Project (Part 2):

Task 1

Introduction

In this task, we aim to implement a 3 layer MLP from scratch without using any in-built libraries. We have chosen sigmoid function as our activation function and used Mean Square Error (MSE) as an estimate for loss. Batch backpropagation has been used in the learning stage with a learning rate of 2. In this experiment we will be discussing the reasons for choosing all the parameters, along with the flow of the code and analysis of the result.

Method of Implementation

A series of steps were followed in order for us to achieve what we needed. We will be going through them in a step-by-step approach.

Step 1: Loading the data from the MATLAB files

In this step, we first loaded the data into our python environment and stored it in the form of a list. We did this to both the training and testing datasets.

We then split the data into training and validation sets using a 75-25 split. Our training data originally had 2000 values in it. We used 1500 for the training set and 500 for the validation set. Since we have two sets of training and validation datasets for each class, we combine the training and validation sets into one using “np.vstack” which vertically stacks our data after combining two lists. We repeat the same for the testing set too.

Thus, we have X_train, X_test, X_val, y_val, y_train and y_test as our data within the python environment. We will work on this data throughout our project.

Step 2: Normalizing the data

We have to normalize the data that we have extracted from the matlab files. Normalization helps in equal scaling of features so that larger values cannot dominate the principal components, thereby ensuring equal contribution of each feature to the PCA. It also centers the data around 0, so that consistency is maintained in the calculation of covariance matrix and PCA captures directions of maximum variance with proper accuracy.

In order to achieve normalized data, we define a normalization function which takes X_train, X_test and X_val as its arguments and normalizes them into new variables X_train_norm, X_test_norm and X_val_norm respectively.

After normalization, we update our current data, that is, the data which we are going to be using to pass into the model.

Step 3: Designing the MLP

The design process of the MLP takes place in a step-by-step fashion.

1. **Defining the activation function and its derivative.**

   We have used sigmoid function as our activation function in both the hidden and the output layers. It is commonly used in neural networks because of its non-linear properties, particularly when dealing with binary classification problems.

   The sigmoid function outputs values in the range of 0 to 1. This makes it particularly suitable for binary classification, where we need the output as a probability for a given class. In our case, that would be either class 0 or class 1.

$$\text{Sigmoid}(z) = \frac{1}{1+e^{-z}} \qquad \text{Derivative of sigmoid}: \frac{dA}{dz} = A \cdot (1-A)$$

Fig 1: Sigmoid Function and its derivative (A is the output from the sigmoid)

   Non-linear functionality is crucial in neural networks to identify complex patterns in the data. The sigmoid function does just this by allowing the network to capture non-linear relationships between features. Our data seems to have a considerable amount of non-linearity in it and the sigmoid function will be useful in identifying it.

   Sigmoid is differentiable, and its gradient is well-defined. The derivative of the sigmoid function is used in our project to implement updation of weights during backpropagation. The derivative "A(1-A)" scales the error signal at each layer, ensuring the update is proportional to the activation's contribution to the error.

2. **Initializing the weights and the bias.**

   Initializing weights is an important prerequisite for model building. The selection of weights is crucial as weights that are too high may lead to a vanishing gradient and weights that are too low may lead to an exploding gradient.

   In our project we have initialized the weights using a Gaussian distribution (as shown in the figure below).

$$W \sim \mathcal{N}(0, 0.01^2)$$

   Fig 2: A normal distribution with a mean of 0 and a standard deviation of 0.01

   We have used a small variance of 0.01 so that the network starts with small random weights because high weights can lead to the destabilization of the training process.

   Biases allow the activation function to shift, enabling the network to better fit the data. Without biases, all layers would pass through the origin (0,0), which will limit the model's ability to learn complex patterns.

   We have initialized bias to 0 in our project since they will be adjusted during training. We have used "np.random.seed" to ensure that random numbers are generated every time the code runs. This ensures consistency.

3. **Forward Passing and Back Propagation.**

The **forward pass** is the step where input data is passed through the network to make predictions. For this we define a function “forward_pass” which takes X, W1, b1, W2 and b2 as its parameters.

We first perform linear transformation for the Hidden Layer which is given by Z1 in our code. Our input data (given by X) has a shape (m, input_size), where m is the number of samples. We are using W1 as our weight matrix for the input to hidden layer computation. Bias is given by the “b1” vector for the hidden layer and the result Z1 is obtained by linear combination of inputs, weights and bias. Z1 is the net-activation we get before applying the actual activation function which, in our case, is the sigmoid function. We get output A1 after applying the activation function.

After we get an output from the hidden layer, we perform linear transformation on it again using different sets of weights (W2) and bias (B2) for the hidden to output layer transition. Z2 represents the weighted sum of the hidden layer output before applying the activation function to get the final output. For our final output, we get A2 which gives the predicted probability for each class.

The **backward pass** computes the gradients of the loss function with respect to the weights and biases, using the chain rule of calculus. For this we define a function “ backpropagation” which takes X, Y, Z1, A1, Z2, A2, W1 and W2 as its parameters.

We are using Batch backpropagation method which computes the error at the very end of neural network processing and then implements it into the network to update the weights.

We first calculate the gradient for the output Layer which is given by variable dZ2. We use A2 which is the predicted output we got from the forward pass and Y which is the actual target label to calculate dZ2 which is the error term for the output layer, representing how much the output layer’s predictions differ from the actual values. .

We compute the gradients of W1 and W2 which is the derivative of the loss with respect to W1 and W2 respectively. They tell us how much the weights of the input, hidden and output layer should be adjusted to reduce the error. They are given by dW1 and dW2 respectively.

Similarly we also calculate the gradient of biases “b1” and “b2”. The gradient of b1 is the sum of the errors in the hidden layer and the gradient of b2 is the sum of the errors in the output layer, averaged over all training samples.

Additionally, we calculate the gradient for the hidden layer which is given by dZ1. The error term for the hidden layer, dZ1, is computed by back-propagating the error from the output layer through the hidden layer weights (W2).

The forward and backward pass algorithms work together to improve the performance of the model by updating the weights.

4. **Defining the training and testing functions.**

We use the **training function** for executing the process of training the neural network, which involves the forward pass, backward pass, and updating the parameters (weights and biases) to minimize the error (loss). It iterates over the training data multiple times (in the form of epochs), performing these steps and adjusting the parameters to improve the model's predictions. We define the function as "train" which takes X_train, y_train, X_val, y_val, nH, learning_rate and max_epochs as the parameters.

In our project, we are taking the learning rate as 2 and max_epochs as 1000(which means it will iterate for a maximum of 1000 times).

We first initialize the weights and biases using the function "initialize_weights" which takes input_size, hidden_size and output_size as the parameters.

Our function iterates through the number of epochs (meaning iterations). In each epoch it does the following operations

- **Forward Pass**: It calculates the predictions using the current weights and biases. This includes computing the intermediate outputs and applying activation functions.We use the function "forward_pass" as discussed above and Z1, A1, Z2, A2 are the values that we get from the function.
- **Calculating losses**: We calculate the Mean Squared Error (MSE) to check how well the network is performing on the training set.
- **Backward Pass (Backpropagation)**: The gradients of the loss with respect to the weights and biases are computed using backpropagation. This tells the model how to adjust the weights to reduce the loss. We use the function "backpropagation" as discussed above and dW1, db1, dW2, db2 are the values we get from which we will use for updating the weights.
- **Weight Updation**: We update the weights and biases using **gradient descent**, where each parameter is adjusted by subtracting the product of the gradient and the learning rate.

After we update the weights for the training set, we perform a forward pass on the validation data. We do this to check how well the model is generalizing. The validation loss is also tracked so that we can monitor overfitting.

Finally, the function returns the final weights and biases, along with the loss values for each epoch. We use these for visual analysis, that is, plotting the learning curves.

We use the **testing function** for evaluating the performance of the network on unseen data by seeing how well the model adjusts to new data by applying the trained weights and biases and calculating the accuracy and loss. We define a function "test" which takes X_test, y_test, W1, b1, W2 and b2 as its parameters.

The function starts by performing a forward pass using the trained weights (given by W1, W2) and biases (given by b1, b2). The output of the forward pass is the predicted values (A2_test), which are the network's raw output for the test set representing the probability

that each sample belongs to class 1. We keep a **threshold** of 0.5 using which we decide whether to classify it as class 0 or class 1 by converting probabilities greater than or equal to 0.5 to class 1, and those less than 0.5 to class 0.

We compute the **accuracy by comparing** the predictions to the true labels (given by y_test).

We calculate the loss to quantify how far off the predictions are from the actual values. In this case, we use Mean Squared Error (MSE), which is calculated as the difference between the predicted probabilities (given by A2_test) and the actual labels (given by y_test).

The function returns the accuracy and loss as its return values which we use to plot our visual representation of the problem.

Step 4: Putting it all together.

In the main function, we run the model for all values of nH. “nH” tells us the number of hidden layers we are using in the network.

The flow of the **main** function is given as follows:

- The load_data() function loads training, validation, and test datasets.
- We normalize the data by calling normalize_data() which standardizes the input features (X_train, X_val, X_test).
- Iterate Over Different nH Values:
    - For each configuration of hidden nodes (nH = 2, 4, 6, 8, 10), the model parameters (W1, b1, W2, b2) are initialized.
    - The model is trained using the train() function, and the training and validation losses are computed.
- After training, the model is tested on the test data, and the accuracy and loss are recorded.
- We plot the learning curves for training and validation losses for each value of nH.
- Report Results: The best test accuracy and the corresponding number of hidden units (nH) are printed.

Results And Observations

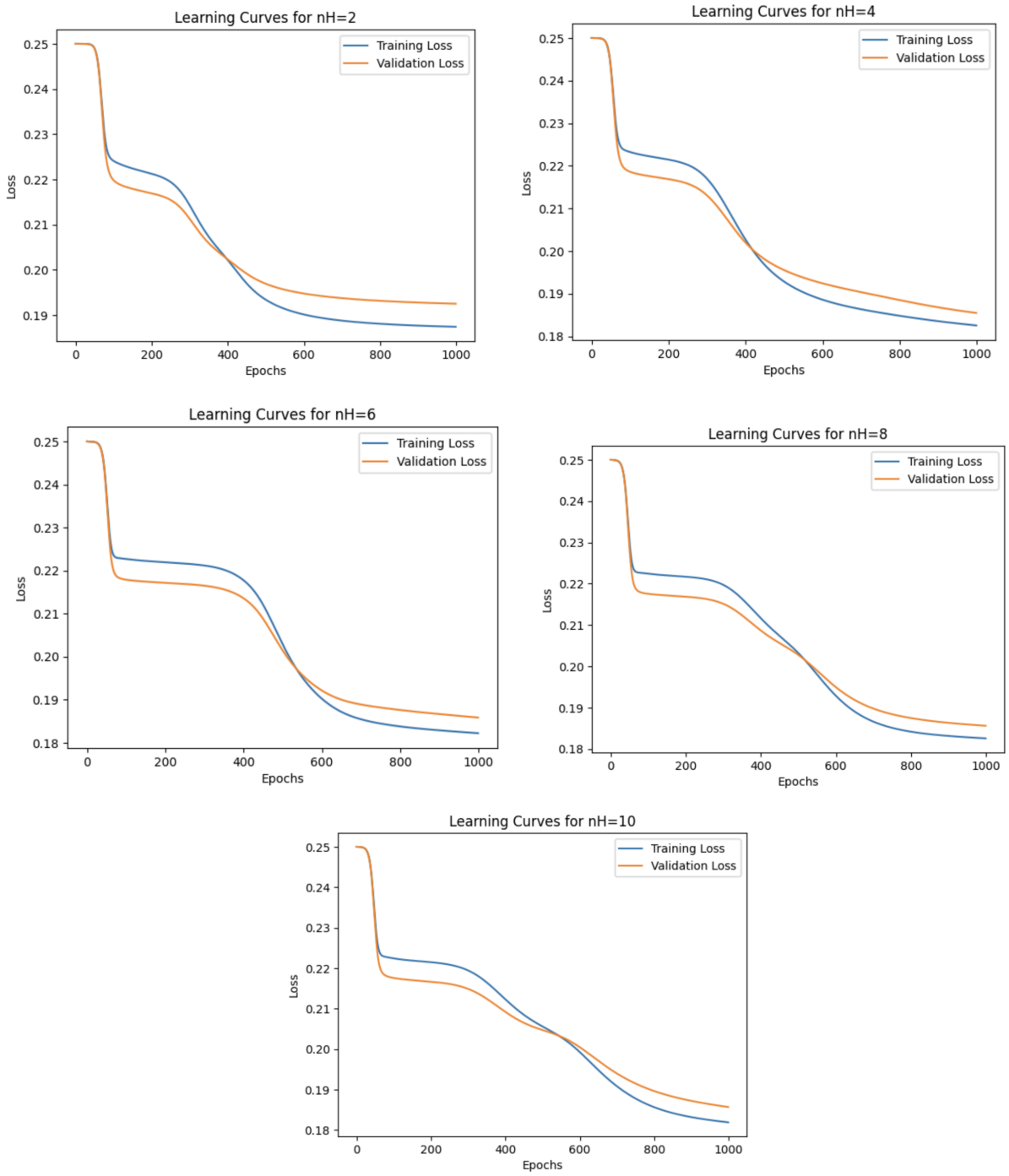

Fig 3: Distribution of learning curves for each value of nH (2,4,6,8,10)

From the above learning curves we can derive the following:

1. As we can see, the training and validation losses decrease consistently for all values of nH. This shows us that the model is learning effectively during training. Ideally, the loss

should decrease as the network constantly keeps learning from its mistakes. This is what backpropagation does in order to make the network more efficient.

2. We see that the training and validation losses converge well across all nH values, with minimal overfitting. We can notice that the gap between training and validation losses is small. This generally means that our model is good at generalization.
3. The biggest change we can notice is that for smaller values of nH, that is, 2 and 4 the network reduces the loss but is not able to identify complex patterns. This is something that higher values of nH do better. For example, we see that for nH = 8, we see that the learning curve has become smoother. This shows us that networks with higher capacity model the data better.
4. We also notice that contrary to the belief that increasing nH will give less losses, the curve for nH = 8 and nH = 10 show similar behaviour. This tells us that nH has reached its optimal value and that increasing it beyond this point is not going to increase our model accuracy.

```
Out of all the nH, the value with the best accuracy is nH = 8 with
accuracy: 0.728
```

This is the output we get at the end of the code execution. This shows that we are getting the most accuracy when there are 8 hidden layers in our neural network.

Conclusion

We have built a 3 layer MLP which classifies the data with a maximum accuracy of 72.8%. From this task we conclude that increasing nH (the number of hidden layers) improves the network's learning capacity but only up to a certain point. Beyond that, the performance of the network stabilizes. This suggests an optimal range of nH around 6–8 for this task.

Task 2

Introduction

In this task, we perform the classification task, using a convolutional neural network (CNN). The dataset which we are using is the CIFAR-10 dataset. We perform experiments on the data by changing the parameters and observing how it affects the accuracy.

The CIFAR-10 dataset is a widely used benchmark dataset in machine learning and computer vision. It is designed for image classification tasks and consists of the following features:

The dataset contains 60,000 color images divided into 10 classes. Each image is labeled as one of the following categories: airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck. Each image has a resolution of 32x32 pixels and consists of 3 color channels (RGB). The dataset is split into 50,000 training images and 10,000 testing images.

We will be looking at the flow of implementation of our CNN and analyse our results.

Method of Implementation

Step 1: Import the necessary and identify the GPU

First, we import all the necessary libraries. Since this is a computationally expensive task, we need to make sure that we are using the highest quality of GPU available on Google Colab.

Step 2: Loading, Normalizing and Encoding the Data

In this step we load the CIFAR-10 dataset from the library. We then scale the pixel values to the range of 0 to 1 in order to make sure that it's uniform and easier for the model to process.

Encoding is an important step so as to match the softmax function that we are using in the output layer. We use the “one-hot” encoding technique to convert the data into categorical variables which can be processed by the model easily.

Step 3: Creating the Convolutional Neural Network

Our first step involves adding a **2D convolutional layer** to the model using the Keras API. We define a “create_model” function for this purpose which takes kernel size and whether to use batch normalization or not as its two parameters.

We start off by using the “model.add()” line to add a layer to the neural network. “Conv2D” takes the form “Conv2D(32, kernel_size_first_layer, padding='same', input_shape=(32, 32, 3))”.

This is a 2D convolutional layer that applies convolution operations to the input data.

We use 32 filters and each filter learns a feature map during training. It also captures different patterns and features from the image.

We then specify the kernel size which provides the dimensions of the convolutional filter. By default we set it to (3,3) which means that it is a 3x3 kernel.

We also need to ensure that the output feature map has the same width and height as the input by adding zero-padding around the borders of the input image. Additionally, we define the shape of the input images to this layer and the width and height of the input image which is 32x32x3.
We then apply a **ReLU** Activation function to the model in order to introduce non-linearity to the dataset. This helps the model to learn complex features better.

$$f(x) = \begin{cases} x & \text{if } x > 0, \\ 0 & \text{if } x \leq 0. \end{cases}$$

Fig 4: Mathematical representation of the ReLU activation function

Through **batch-normalization** we normalize the activation function which stabilizes learning for the model.

We use **max-pooling** to reduce the spatial dimensions of the feature map in order to increase the computational efficiency.

Next, we add all the **convolutional blocks** according to the requirements. It has 12 layers with each layer performing a specific function (like **Max-pooling** and **Convolution**) with varying size of batches and kernel sizes.

For the purpose of probability distribution, we map extracted features to 10 output classes.

At the end, the model is returned as a return value after being created and modified successfully.

Step 4: Training and Evaluating the model
We define a function "train_and_evaluate" which takes "model", "learning_rate", "batch_size" and "epochs" as parameters. We will change these parameters and observe the different values of accuracy. We have used 20 epochs, which means that the network will iterate 20 times to perform the classification. We have assigned a fixed value of "0.001" to the learning rate and "32" to the batch size. Theoretically, having more epochs, low learning rate and lesser batch size will increase the accuracy. Now, we see how we execute the model.
First, we use the **Adam** optimizer to compile the model. Then, we fit the model for the specified number of epochs and evaluate the test set after each iteration.
Finally, we evaluate the final test accuracy and test loss.

Step 5: Performing experiments
We then perform the 7 experiments as required, changing different parameters like batch-size, learning rate, kernel size and removing batch-normalization and print the accuracy obtained in each experiment.

Results and Observations

Result from Colab notebook:

```
Baseline Model
Epoch 1/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 24s 10ms/step - accuracy:
0.3792 - loss: 2.2063 - val_accuracy: 0.5545 - val_loss: 1.2651
Epoch 2/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 29s 6ms/step - accuracy:
0.6285 - loss: 1.0875 - val_accuracy: 0.6856 - val_loss: 0.9258
Epoch 3/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.7108 - loss: 0.8358 - val_accuracy: 0.7090 - val_loss: 0.8530
Epoch 4/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.7542 - loss: 0.7091 - val_accuracy: 0.7708 - val_loss: 0.6637
Epoch 5/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.7770 - loss: 0.6391 - val_accuracy: 0.7965 - val_loss: 0.5927
Epoch 6/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy:
0.8036 - loss: 0.5690 - val_accuracy: 0.7924 - val_loss: 0.6161
Epoch 7/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy:
0.8188 - loss: 0.5216 - val_accuracy: 0.7947 - val_loss: 0.6082
Epoch 8/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.8313 - loss: 0.4822 - val_accuracy: 0.8204 - val_loss: 0.5136
Epoch 9/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy:
0.8423 - loss: 0.4507 - val_accuracy: 0.8144 - val_loss: 0.5430
Epoch 10/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.8516 - loss: 0.4278 - val_accuracy: 0.8321 - val_loss: 0.5017
Epoch 11/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.8603 - loss: 0.3986 - val_accuracy: 0.8187 - val_loss: 0.5345
Epoch 12/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.8651 - loss: 0.3813 - val_accuracy: 0.8315 - val_loss: 0.5132
Epoch 13/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.8741 - loss: 0.3580 - val_accuracy: 0.8352 - val_loss: 0.4912
Epoch 14/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy:
0.8785 - loss: 0.3431 - val_accuracy: 0.8296 - val_loss: 0.5155
Epoch 15/20
```

```
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.8859 - loss: 0.3226 - val_accuracy: 0.8323 - val_loss: 0.5003
Epoch 16/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.8875 - loss: 0.3142 - val_accuracy: 0.8384 - val_loss: 0.4974
Epoch 17/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.8919 - loss: 0.3017 - val_accuracy: 0.8433 - val_loss: 0.4895
Epoch 18/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.8944 - loss: 0.2944 - val_accuracy: 0.8443 - val_loss: 0.4869
Epoch 19/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.9021 - loss: 0.2742 - val_accuracy: 0.8420 - val_loss: 0.4976
Epoch 20/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.9028 - loss: 0.2744 - val_accuracy: 0.8524 - val_loss: 0.4706
Test Accuracy: 0.8524

Experiment 2: Learning Rate 0.05
Epoch 1/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 22s 9ms/step - accuracy:
0.2295 - loss: 4.3872 - val_accuracy: 0.1790 - val_loss: 4.9360
Epoch 2/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 6ms/step - accuracy:
0.2954 - loss: 2.3020 - val_accuracy: 0.3766 - val_loss: 2.1130
Epoch 3/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.4180 - loss: 2.0588 - val_accuracy: 0.5257 - val_loss: 1.6949
Epoch 4/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.4801 - loss: 2.0380 - val_accuracy: 0.6210 - val_loss: 1.3473
Epoch 5/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy:
0.5401 - loss: 1.8815 - val_accuracy: 0.5769 - val_loss: 1.7298
Epoch 6/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.5572 - loss: 1.9634 - val_accuracy: 0.6563 - val_loss: 1.3791
Epoch 7/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.5947 - loss: 1.8144 - val_accuracy: 0.6348 - val_loss: 1.5191
Epoch 8/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.6118 - loss: 1.8834 - val_accuracy: 0.6528 - val_loss: 1.5567
Epoch 9/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy:
0.6302 - loss: 1.8262 - val_accuracy: 0.6798 - val_loss: 1.3776
```

```
Epoch 10/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.6401 - loss: 1.8247 - val_accuracy: 0.6805 - val_loss: 1.5085
Epoch 11/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 6ms/step - accuracy:
0.6528 - loss: 1.8347 - val_accuracy: 0.6341 - val_loss: 1.6857
Epoch 12/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.6599 - loss: 1.8738 - val_accuracy: 0.6675 - val_loss: 2.0688
Epoch 13/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.6743 - loss: 1.8772 - val_accuracy: 0.6926 - val_loss: 1.9810
Epoch 14/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.6820 - loss: 1.9647 - val_accuracy: 0.7289 - val_loss: 1.6564
Epoch 15/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.6960 - loss: 1.8119 - val_accuracy: 0.6839 - val_loss: 1.8473
Epoch 16/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.6966 - loss: 1.8696 - val_accuracy: 0.7008 - val_loss: 2.0788
Epoch 17/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.6989 - loss: 1.9745 - val_accuracy: 0.6330 - val_loss: 2.2306
Epoch 18/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 6ms/step - accuracy:
0.7041 - loss: 1.8651 - val_accuracy: 0.6188 - val_loss: 3.2834
Epoch 19/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.7087 - loss: 2.0068 - val_accuracy: 0.7152 - val_loss: 2.1546
Epoch 20/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.7152 - loss: 1.8978 - val_accuracy: 0.7799 - val_loss: 1.3210
Test Accuracy: 0.7799

Experiment 3: Learning Rate 0.0001
Epoch 1/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 21s 9ms/step - accuracy:
0.2727 - loss: 2.8616 - val_accuracy: 0.4717 - val_loss: 1.4873
Epoch 2/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.4495 - loss: 1.7261 - val_accuracy: 0.5217 - val_loss: 1.3761
Epoch 3/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.5319 - loss: 1.4078 - val_accuracy: 0.6088 - val_loss: 1.1240
Epoch 4/20
```

```
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.5933 - loss: 1.2026 - val_accuracy: 0.5913 - val_loss: 1.1616
Epoch 5/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy:
0.6352 - loss: 1.0568 - val_accuracy: 0.6703 - val_loss: 0.9281
Epoch 6/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.6658 - loss: 0.9690 - val_accuracy: 0.6778 - val_loss: 0.9180
Epoch 7/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.6894 - loss: 0.8847 - val_accuracy: 0.7140 - val_loss: 0.8155
Epoch 8/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.7129 - loss: 0.8230 - val_accuracy: 0.7395 - val_loss: 0.7506
Epoch 9/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 6ms/step - accuracy:
0.7307 - loss: 0.7760 - val_accuracy: 0.7386 - val_loss: 0.7537
Epoch 10/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.7446 - loss: 0.7244 - val_accuracy: 0.7629 - val_loss: 0.6879
Epoch 11/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.7616 - loss: 0.6792 - val_accuracy: 0.7685 - val_loss: 0.6762
Epoch 12/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.7710 - loss: 0.6530 - val_accuracy: 0.7749 - val_loss: 0.6513
Epoch 13/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 6ms/step - accuracy:
0.7816 - loss: 0.6253 - val_accuracy: 0.7861 - val_loss: 0.6179
Epoch 14/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.7839 - loss: 0.6065 - val_accuracy: 0.7858 - val_loss: 0.6245
Epoch 15/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 6ms/step - accuracy:
0.7948 - loss: 0.5837 - val_accuracy: 0.7918 - val_loss: 0.6022
Epoch 16/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.8045 - loss: 0.5509 - val_accuracy: 0.8012 - val_loss: 0.5789
Epoch 17/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.8163 - loss: 0.5248 - val_accuracy: 0.8026 - val_loss: 0.5787
Epoch 18/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.8175 - loss: 0.5182 - val_accuracy: 0.8041 - val_loss: 0.5655
Epoch 19/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.8238 - loss: 0.5010 - val_accuracy: 0.8095 - val_loss: 0.5632
```

```
Epoch 20/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.8297 - loss: 0.4850 - val_accuracy: 0.8172 - val_loss: 0.5389
Test Accuracy: 0.8172

Experiment 4: Kernel Size 7x7
Epoch 1/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 23s 10ms/step - accuracy:
0.3309 - loss: 2.3282 - val_accuracy: 0.5459 - val_loss: 1.3374
Epoch 2/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.5552 - loss: 1.3483 - val_accuracy: 0.6353 - val_loss: 1.0534
Epoch 3/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 6ms/step - accuracy:
0.6573 - loss: 0.9958 - val_accuracy: 0.7098 - val_loss: 0.8160
Epoch 4/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.7102 - loss: 0.8321 - val_accuracy: 0.7107 - val_loss: 0.8527
Epoch 5/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.7400 - loss: 0.7356 - val_accuracy: 0.6902 - val_loss: 0.9277
Epoch 6/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.7709 - loss: 0.6560 - val_accuracy: 0.7884 - val_loss: 0.6146
Epoch 7/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 6ms/step - accuracy:
0.7902 - loss: 0.6001 - val_accuracy: 0.7463 - val_loss: 0.7591
Epoch 8/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.8074 - loss: 0.5499 - val_accuracy: 0.8031 - val_loss: 0.5810
Epoch 9/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.8198 - loss: 0.5166 - val_accuracy: 0.8030 - val_loss: 0.5602
Epoch 10/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.8322 - loss: 0.4767 - val_accuracy: 0.7816 - val_loss: 0.6425
Epoch 11/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.8412 - loss: 0.4590 - val_accuracy: 0.8094 - val_loss: 0.5716
Epoch 12/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 6ms/step - accuracy:
0.8492 - loss: 0.4314 - val_accuracy: 0.8018 - val_loss: 0.5917
Epoch 13/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy:
0.8560 - loss: 0.4065 - val_accuracy: 0.8227 - val_loss: 0.5494
Epoch 14/20
```

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1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.8627 - loss: 0.3912 - val_accuracy: 0.8387 - val_loss: 0.4889
Epoch 15/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.8695 - loss: 0.3723 - val_accuracy: 0.8170 - val_loss: 0.5500
Epoch 16/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.8729 - loss: 0.3576 - val_accuracy: 0.8404 - val_loss: 0.4979
Epoch 17/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.8761 - loss: 0.3469 - val_accuracy: 0.8294 - val_loss: 0.5038
Epoch 18/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.8793 - loss: 0.3346 - val_accuracy: 0.8355 - val_loss: 0.4991
Epoch 19/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy:
0.8851 - loss: 0.3150 - val_accuracy: 0.8108 - val_loss: 0.5778
Epoch 20/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.8895 - loss: 0.3091 - val_accuracy: 0.8335 - val_loss: 0.5284
Test Accuracy: 0.8335

Experiment 5: No Batch Normalization
Epoch 1/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 16s 8ms/step - accuracy:
0.3178 - loss: 1.8163 - val_accuracy: 0.5437 - val_loss: 1.2869
Epoch 2/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 14s 5ms/step - accuracy:
0.5661 - loss: 1.2060 - val_accuracy: 0.6331 - val_loss: 1.0378
Epoch 3/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 7s 5ms/step - accuracy:
0.6299 - loss: 1.0318 - val_accuracy: 0.6914 - val_loss: 0.8903
Epoch 4/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.6770 - loss: 0.9095 - val_accuracy: 0.6953 - val_loss: 0.8889
Epoch 5/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.7097 - loss: 0.8230 - val_accuracy: 0.7386 - val_loss: 0.7500
Epoch 6/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 7s 4ms/step - accuracy:
0.7241 - loss: 0.7789 - val_accuracy: 0.7333 - val_loss: 0.7595
Epoch 7/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.7389 - loss: 0.7380 - val_accuracy: 0.7473 - val_loss: 0.7282
Epoch 8/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 5ms/step - accuracy:
0.7551 - loss: 0.7088 - val_accuracy: 0.7660 - val_loss: 0.6790
```

```
Epoch 9/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.7561 - loss: 0.6982 - val_accuracy: 0.7719 - val_loss: 0.6715
Epoch 10/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy:
0.7647 - loss: 0.6684 - val_accuracy: 0.7587 - val_loss: 0.7161
Epoch 11/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 7s 5ms/step - accuracy:
0.7699 - loss: 0.6535 - val_accuracy: 0.7623 - val_loss: 0.7137
Epoch 12/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.7691 - loss: 0.6537 - val_accuracy: 0.7726 - val_loss: 0.6639
Epoch 13/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.7787 - loss: 0.6268 - val_accuracy: 0.7765 - val_loss: 0.6622
Epoch 14/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.7850 - loss: 0.6189 - val_accuracy: 0.7765 - val_loss: 0.6782
Epoch 15/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.7853 - loss: 0.6100 - val_accuracy: 0.7814 - val_loss: 0.6604
Epoch 16/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.7860 - loss: 0.6043 - val_accuracy: 0.7772 - val_loss: 0.6786
Epoch 17/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy:
0.7904 - loss: 0.6018 - val_accuracy: 0.7715 - val_loss: 0.6873
Epoch 18/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 7s 4ms/step - accuracy:
0.7918 - loss: 0.5957 - val_accuracy: 0.7908 - val_loss: 0.6274
Epoch 19/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 7s 5ms/step - accuracy:
0.7935 - loss: 0.5786 - val_accuracy: 0.7931 - val_loss: 0.6271
Epoch 20/20
1563/1563 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy:
0.7934 - loss: 0.5842 - val_accuracy: 0.7940 - val_loss: 0.6367
Test Accuracy: 0.7940

Experiment 6: Batch Size 16
Epoch 1/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 22s 4ms/step - accuracy:
0.3757 - loss: 2.2098 - val_accuracy: 0.5905 - val_loss: 1.1923
Epoch 2/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step - accuracy:
0.6384 - loss: 1.0478 - val_accuracy: 0.7099 - val_loss: 0.8398
Epoch 3/20
```

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3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 20s 4ms/step - accuracy:
0.7135 - loss: 0.8255 - val_accuracy: 0.7391 - val_loss: 0.7579
Epoch 4/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 20s 4ms/step - accuracy:
0.7534 - loss: 0.7023 - val_accuracy: 0.7514 - val_loss: 0.7096
Epoch 5/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step - accuracy:
0.7827 - loss: 0.6215 - val_accuracy: 0.7917 - val_loss: 0.6101
Epoch 6/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step - accuracy:
0.8011 - loss: 0.5704 - val_accuracy: 0.7967 - val_loss: 0.5831
Epoch 7/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step - accuracy:
0.8204 - loss: 0.5225 - val_accuracy: 0.8094 - val_loss: 0.5744
Epoch 8/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 20s 4ms/step - accuracy:
0.8300 - loss: 0.4876 - val_accuracy: 0.8074 - val_loss: 0.5698
Epoch 9/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step - accuracy:
0.8398 - loss: 0.4639 - val_accuracy: 0.8041 - val_loss: 0.5717
Epoch 10/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step - accuracy:
0.8525 - loss: 0.4227 - val_accuracy: 0.8208 - val_loss: 0.5365
Epoch 11/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step - accuracy:
0.8557 - loss: 0.4083 - val_accuracy: 0.8289 - val_loss: 0.5109
Epoch 12/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 22s 5ms/step - accuracy:
0.8613 - loss: 0.3934 - val_accuracy: 0.8393 - val_loss: 0.4820
Epoch 13/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 14s 5ms/step - accuracy:
0.8658 - loss: 0.3783 - val_accuracy: 0.8345 - val_loss: 0.4971
Epoch 14/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 14s 4ms/step - accuracy:
0.8697 - loss: 0.3620 - val_accuracy: 0.8307 - val_loss: 0.5158
Epoch 15/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 19s 4ms/step - accuracy:
0.8782 - loss: 0.3479 - val_accuracy: 0.8226 - val_loss: 0.5342
Epoch 16/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 21s 4ms/step - accuracy:
0.8800 - loss: 0.3348 - val_accuracy: 0.8223 - val_loss: 0.5629
Epoch 17/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 21s 4ms/step - accuracy:
0.8844 - loss: 0.3288 - val_accuracy: 0.8469 - val_loss: 0.4718
Epoch 18/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 14s 4ms/step - accuracy:
0.8903 - loss: 0.3114 - val_accuracy: 0.8340 - val_loss: 0.5286
```

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Epoch 19/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 20s 4ms/step - accuracy:
0.8927 - loss: 0.3031 - val_accuracy: 0.8468 - val_loss: 0.4818
Epoch 20/20
3125/3125 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step - accuracy:
0.8952 - loss: 0.2929 - val_accuracy: 0.8493 - val_loss: 0.4865
Test Accuracy: 0.8493

Experiment 7: Batch Size 256
Epoch 1/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 21s 57ms/step - accuracy:
0.3297 - loss: 2.4657 - val_accuracy: 0.1066 - val_loss: 3.6690
Epoch 2/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 26ms/step - accuracy: 0.5406
- loss: 1.3533 - val_accuracy: 0.2550 - val_loss: 2.5826
Epoch 3/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 26ms/step - accuracy: 0.6403
- loss: 1.0515 - val_accuracy: 0.5677 - val_loss: 1.2708
Epoch 4/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 26ms/step - accuracy:
0.6958 - loss: 0.8797 - val_accuracy: 0.6833 - val_loss: 0.9165
Epoch 5/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 25ms/step - accuracy: 0.7281
- loss: 0.7750 - val_accuracy: 0.7182 - val_loss: 0.8311
Epoch 6/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 26ms/step - accuracy: 0.7524
- loss: 0.7185 - val_accuracy: 0.7671 - val_loss: 0.7045
Epoch 7/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 25ms/step - accuracy: 0.7727
- loss: 0.6446 - val_accuracy: 0.7583 - val_loss: 0.7152
Epoch 8/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 25ms/step - accuracy: 0.7876
- loss: 0.6052 - val_accuracy: 0.7355 - val_loss: 0.7965
Epoch 9/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 26ms/step - accuracy: 0.8006
- loss: 0.5643 - val_accuracy: 0.8016 - val_loss: 0.5874
Epoch 10/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 25ms/step - accuracy: 0.8167
- loss: 0.5170 - val_accuracy: 0.7778 - val_loss: 0.6716
Epoch 11/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 25ms/step - accuracy: 0.8228
- loss: 0.5021 - val_accuracy: 0.7903 - val_loss: 0.6212
Epoch 12/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 25ms/step - accuracy: 0.8358
- loss: 0.4678 - val_accuracy: 0.8081 - val_loss: 0.5637
Epoch 13/20
```

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196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 25ms/step - accuracy: 0.8430
- loss: 0.4501 - val_accuracy: 0.7969 - val_loss: 0.6206
Epoch 14/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 25ms/step - accuracy: 0.8473
- loss: 0.4263 - val_accuracy: 0.8138 - val_loss: 0.5540
Epoch 15/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 25ms/step - accuracy: 0.8563
- loss: 0.3972 - val_accuracy: 0.8176 - val_loss: 0.5494
Epoch 16/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 25ms/step - accuracy: 0.8663
- loss: 0.3791 - val_accuracy: 0.8162 - val_loss: 0.5558
Epoch 17/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 25ms/step - accuracy: 0.8667
- loss: 0.3754 - val_accuracy: 0.8125 - val_loss: 0.5913
Epoch 18/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 25ms/step - accuracy: 0.8719
- loss: 0.3629 - val_accuracy: 0.8184 - val_loss: 0.5699
Epoch 19/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 26ms/step - accuracy: 0.8846
- loss: 0.3276 - val_accuracy: 0.8279 - val_loss: 0.5445
Epoch 20/20
196/196 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5s 25ms/step - accuracy: 0.8842
- loss: 0.3260 - val_accuracy: 0.8317 - val_loss: 0.5269
Test Accuracy: 0.8317
Baseline Accuracy: 0.8524
Learning Rate 0.05 Accuracy: 0.7799
Learning Rate 0.0001 Accuracy: 0.8172
Kernel Size 7x7 Accuracy: 0.8335
No Batch Normalization Accuracy: 0.7940
Batch Size 16 Accuracy: 0.8493
Batch Size 256 Accuracy: 0.8317
```

We observe the following from the results:
From the results, we can observe the following trends:

1. **Baseline Accuracy (0.8524):** We observe that the baseline model performs well. This shows us that the network is generally capable of learning and classifying the CIFAR-10 dataset effectively.

2. **Accuracy of 0.7799 when Learning Rate is increased from 0.001 to 0.05**.
We notice that a high learning rate results in lower accuracy. This may be due to unstable updates that prevent convergence. The model also takes less time to converge since it learns faster.

3. **Accuracy of 0.8172 when Learning Rate is decreased from 0.001 to 0.0001.**

This shows us that a very low learning rate also decreases accuracy as it slows convergence and may not reach optimal solutions within the set epochs. Thus, we may need to use more epochs to reach a more optimal solution.

4. **When kernel size is increased from 3x3 to 7x7, we get an accuracy of 0.8335.**
We notice that increasing the kernel size slightly improves accuracy when compared to the baseline. This shows us that larger kernels capture more global features but may lose finer details. The model also converges faster.

5. **Without Batch Normalization, we get an accuracy of 0.7940.**
This shows us that removing batch normalization reduces accuracy significantly. Hence, we can say with proof that batch normalization stabilizes training and helps the model converge better.

6. **Decreasing batch size to 16 gives an accuracy of 0.8493.**
This shows us that a smaller batch size performs slightly better than the testing model. This might be due to more precise gradient updates, since the model is able to study finer details and be more precise. However, this increases the time taken by the model to converge too.

7. **Increasing batch size to 256 gives an accuracy of 0.8317**.
We notice that a larger batch size results in slightly lower accuracy than the baseline. This might be due to less precise gradient updates, since the model is not able to study finer details and thus is generally less precise.

8. **General Trend.**
We also notice a general trend of increasing accuracy and decreasing loss after each epoch in each experiment. This shows us that the model is learning after each iteration and applying it the following epoch to increase its effectiveness.

Conclusion

From this task we derive the following conclusions:

1. We see that a balanced learning rate and appropriate batch normalization are important for optimal performance.
2. We also conclude that larger kernel sizes and smaller batch sizes can slightly enhance performance but need to be tuned based on the problem.
3. Convolutional Neural Networks learn after each epoch in order to increase their effectiveness.