

SML PROJECT REPORT CIFAR-10 DATASET CLASSIFICATION

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Methods used for classification of the Dataset:

Logistic Regression:

A basic linear model used for classification problems. It uses the probability of one event taking place by having the log odds for the event be a linear combination of one or more variables.

Deep Neural Networks with Convolution Layers:

Deep Neural Networks is a multi-layer model which comprises of layers and each layers have many neurons which have activation functions like sigmoid or relu. There is an initial input layer and an output layer and many in between hidden layers consisting of connected neurons. In addition to the neural network, I am going to be using convolution layers which are used to detect features in an image and after feature selection from convolution layers the output is flattened and passed onto a fully connected neural network with a SoftMax function at the output layer to classify each image into the 10 categories we have in the dataset.

Analysis of the Results:

Logistic Regression:

Confusion Matrix:

Actual	airplane	497	45	46	36	22	27	23	53	172	79
	automobile	60	490	23	38	22	36	39	52	80	160
	bird	99	44	288	91	118	72	153	67	46	22
	cat	44	61	101	265	50	191	136	53	35	64
	deer	58	25	137	74	299	85	162	107	24	29
	dog	43	42	93	161	76	355	88	70	47	25
	frog	16	43	68	120	94	81	500	35	16	27
	horse	49	50	67	62	84	79	41	461	32	75
	ship	150	68	23	26	9	49	9	19	545	102
	truck	68	182	21	27	17	25	47	50	88	475
		airplane	automobile	bird	cat	deer	dog	frog	horse	ship	truck

Classification Report:

	precision	recall	f1-score	support
airplane	0.46	0.50	0.48	1000
automobile	0.47	0.49	0.48	1000
bird	0.33	0.29	0.31	1000
cat	0.29	0.27	0.28	1000
deer	0.38	0.30	0.33	1000
dog	0.35	0.35	0.36	1000
frog	0.42	0.50	0.45	1000
horse	0.48	0.46	0.47	1000
ship	0.50	0.55	0.52	1000
truck	0.45	0.47	0.46	1000
accuracy			0.42	10000
macro avg	0.41	0.42	0.41	10000
weighted avg	0.41	0.42	0.41	10000

For Logistic Regression the highest f1-score was of identifying airplanes and automobiles so it is performing best at identifying these two objects.

Accuracy of Model:

41.75%

Deep Neural Networks with Convolution Layers:

Confusion Matrix:

Actual	airplane	778	11	19	18	11	3	6	6	110	38
	automobile	13	857	4	6	2	6	3	0	39	70
	bird	88	6	568	98	58	65	61	24	21	11
	cat	26	7	61	637	31	102	69	28	22	17
	deer	19	2	78	104	630	42	52	57	10	6
	dog	7	1	50	226	26	616	25	35	8	6
	frog	4	4	43	70	17	16	831	3	7	5
	horse	20	4	29	76	46	40	9	754	5	17
	ship	50	9	8	17	5	1	7	0	887	16
	truck	21	39	5	17	0	3	3	5	27	880
		airplane	automobile	bird	cat	deer	dog	frog	horse	ship	truck

Classification Report:

	precision	recall	f1-score	support
airplane	0.76	0.78	0.77	1000
automobile	0.91	0.86	0.88	1000
bird	0.66	0.57	0.61	1000
cat	0.50	0.64	0.56	1000
deer	0.76	0.63	0.69	1000
dog	0.69	0.62	0.65	1000
frog	0.78	0.83	0.80	1000
horse	0.83	0.75	0.79	1000
ship	0.78	0.89	0.83	1000
truck	0.83	0.88	0.85	1000
accuracy			0.74	10000
macro avg	0.75	0.74	0.74	10000
weighted avg	0.75	0.74	0.74	10000

For Deep Neural Network the highest f1-score was of automobile so it was able to detect automobiles with a very high accuracy.

Accuracy trend throughout the Epochs with respect to Training and Testing Data:



We can see at the end that our deep learning model is overfitting at the end as accuracy on training data increases but accuracy on test data does not increase.

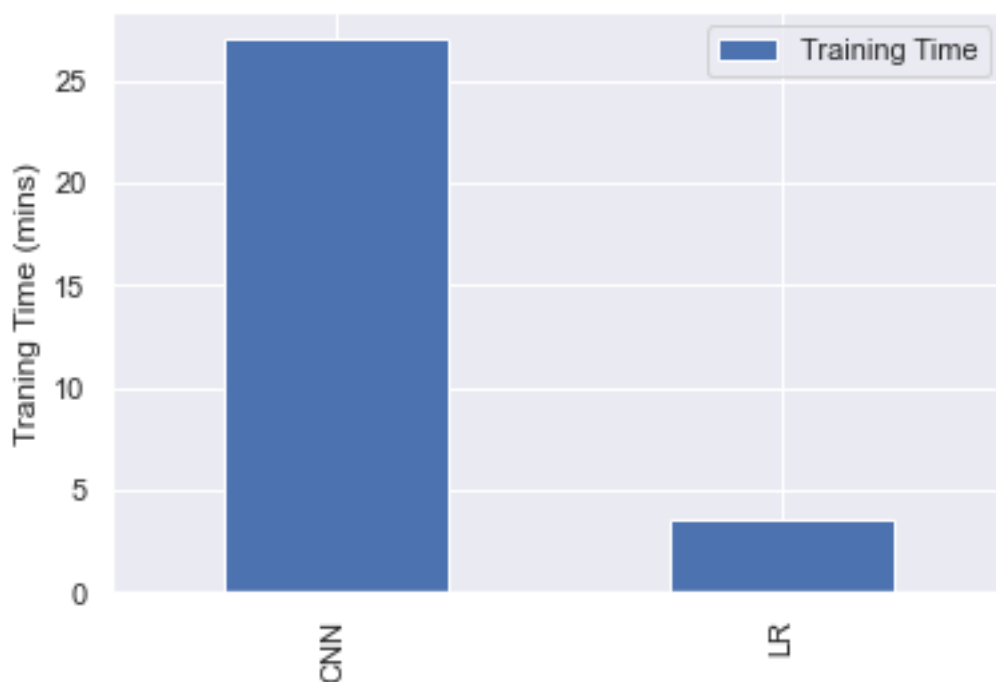
Accuracy of Model:

74.38%

Comparison of Results:

Convergence Speed and Overall Training Time:

For logistic regression the overall training time and convergence speed was very fast as logistic regression is a simple model which calculates the probability of one event taking place and it does not have any layers. The Number of computations was also very less. Compared to deep neural network with convolution layers. I ran the deep neural network for 10 epochs and the model had 9 hidden layers each epochs took about 160 seconds to complete so in total the whole training took about 1600 seconds which is about 27 minutes. Which is very high in comparison to logistic regression which was only around 3.5 minutes.

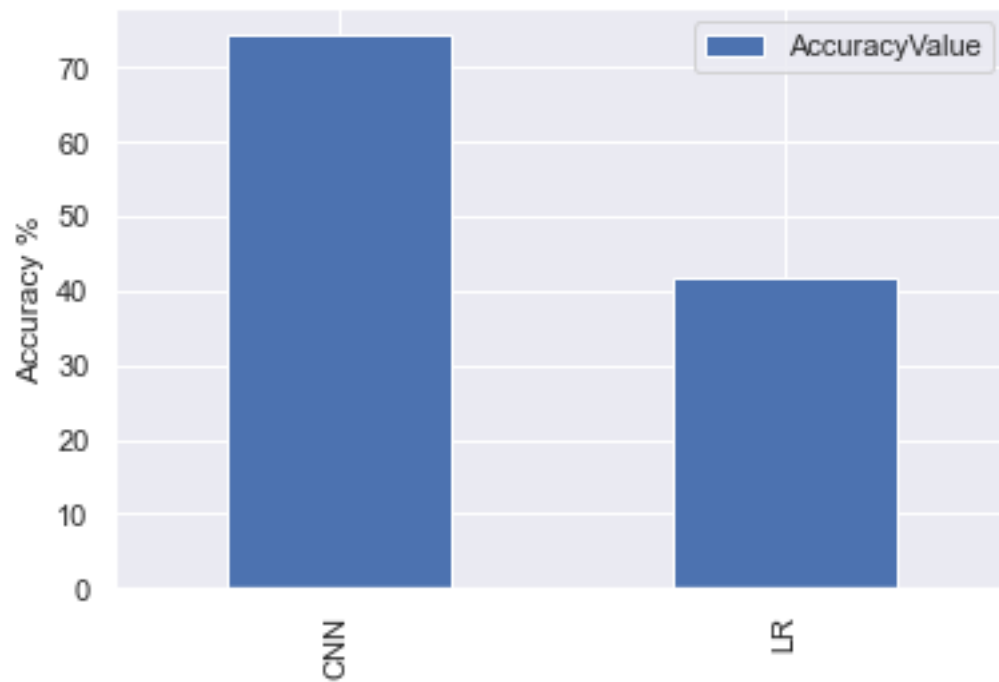


Resources Used:

Logistic Regression used a bare minimum of my computer resources to train and a lot less computations were involved compared to the deep neural network with convolution layers which was using around 95 – 99 percent of CPU usage for about 27 minutes so deep learning networks are very resource hungry to train.

Accuracy:

This is where logistic regression was very terrible as it was only about to get an accuracy of 41.75 % which is below the 50% threshold as compared to the deep neural network which had an accuracy of 74.38% about 80 percent better than the logistic regression model which is huge and should be the case because deep learning model is many times more complicated than a simple model than logistics regression and it uses the convolution layers to detect the features instead of just looking at each pixel value.



Conclusion:

Deep neural network with Convolution layers was considerably better than a simple logistic regression model for image classification of this dataset. Which is primary because of the convolution layers that are present in the deep neural network.

SML Project

May 5, 2022

1 Project Code

```
[18]: import tensorflow
import keras
from keras.datasets import cifar10
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
import sklearn.metrics as metrics
from sklearn.metrics import classification_report, confusion_matrix, \
    f1_score, accuracy_score, precision_score, recall_score, roc_auc_score
from sklearn.model_selection import RepeatedStratifiedKFold, StratifiedKFold
from sklearn.preprocessing import OneHotEncoder
import ssl
ssl._create_default_https_context = ssl._create_unverified_context
import seaborn as sns; sns.set()
from tensorflow.keras import datasets, layers, models
import time
from datetime import datetime

import warnings
warnings.filterwarnings(action="ignore")
```

1.1 Loading and Exploring the Data Set

```
[2]: # define num_class
num_classes = 10

# load dataset keras will download cifar-10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
```

Looking and the Shape and see the first images in the data set

```
[3]: print("x_train shape : ",x_train.shape)
print("Y_train sahpe : ",y_train.shape)
```

```
x_train shape : (50000, 32, 32, 3)
Y_train shape : (50000, 1)
```

Changing shape of Y values to single dimension number array

```
[4]: y_train = y_train.reshape(-1,)
      y_test = y_test.reshape(-1,)
      print("y_train",y_train)
      print("y_train shape",y_train.shape)
```

```
y_train [6 9 9 ... 9 1 1]
y_train shape (50000,)
```

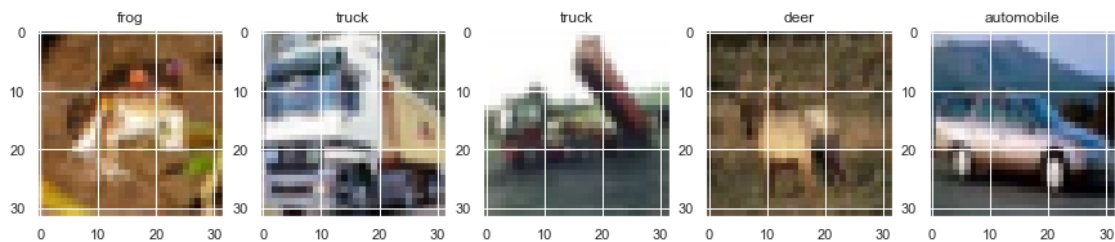
Setting up the labels for the data

```
[5]: labels = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog',
               ↪ 'horse', 'ship', 'truck']
```

Printing out the first few pictures with labels

```
[7]: fig, axes = plt.subplots(ncols=5,figsize=(15, 15))

      for i in range(5):
          axes[i].set_title(labels[y_train[i]])
          axes[i].imshow(x_train[i])
```



2 Staring Machine Learning with First Model Linear Regression

2.0.1 Preprocessing the data to be passed into the Model

```
[6]: x_train_resapedto2d = x_train.reshape(50000,32*32*3)
      x_test_resapedto2d = x_test.reshape(10000 ,32*32*3)
```

Printing out new shape of data to be passed to Logistic Regression Modelb

```
[7]: print("X_train shape",x_train_resapedto2d.shape)
      print("X_test shape",x_test_resapedto2d.shape)
```

```
X_train shape (50000, 3072)
X_test shape (10000, 3072)
```

Normalizing the dataset by dividing each value by 255 because each value is RGB value which ranges from 0 -255 so diving it by 255 will give us a number between 0 - 1.

```
[8]: x_train_reshapedto2d_normalized = x_train_reshapedto2d/255
     x_test_reshapedto2d_normalized = x_test_reshapedto2d/255
```

Printing out the first few lines of data to be passed to the model

```
[9]: x_train_reshapedto2d_normalized
```

```
[9]: array([[0.23137255, 0.24313725, 0.24705882, ..., 0.48235294, 0.36078431,
           0.28235294],
          [0.60392157, 0.69411765, 0.73333333, ..., 0.56078431, 0.52156863,
           0.56470588],
          [1.          , 1.          , 1.          , ..., 0.31372549, 0.3372549 ,
           0.32941176],
          ...,
          [0.1372549 , 0.69803922, 0.92156863, ..., 0.04705882, 0.12156863,
           0.19607843],
          [0.74117647, 0.82745098, 0.94117647, ..., 0.76470588, 0.74509804,
           0.67058824],
          [0.89803922, 0.89803922, 0.9372549 , ..., 0.63921569, 0.63921569,
           0.63137255]])
```

2.0.2 Training the Logistic Regression Model

Setting the parameters of Logistic Regression Model. We are going to use sparse regression with l2 penalty.

```
[21]: logisticRegStartTime = time.time()
     logregmodel = LogisticRegression(C=0.01, multi_class='multinomial',
     ↪solver='sag',penalty='l2')
     logregmodel.fit(x_train_reshapedto2d_normalized,y_train)
     logisticRegEndTime = time.time()
```

```
[24]: time_intervalLG = logisticRegEndTime - logisticRegStartTime
     print("Time Taken To Train The data ",time_intervalLG/60)
```

Time Taken To Train The data 3.5329426407814024

2.0.3 Predicting and Collecting the Results

```
[26]: predictionsLogReg = logregmodel.predict(x_test_reshapedto2d_normalized)
```

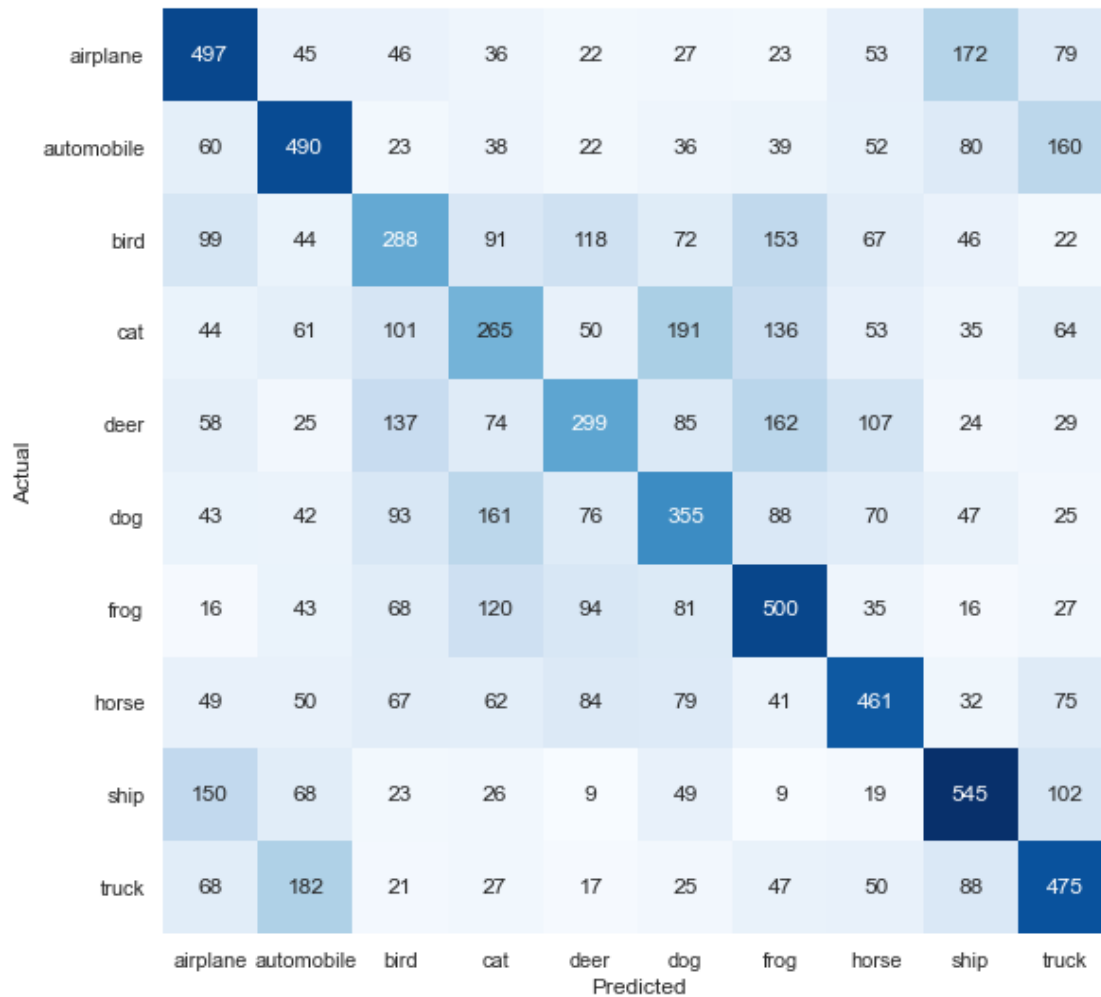
```
[27]: conmaxReg = confusion_matrix(y_test, predictionsLogReg)
```

Confusion Matrix of the Result

```
[28]: plt.figure(figsize=(9,9))
```



```
sns.heatmap(conmaxReg, cbar=False, xticklabels=labels,
            yticklabels=labels,fmt='d',annot=True, cmap=plt.cm.Blues)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



Classificaiton Report of the Classes

```
[29]: print(classification_report(y_test,predictionsLogReg,target_names=labels))
```

	precision	recall	f1-score	support
airplane	0.46	0.50	0.48	1000
automobile	0.47	0.49	0.48	1000
bird	0.33	0.29	0.31	1000
cat	0.29	0.27	0.28	1000
deer	0.38	0.30	0.33	1000

dog	0.35	0.35	0.36	1000
frog	0.42	0.50	0.45	1000
horse	0.48	0.46	0.47	1000
ship	0.50	0.55	0.52	1000
truck	0.45	0.47	0.46	1000
accuracy			0.42	10000
macro avg	0.41	0.42	0.41	10000
weighted avg	0.41	0.42	0.41	10000

Overall Accuracy Of the Mode

```
[30]: print("Accuracy of Logistic Regression Model is :␣
↪",accuracy_score(predictionsLogReg,y_test))
```

Accuray of Logistic Regression Model is : 0.4175

3 Machine Learning with Deep Neural Network with Convolution Layer

Traning a simple neural network

```
[32]: model2 = keras.Sequential([
    keras.layers.Dense(3072, input_shape=(3072,), activation='relu'),
    keras.layers.Dense(1536, activation='relu'),
    keras.layers.Dense(10, activation='softmax')
])

model2.compile(optimizer='adam',
               loss='sparse_categorical_crossentropy',
               metrics=['accuracy'])

model2.fit(x_train_reshapedto2d_normalized, y_train, epochs=10)
```

```
Epoch 1/10
1563/1563 [=====] - 65s 42ms/step - loss: 1.8888 -
accuracy: 0.3256
Epoch 2/10
1563/1563 [=====] - 66s 42ms/step - loss: 1.6716 -
accuracy: 0.3983
Epoch 3/10
1563/1563 [=====] - 60s 38ms/step - loss: 1.6011 -
accuracy: 0.4251
Epoch 4/10
1563/1563 [=====] - 60s 39ms/step - loss: 1.5537 -
accuracy: 0.4427
Epoch 5/10
1563/1563 [=====] - 62s 40ms/step - loss: 1.5189 -
```

```

accuracy: 0.4531
Epoch 6/10
1563/1563 [=====] - 62s 40ms/step - loss: 1.4923 -
accuracy: 0.4663
Epoch 7/10
1563/1563 [=====] - 62s 40ms/step - loss: 1.4706 -
accuracy: 0.4747
Epoch 8/10
1563/1563 [=====] - 63s 40ms/step - loss: 1.4542 -
accuracy: 0.4806
Epoch 9/10
1563/1563 [=====] - 61s 39ms/step - loss: 1.4372 -
accuracy: 0.4852
Epoch 10/10
1563/1563 [=====] - 63s 41ms/step - loss: 1.4199 -
accuracy: 0.4913

```

[32]: <keras.callbacks.History at 0x290414f1640>

Checking Accuracy of the Deep Neural Network

```
[33]: model2.evaluate(x_test_resapedto2d_normalized,y_test)
```

```

313/313 [=====] - 2s 6ms/step - loss: 1.4737 -
accuracy: 0.4732

```

[33]: [1.4736998081207275, 0.4731999933719635]

Testing and training with convolution layers added in the Neural Network

```
[31]: x_train_covnn = x_train/255
      x_test_covnn = x_test/255
```

```
[39]: model4 = keras.Sequential([
    keras.layers.Conv2D(filters=32, kernel_size=(3, 3), activation='relu',
↳input_shape=(32,32,3),strides=1,padding="same"),
    keras.layers.Conv2D(filters=64, kernel_size=(3, 3),
↳activation='relu',strides=1,padding="same"),
    keras.layers.Conv2D(filters=128, kernel_size=(3, 3),
↳activation='relu',strides=1,padding="same"),
    keras.layers.MaxPooling2D((2, 2)),
    #keras.layers.AveragePooling2D((2, 2)),

    keras.layers.Conv2D(filters=32, kernel_size=(3, 3), activation='relu'),
    keras.layers.Conv2D(filters=64, kernel_size=(3, 3), activation='relu'),
    keras.layers.Conv2D(filters=128, kernel_size=(3, 3), activation='relu'),
    keras.layers.MaxPooling2D((2, 2)),
    #keras.layers.AveragePooling2D((2, 2)),

```

```

keras.layers.Flatten(),
keras.layers.Dense(128, activation='relu'),
keras.layers.Dense(10, activation='softmax')
])

model4.compile(optimizer='adam',
               loss='sparse_categorical_crossentropy',
               metrics=['accuracy'])

DNNCNNstarttime = time.time()
ModelTrainingData = model4.fit(x_train_covnn, y_train,
                                epochs=10, batch_size=50, validation_data=(x_test_covnn, y_test))
DNNCNNendtime = time.time()

```

```

Epoch 1/10
1000/1000 [=====] - 161s 161ms/step - loss: 1.5576 -
accuracy: 0.4268 - val_loss: 1.2132 - val_accuracy: 0.5629
Epoch 2/10
1000/1000 [=====] - 157s 157ms/step - loss: 1.0785 -
accuracy: 0.6167 - val_loss: 1.0396 - val_accuracy: 0.6380
Epoch 3/10
1000/1000 [=====] - 159s 159ms/step - loss: 0.8698 -
accuracy: 0.6906 - val_loss: 0.8521 - val_accuracy: 0.6962
Epoch 4/10
1000/1000 [=====] - 161s 161ms/step - loss: 0.7293 -
accuracy: 0.7436 - val_loss: 0.7974 - val_accuracy: 0.7266
Epoch 5/10
1000/1000 [=====] - 163s 163ms/step - loss: 0.6254 -
accuracy: 0.7793 - val_loss: 0.7352 - val_accuracy: 0.7493
Epoch 6/10
1000/1000 [=====] - 163s 163ms/step - loss: 0.5362 -
accuracy: 0.8099 - val_loss: 0.7215 - val_accuracy: 0.7569
Epoch 7/10
1000/1000 [=====] - 163s 163ms/step - loss: 0.4597 -
accuracy: 0.8374 - val_loss: 0.8014 - val_accuracy: 0.7379
Epoch 8/10
1000/1000 [=====] - 158s 158ms/step - loss: 0.3964 -
accuracy: 0.8586 - val_loss: 0.7822 - val_accuracy: 0.7550
Epoch 9/10
1000/1000 [=====] - 170s 170ms/step - loss: 0.3314 -
accuracy: 0.8822 - val_loss: 0.8295 - val_accuracy: 0.7536
Epoch 10/10
1000/1000 [=====] - 165s 165ms/step - loss: 0.2826 -
accuracy: 0.8984 - val_loss: 0.9567 - val_accuracy: 0.7438

```

```
[40]: model4.summary()
```

```
Model: "sequential_7"
```

Layer (type)	Output Shape	Param #
conv2d_50 (Conv2D)	(None, 32, 32, 32)	896
conv2d_51 (Conv2D)	(None, 32, 32, 64)	18496
conv2d_52 (Conv2D)	(None, 32, 32, 128)	73856
max_pooling2d_6 (MaxPooling2D)	(None, 16, 16, 128)	0
conv2d_53 (Conv2D)	(None, 14, 14, 32)	36896
conv2d_54 (Conv2D)	(None, 12, 12, 64)	18496
conv2d_55 (Conv2D)	(None, 10, 10, 128)	73856
max_pooling2d_7 (MaxPooling2D)	(None, 5, 5, 128)	0
flatten_7 (Flatten)	(None, 3200)	0
dense_21 (Dense)	(None, 128)	409728
dense_22 (Dense)	(None, 10)	1290
Total params: 633,514		
Trainable params: 633,514		
Non-trainable params: 0		

```
[42]: time_intervalDNNCNN = DNNCNNEndtime - DNNCNNstarttime
      print("Time Taken To Train The data ",time_intervalDNNCNN/60)
```

Time Taken To Train The data 27.020609664916993

Accuracy Graphs

```
[43]: plt.plot(ModelTrainingData.history['accuracy'],label='Accuracy Training Data')
      plt.plot(ModelTrainingData.history['val_accuracy'],label='Accuracy Test Data')
      plt.legend()
      plt.show()
```



Checking the accuracy of the CNN Model

```
[44]: model4.evaluate(x_test_covnn,y_test)
```

```
313/313 [=====] - 9s 27ms/step - loss: 0.9567 -  
accuracy: 0.7438
```

```
[44]: [0.956702470779419, 0.7437999844551086]
```

Making the confusion matrix

```
[45]: predictions = model4.predict(x_test_covnn)
```

```
[47]: predictionsCNN = [np.argmax(i) for i in predictions]
```

```
[48]: conmaxCNN = confusion_matrix(y_test, predictionsCNN)
```

```
[49]: plt.figure(figsize=(9,9))  
sns.heatmap(conmaxCNN, cbar=False, xticklabels=labels,  
           yticklabels=labels,fmt='d',annot=True, cmap=plt.cm.Blues)  
plt.xlabel('Predicted')  
plt.ylabel('Actual')  
plt.show()
```

Actual	airplane	778	11	19	18	11	3	6	6	110	38
	automobile	13	857	4	6	2	6	3	0	39	70
	bird	88	6	568	98	58	65	61	24	21	11
	cat	26	7	61	637	31	102	69	28	22	17
	deer	19	2	78	104	630	42	52	57	10	6
	dog	7	1	50	226	26	616	25	35	8	6
	frog	4	4	43	70	17	16	831	3	7	5
	horse	20	4	29	76	46	40	9	754	5	17
	ship	50	9	8	17	5	1	7	0	887	16
	truck	21	39	5	17	0	3	3	5	27	880
		airplane	automobile	bird	cat	deer	dog	frog	horse	ship	truck
		Predicted									

```
[50]: print(classification_report(y_test,predictionsCNN,target_names=labels))
```

	precision	recall	f1-score	support
airplane	0.76	0.78	0.77	1000
automobile	0.91	0.86	0.88	1000
bird	0.66	0.57	0.61	1000
cat	0.50	0.64	0.56	1000
deer	0.76	0.63	0.69	1000
dog	0.69	0.62	0.65	1000
frog	0.78	0.83	0.80	1000
horse	0.83	0.75	0.79	1000
ship	0.78	0.89	0.83	1000
truck	0.83	0.88	0.85	1000
accuracy			0.74	10000

macro avg	0.75	0.74	0.74	10000
weighted avg	0.75	0.74	0.74	10000

3.0.1 Overall Accuracy of the Model

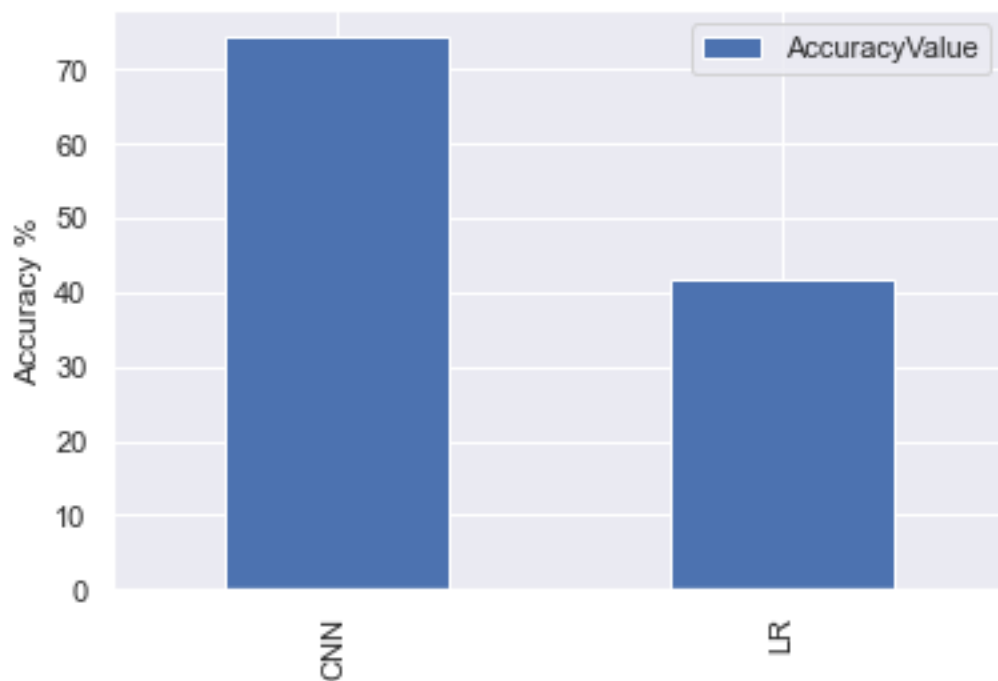
```
[51]: print("Accuray of CNN Model is : ",accuracy_score(predictionsCNN,y_test))
```

Accuray of CNN Model is : 0.7438

Accuracy Comparison

```
[71]: plotdataacc = pd.DataFrame(
        {"AccuracyValue": [74.38,41.75]},
        index=["CNN", "LR"])
plotdataacc.plot(kind="bar")
plt.ylabel("Accuracy %")
```

```
[71]: Text(0, 0.5, 'Accuracy %')
```



```
[72]: plotdatatimetaken = pd.DataFrame(
        {"Training Time": [27.02,3.53]},
        index=["CNN", "LR"])
plotdatatimetaken.plot(kind="bar")
plt.ylabel("Traning Time (mins)")
```



```
[72]: Text(0, 0.5, 'Traning Time (mins)')
```

