: 0.1000
Epoch 39/50 ----- 7s 8ms/step - loss: 2.3036 - accuracy: 0.0990 - val_loss: 2.3035 - val_accuracy: 0.1000
Epoch 40/50 ----- 7s 8ms/step - loss: 2.3035 - accuracy: 0.1022 - val_loss: 2.3033 - val_accuracy: 0.1000
Epoch 41/50 ----- 7s 8ms/step - loss: 2.3038 - accuracy: 0.0981 - val_loss: 2.3029 - val_accuracy: 0.1000
Epoch 42/50 ----- 7s 8ms/step - loss: 2.3035 - accuracy: 0.0997 - val_loss: 2.3038 - val_accuracy: 0.1000
Epoch 43/50 ----- 7s 8ms/step - loss: 2.3036 - accuracy: 0.1004 - val_loss: 2.3030 - val_accuracy: 0.1000
Epoch 44/50 ----- 7s 8ms/step - loss: 2.3035 - accuracy: 0.1005 - val_loss: 2.3033 - val_accuracy: 0.1000
Epoch 45/50 ----- 7s 8ms/step - loss: 2.3035 - accuracy: 0.1000 - val_loss: 2.3039 - val_accuracy: 0.1000
Epoch 46/50 ----- 7s 8ms/step - loss: 2.3036 - accuracy: 0.1007 - val_loss: 2.3033 - val_accuracy: 0.1000
Epoch 47/50 ----- 7s 8ms/step - loss: 2.3034 - accuracy: 0.1005 - val_loss: 2.3042 - val_accuracy: 0.1000
Epoch 48/50 ----- 7s 8ms/step - loss: 2.3038 - accuracy: 0.0991 - val_loss: 2.3031 - val_accuracy: 0.1000
Epoch 49/50 ----- 7s 8ms/step - loss: 2.3037 - accuracy: 0.0985 - val_loss: 2.3037 - val_accuracy: 0.1000
Epoch 50/50 ----- 7s 8ms/step - loss: 2.3036 - accuracy: 0.1019 - val_loss: 2.3034 - val_accuracy: 0.1000
test loss: 2.3034255504608154
test accuracy: 0.10000000149011612
```

Results with 0.7 dropout: The results obtained with 0.7 dropout are not as good as the one without any modifications. Dropout is used for regularization. When the model performs well on training data and does not perform well on test data, dropout is used to regularize by dropping out least contributing nodes from the network. But the percent of nodes dropped has an impact on the performance of the model. When more nodes are dropped, the network becomes sparse and may perform poorly.

Test Accuracy: 74.48%

Test Loss: 0.7895

```
[53] model = Sequential()
model.add(Conv2D(filters = 32, kernel_size = (3,3), padding='same', input_shape = input_shape))
# model.add(Conv2D(filters = 32, kernel_size = (7,7), padding='same', input_shape = input_shape))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 32, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
# model.add(Dropout(0.2))
model.add(Dropout(0.7))

model.add(Conv2D(filters = 64, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 64, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
# model.add(Dropout(0.3))
model.add(Dropout(0.7))

model.add(Conv2D(filters = 128, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 128, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
# model.add(Dropout(0.4))
model.add(Dropout(0.7))

model.add(Flatten())

model.add(Dense(units = 10, activation = 'softmax'))

[54] # https://keras.io/optimizers/
model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.01), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.01), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.0001), metrics=['accuracy'])

[55] model.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, verbose=1, validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

Epoch 23/50
782/782 [-----] - 8s 10ms/step - loss: 0.8087 - accuracy: 0.6954 - val_loss: 0.7781 - val_accuracy: 0.7404
Epoch 24/50
782/782 [-----] - 8s 10ms/step - loss: 0.8729 - accuracy: 0.6982 - val_loss: 0.7682 - val_accuracy: 0.7435
Epoch 25/50
782/782 [-----] - 8s 10ms/step - loss: 0.8705 - accuracy: 0.6987 - val_loss: 0.9734 - val_accuracy: 0.6902
Epoch 26/50
782/782 [-----] - 8s 10ms/step - loss: 0.8589 - accuracy: 0.7034 - val_loss: 0.6708 - val_accuracy: 0.7787
Epoch 27/50
782/782 [-----] - 8s 10ms/step - loss: 0.8607 - accuracy: 0.7029 - val_loss: 0.6667 - val_accuracy: 0.7718
Epoch 28/50
782/782 [-----] - 8s 10ms/step - loss: 0.8566 - accuracy: 0.7042 - val_loss: 0.9124 - val_accuracy: 0.6964
Epoch 29/50
782/782 [-----] - 8s 10ms/step - loss: 0.8437 - accuracy: 0.7090 - val_loss: 0.8672 - val_accuracy: 0.7086
Epoch 30/50
782/782 [-----] - 8s 10ms/step - loss: 0.8392 - accuracy: 0.7103 - val_loss: 0.9366 - val_accuracy: 0.7019
Epoch 31/50
782/782 [-----] - 8s 10ms/step - loss: 0.8424 - accuracy: 0.7087 - val_loss: 1.0572 - val_accuracy: 0.6695
Epoch 32/50
782/782 [-----] - 8s 10ms/step - loss: 0.8330 - accuracy: 0.7139 - val_loss: 0.6269 - val_accuracy: 0.7774
Epoch 33/50
782/782 [-----] - 8s 10ms/step - loss: 0.8249 - accuracy: 0.7154 - val_loss: 0.7559 - val_accuracy: 0.7421
Epoch 34/50
782/782 [-----] - 8s 10ms/step - loss: 0.8212 - accuracy: 0.7170 - val_loss: 0.7322 - val_accuracy: 0.7652
Epoch 35/50
782/782 [-----] - 8s 10ms/step - loss: 0.8203 - accuracy: 0.7150 - val_loss: 0.6736 - val_accuracy: 0.7731
Epoch 36/50
782/782 [-----] - 8s 10ms/step - loss: 0.8122 - accuracy: 0.7168 - val_loss: 0.7035 - val_accuracy: 0.7571
Epoch 37/50
782/782 [-----] - 8s 10ms/step - loss: 0.8119 - accuracy: 0.7190 - val_loss: 0.7681 - val_accuracy: 0.7362
Epoch 38/50
782/782 [-----] - 8s 10ms/step - loss: 0.8110 - accuracy: 0.7208 - val_loss: 0.6677 - val_accuracy: 0.7793
Epoch 39/50
782/782 [-----] - 8s 10ms/step - loss: 0.8067 - accuracy: 0.7226 - val_loss: 0.7138 - val_accuracy: 0.7646
Epoch 40/50
782/782 [-----] - 8s 10ms/step - loss: 0.7955 - accuracy: 0.7246 - val_loss: 0.6804 - val_accuracy: 0.7664
Epoch 41/50
782/782 [-----] - 8s 10ms/step - loss: 0.8003 - accuracy: 0.7242 - val_loss: 0.7772 - val_accuracy: 0.7469
Epoch 42/50
782/782 [-----] - 8s 10ms/step - loss: 0.8035 - accuracy: 0.7248 - val_loss: 0.6394 - val_accuracy: 0.7824
Epoch 43/50
782/782 [-----] - 8s 10ms/step - loss: 0.7888 - accuracy: 0.7269 - val_loss: 1.0327 - val_accuracy: 0.6610
Epoch 44/50
782/782 [-----] - 8s 10ms/step - loss: 0.7910 - accuracy: 0.7277 - val_loss: 0.6738 - val_accuracy: 0.7769
Epoch 45/50
782/782 [-----] - 8s 10ms/step - loss: 0.7865 - accuracy: 0.7287 - val_loss: 0.6369 - val_accuracy: 0.7837
Epoch 46/50
782/782 [-----] - 8s 11ms/step - loss: 0.7888 - accuracy: 0.7300 - val_loss: 0.7020 - val_accuracy: 0.7603
Epoch 47/50
782/782 [-----] - 8s 10ms/step - loss: 0.7801 - accuracy: 0.7324 - val_loss: 0.9720 - val_accuracy: 0.6883
Epoch 48/50
782/782 [-----] - 8s 10ms/step - loss: 0.7782 - accuracy: 0.7323 - val_loss: 0.6557 - val_accuracy: 0.7800
Epoch 49/50
782/782 [-----] - 8s 10ms/step - loss: 0.7811 - accuracy: 0.7323 - val_loss: 0.6618 - val_accuracy: 0.7726
Epoch 50/50
782/782 [-----] - 8s 10ms/step - loss: 0.7736 - accuracy: 0.7347 - val_loss: 0.7895 - val_accuracy: 0.7448
Test loss: 0.789471626817383
Test accuracy: 0.7448999733890504
```

Results with 16 batch size: Batch size has an impact on the accuracy of the model by controlling the estimate of error in gradient descent. Lower batch size implies the weights will be updated several times in each epoch. A smaller batch size with a low learning rate works better on most of the scenarios. The results obtained with the batch size of 16 were as follows:

Test Accuracy: 82.62%

Test Loss: 0.6175

```
[56] x_batch_size = 64
batch_size = 16
num_classes = 10
epochs = 50

[57] x = input_image_dimensions
img_rows, img_cols = 28, 28
# Use the data to split between train and test sets
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
if K.image_data_format() == 'channels_first':
    x_train = x_train.reshape(x_train.shape[0], 3, img_rows, img_cols)
    x_test = x_test.reshape(x_test.shape[0], 3, img_rows, img_cols)
    input_shape = (3, img_rows, img_cols)
else:
    x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 3)
    x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 3)
    input_shape = (img_rows, img_cols, 3)

[58] x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
x_test /= 255
print(x_train.shape, x_train.shape)
print(x_test.shape[0], 'Testing samples')

# convert class vectors to binary class matrices
y_train = to_categorical(y_train, num_classes)
y_test = to_categorical(y_test, num_classes)

x_train_shape = (50000, 28, 28, 3)
50000 training samples
10000 testing samples

[59] model = Sequential()
model.add(Conv2D(filters = 32, kernel_size = (3,3), padding='same', input_shape = input_shape))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 32, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.2))
# model.add(Dropout(0.2))

model.add(Conv2D(filters = 64, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 64, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.2))
# model.add(Dropout(0.2))

model.add(Conv2D(filters = 128, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 128, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.4))
# model.add(Dropout(0.4))

model.add(Flatten())
model.add(Dense(units = 10, activation = 'softmax'))

[60] # https://keras.io/optimizers/
model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.01), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.RMSprop(lr=0.01), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adadelta(lr=0.0001), metrics=['accuracy'])

[61] model.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, verbose=1, validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

Epoch 23/50
1325/1325 [-----] - 19s 6ms/step - loss: 0.5042 - accuracy: 0.8175 - val_loss: 0.6410 - val_accuracy: 0.8084
Epoch 24/50
1325/1325 [-----] - 19s 6ms/step - loss: 0.5064 - accuracy: 0.8198 - val_loss: 0.5782 - val_accuracy: 0.8248
Epoch 25/50
1325/1325 [-----] - 19s 6ms/step - loss: 0.5515 - accuracy: 0.8201 - val_loss: 0.5950 - val_accuracy: 0.8214
Epoch 26/50
1325/1325 [-----] - 19s 6ms/step - loss: 0.5430 - accuracy: 0.8221 - val_loss: 0.5586 - val_accuracy: 0.8369
Epoch 27/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.5444 - accuracy: 0.8228 - val_loss: 0.5620 - val_accuracy: 0.8245
Epoch 28/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.5152 - accuracy: 0.8272 - val_loss: 0.5449 - val_accuracy: 0.8300
Epoch 29/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.5216 - accuracy: 0.8310 - val_loss: 0.5680 - val_accuracy: 0.8368
Epoch 30/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.5224 - accuracy: 0.8318 - val_loss: 0.6098 - val_accuracy: 0.8167
Epoch 31/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.5173 - accuracy: 0.8326 - val_loss: 0.5979 - val_accuracy: 0.8233
Epoch 32/50
1325/1325 [-----] - 19s 6ms/step - loss: 0.5104 - accuracy: 0.8363 - val_loss: 0.5944 - val_accuracy: 0.8245
Epoch 33/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.5060 - accuracy: 0.8377 - val_loss: 0.5880 - val_accuracy: 0.8229
Epoch 34/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.5075 - accuracy: 0.8357 - val_loss: 0.5845 - val_accuracy: 0.8211
Epoch 35/50
1325/1325 [-----] - 19s 6ms/step - loss: 0.5021 - accuracy: 0.8382 - val_loss: 0.5725 - val_accuracy: 0.8319
Epoch 36/50
1325/1325 [-----] - 19s 6ms/step - loss: 0.4931 - accuracy: 0.8410 - val_loss: 0.5642 - val_accuracy: 0.8258
Epoch 37/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.4910 - accuracy: 0.8446 - val_loss: 0.5705 - val_accuracy: 0.8195
Epoch 38/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.4881 - accuracy: 0.8450 - val_loss: 0.5708 - val_accuracy: 0.8247
Epoch 39/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.4812 - accuracy: 0.8457 - val_loss: 0.5978 - val_accuracy: 0.8101
Epoch 40/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.4801 - accuracy: 0.8475 - val_loss: 0.5529 - val_accuracy: 0.8426
Epoch 41/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.4750 - accuracy: 0.8491 - val_loss: 0.6176 - val_accuracy: 0.8271
Epoch 42/50
1325/1325 [-----] - 19s 6ms/step - loss: 0.4764 - accuracy: 0.8510 - val_loss: 0.5852 - val_accuracy: 0.8352
Epoch 43/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.4791 - accuracy: 0.8476 - val_loss: 0.5450 - val_accuracy: 0.8446
Epoch 44/50
1325/1325 [-----] - 17s 6ms/step - loss: 0.4657 - accuracy: 0.8504 - val_loss: 0.5802 - val_accuracy: 0.8386
Epoch 45/50
1325/1325 [-----] - 17s 6ms/step - loss: 0.4670 - accuracy: 0.8517 - val_loss: 0.6211 - val_accuracy: 0.8244
Epoch 46/50
1325/1325 [-----] - 17s 6ms/step - loss: 0.4633 - accuracy: 0.8511 - val_loss: 0.5654 - val_accuracy: 0.8403
Epoch 47/50
1325/1325 [-----] - 19s 6ms/step - loss: 0.4607 - accuracy: 0.8537 - val_loss: 0.6170 - val_accuracy: 0.8321
Epoch 48/50
1325/1325 [-----] - 18s 6ms/step - loss: 0.4599 - accuracy: 0.8528 - val_loss: 0.6263 - val_accuracy: 0.8226
Epoch 49/50
1325/1325 [-----] - 17s 6ms/step - loss: 0.4495 - accuracy: 0.8560 - val_loss: 0.6247 - val_accuracy: 0.8271
Epoch 50/50
1325/1325 [-----] - 19s 6ms/step - loss: 0.4575 - accuracy: 0.8562 - val_loss: 0.6175 - val_accuracy: 0.8262
Test loss: 0.6175/0.6175
Test accuracy: 0.8262/0.8262
```

Results with 256 batch size: Batch size has an impact on the accuracy of the model by controlling the estimate of error in gradient descent. Higher batch size implies the weights will be updated lesser number of times in each epoch. A larger batch size with a high learning rate generally works together. The results obtained with the batch size of 256 were as follows:

Test Accuracy: 83.25%

Test Loss: 0.5727

```

batch_size = 32
batch_size = 256
num_classes = 10
epochs = 50

# Input image dimensions
img_rows, img_cols = 32, 32
# Use data, split into train and test sets
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
# Image data format() == 'channels_first'
x_train = x_train.reshape(x_train.shape[0], 3, img_rows, img_cols)
x_test = x_test.reshape(x_test.shape[0], 3, img_rows, img_cols)
input_shape = (3, img_rows, img_cols)
else:
    x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 3)
    x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 3)
    input_shape = (img_rows, img_cols, 3)

x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
x_test /= 255
print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'training samples')
print(x_test.shape[0], 'testing samples')

# Convert class vectors to binary class matrices
y_train = to_categorical(y_train, num_classes)
y_test = to_categorical(y_test, num_classes)

x_train_shape = (50000, 32, 32, 3)
25000 training samples
10000 testing samples

model = Sequential()
model.add(Conv2D(filters = 32, kernel_size = (3,3), padding='same', input_shape = input_shape))
model.add(Activation('relu'))
model.add(Conv2D(filters = 32, kernel_size = (7,7), padding='same', input_shape = input_shape))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 32, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.2))
model.add(Dropout(0.2))

model.add(Conv2D(filters = 64, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 64, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.3))
model.add(Dropout(0.3))

model.add(Conv2D(filters = 128, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 128, kernel_size = (3,3), padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.4))
model.add(Dropout(0.4))

model.add(Flatatten())
model.add(Dense(units = 10, activation = 'softmax'))

# Compile loss, optimizer, metrics
model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.01), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.001), metrics=['accuracy'])
# model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(lr=0.0001), metrics=['accuracy'])

model.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, verbose=1, validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

Epoch 23/50 | 6s 30ms/step | loss: 0.4494 | accuracy: 0.8407 | val_loss: 0.6727 | val_accuracy: 0.7808
Epoch 24/50 | 6s 20ms/step | loss: 0.4398 | accuracy: 0.8465 | val_loss: 0.6549 | val_accuracy: 0.7959
Epoch 25/50 | 6s 20ms/step | loss: 0.4245 | accuracy: 0.8511 | val_loss: 0.6401 | val_accuracy: 0.7948
Epoch 26/50 | 6s 18ms/step | loss: 0.4275 | accuracy: 0.8511 | val_loss: 0.5549 | val_accuracy: 0.8179
Epoch 27/50 | 6s 30ms/step | loss: 0.4151 | accuracy: 0.8539 | val_loss: 0.5558 | val_accuracy: 0.8183
Epoch 28/50 | 6s 18ms/step | loss: 0.4010 | accuracy: 0.8588 | val_loss: 0.5596 | val_accuracy: 0.8205
Epoch 29/50 | 6s 30ms/step | loss: 0.3987 | accuracy: 0.8588 | val_loss: 0.6044 | val_accuracy: 0.8110
Epoch 30/50 | 6s 18ms/step | loss: 0.3915 | accuracy: 0.8612 | val_loss: 0.5260 | val_accuracy: 0.8294
Epoch 31/50 | 6s 20ms/step | loss: 0.3767 | accuracy: 0.8670 | val_loss: 0.6708 | val_accuracy: 0.8061
Epoch 32/50 | 6s 30ms/step | loss: 0.3714 | accuracy: 0.8687 | val_loss: 0.6285 | val_accuracy: 0.8114
Epoch 33/50 | 6s 30ms/step | loss: 0.3686 | accuracy: 0.8704 | val_loss: 0.6222 | val_accuracy: 0.8166
Epoch 34/50 | 6s 20ms/step | loss: 0.3614 | accuracy: 0.8719 | val_loss: 0.6170 | val_accuracy: 0.8118
Epoch 35/50 | 6s 18ms/step | loss: 0.3501 | accuracy: 0.8755 | val_loss: 0.7147 | val_accuracy: 0.7901
Epoch 36/50 | 6s 30ms/step | loss: 0.3480 | accuracy: 0.8760 | val_loss: 0.5864 | val_accuracy: 0.8209
Epoch 37/50 | 6s 18ms/step | loss: 0.3431 | accuracy: 0.8761 | val_loss: 0.6202 | val_accuracy: 0.8115
Epoch 38/50 | 6s 20ms/step | loss: 0.3407 | accuracy: 0.8812 | val_loss: 0.6215 | val_accuracy: 0.8146
Epoch 39/50 | 6s 18ms/step | loss: 0.3314 | accuracy: 0.8821 | val_loss: 0.6085 | val_accuracy: 0.8188
Epoch 40/50 | 6s 20ms/step | loss: 0.3292 | accuracy: 0.8829 | val_loss: 0.6130 | val_accuracy: 0.8255
Epoch 41/50 | 6s 30ms/step | loss: 0.3167 | accuracy: 0.8875 | val_loss: 0.7196 | val_accuracy: 0.7992
Epoch 42/50 | 6s 30ms/step | loss: 0.3162 | accuracy: 0.8877 | val_loss: 0.5568 | val_accuracy: 0.8375
Epoch 43/50 | 6s 18ms/step | loss: 0.3121 | accuracy: 0.8890 | val_loss: 0.5680 | val_accuracy: 0.8424
Epoch 44/50 | 6s 18ms/step | loss: 0.3063 | accuracy: 0.8912 | val_loss: 0.5917 | val_accuracy: 0.8378
Epoch 45/50 | 6s 20ms/step | loss: 0.2964 | accuracy: 0.8952 | val_loss: 0.5581 | val_accuracy: 0.8370
Epoch 46/50 | 6s 18ms/step | loss: 0.2909 | accuracy: 0.8917 | val_loss: 0.6610 | val_accuracy: 0.8192
Epoch 47/50 | 6s 18ms/step | loss: 0.2907 | accuracy: 0.8967 | val_loss: 0.6140 | val_accuracy: 0.8091
Epoch 48/50 | 6s 30ms/step | loss: 0.2906 | accuracy: 0.8975 | val_loss: 0.6191 | val_accuracy: 0.8250
Epoch 49/50 | 6s 20ms/step | loss: 0.2892 | accuracy: 0.8973 | val_loss: 0.5550 | val_accuracy: 0.8359
Epoch 50/50 | 6s 20ms/step | loss: 0.2801 | accuracy: 0.9002 | val_loss: 0.5727 | val_accuracy: 0.8323
Test loss: 0.572666195373532
Test accuracy: 0.8325000000000001

```

CONCLUSION

This project was aimed at learning about Convolutional Neural Network and Hyperparameter tuning of the neural network to enhance accuracy. Key learning from the project was on how to build a convolutional neural network to perform image classification using Keras framework. It was observed on how the model's accuracy varies with various parameters. It was also learnt what parameters to be used in a particular use case and how to tune those parameters to achieve better results.