Simran_Goindani_Ashir_Mehta_DS5220_Final_Project

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0.1 Importing Libraries

[1]:
```
import keras
from keras.datasets import cifar10
from sklearn.model_selection import KFold
from sklearn.model_selection import train_test_split as train_test_split
from sklearn.preprocessing import StandardScaler, MinMaxScaler
import sklearn.metrics as skm
from sklearn import svm
import os, time
import matplotlib.pyplot as plt
import numpy as np
import time
import pandas as pd
```

0.2 Model Development

0.2.1 SVM with different Kernel

Loading Data

[2]:
```
classesName = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
↪'ship', 'truck']
```

[3]:
```
#Loading the dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
#Splitting the data into validation
x_val = x_train[49000:, :].astype(np.float)
#Converting target variable to 1d array
y_val = np.squeeze(y_train[49000:, :])
x_train = x_train[:49000, :].astype(np.float)
y_train = np.squeeze(y_train[:49000, :])
y_test = np.squeeze(y_test)
x_test = x_test.astype(np.float)
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170500096/170498071 [==============================] - 3s 0us/step
```

```
170508288/170498071 [==============================] - 3s 0us/step

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4:
DeprecationWarning: `np.float` is a deprecated alias for the builtin `float`. To
silence this warning, use `float` by itself. Doing this will not modify any
behavior and is safe. If you specifically wanted the numpy scalar type, use
`np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  after removing the cwd from sys.path.
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:7:
DeprecationWarning: `np.float` is a deprecated alias for the builtin `float`. To
silence this warning, use `float` by itself. Doing this will not modify any
behavior and is safe. If you specifically wanted the numpy scalar type, use
`np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  import sys
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:10:
DeprecationWarning: `np.float` is a deprecated alias for the builtin `float`. To
silence this warning, use `float` by itself. Doing this will not modify any
behavior and is safe. If you specifically wanted the numpy scalar type, use
`np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  # Remove the CWD from sys.path while we load stuff.
```

[4]:
```
print("Train image shape " , x_train.shape)
print("Train label shape :", y_train.shape)
print("Validate image shape :", x_val.shape)
print("Validate label shape : ", y_val.shape)
print("Test image shape : ", x_test.shape)
print("Test label shape : ", y_test.shape)
```

```
Train image shape  (49000, 32, 32, 3)
Train label shape : (49000,)
Validate image shape : (1000, 32, 32, 3)
Validate label shape :  (1000,)
Test image shape :  (10000, 32, 32, 3)
Test label shape :  (10000,)
```

Reshaping and Normalizing Data

[5]:
```
print(x_train.shape)
print(y_train.shape)

x_train = np.reshape(x_train, (x_train.shape[0], -1))
x_val = np.reshape(x_val, (x_val.shape[0], -1))
```

```
x_test = np.reshape(x_test, (x_test.shape[0], -1))

#Normalizing the data
x_train = ((x_train / 255) * 2) - 1
```

```
(49000, 32, 32, 3)
(49000,)
```

[6]:
```
#Selecting a smaller subset of data to train
x_train = x_train[:3000,:]
y_train = y_train[:3000]
print(y_train)
print(x_train.shape)
print(y_train.shape)
```

```
[6 9 9 … 6 6 4]
(3000, 3072)
(3000,)
```

SVM Model

[7]:
```
#Created a function that takes model and test data as input and returns the␣
↪test accuracy
def svm_models_acc(model, x_test, y_test):

  return np.mean(model.predict(x_test) == y_test)
```

[8]:
```
# Created a common SVM model for all the types of kernel and without kernel
def svm_models(x_train, y_train, x_val, y_val, x_test, y_test, kernel, c):
  train_acc, val_acc = [], []
  temp_df = pd.DataFrame()

  #Checking if kernel is rbf and then creating a model with an additional␣
↪parameter gamma for kernel = rbf
  if kernel == "rbf":
    #Fitting the model for different values of regularization parameter
    for i in c:
      svm_model = svm.SVC(probability = False, kernel = kernel, C = i, gamma =␣
↪'auto')
      svm_model.fit(x_train, y_train)

      ypred_train = svm_model.predict(x_train)
      acc_train = np.mean(ypred_train == y_train)
      train_acc.append(acc_train * 100)

      ypred_test = svm_model.predict(x_val)
      acc_test = np.mean(ypred_test == y_val)
```

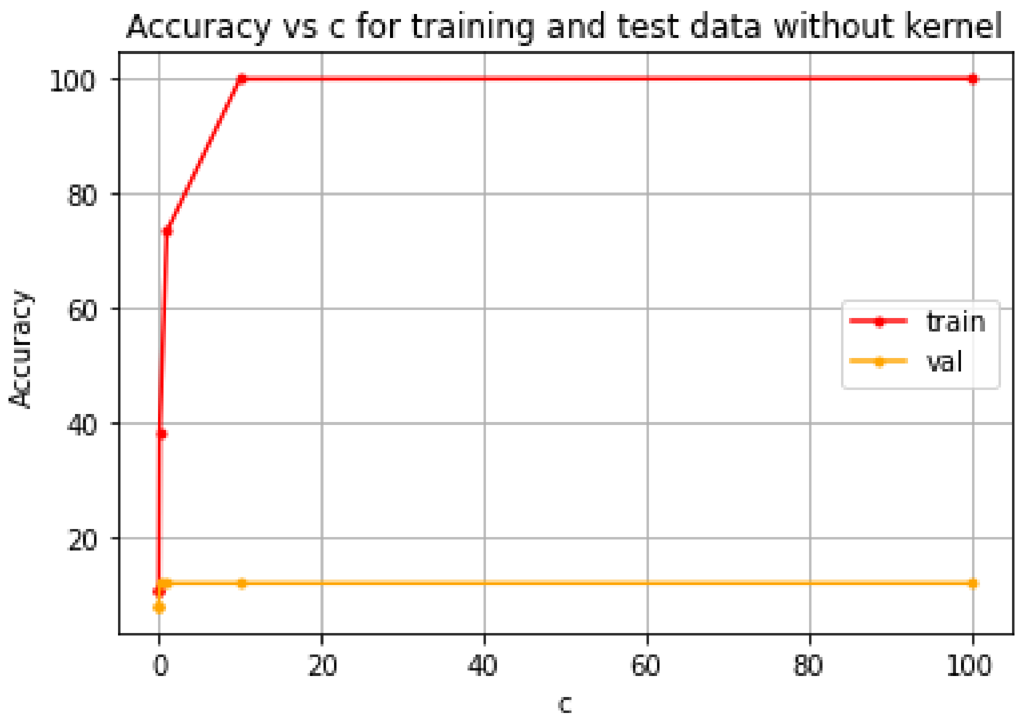
```
    val_acc.append(acc_test * 100)

    #When regularization parameter is 1 the model achieves best accuracy and␣
↪it does not overfit so storing the test accuracy when C = 1
    if i == 1:
      test_acc = svm_models_acc(svm_model, x_test, y_test)

  temp_df['Regularization Parameter'] = c
  temp_df['Training Accuracy'] = train_acc
  temp_df['Validation Accuracy'] = val_acc

  plt.plot(c, train_acc,'.-',color = 'red')
  plt.plot(c, val_acc,'.-',color = 'orange')
  plt.xlabel('c')
  plt.ylabel('Accuracy')
  plt.title("Accuracy vs c for training and test data with " + str(kernel) +␣
↪" kernel")
  plt.legend(["train", "val"])
  plt.grid()
  plt.show()

  return test_acc, temp_df

#Checking if the argument is given no kernel then creating a svm model␣
↪without a kernel
elif kernel == 'No kernel':
  #Fitting the model for different values of regularization parameter
  for i in c:
    svm_model = svm.SVC(probability = False, C = i)
    svm_model.fit(x_train, y_train)

    ypred_train = svm_model.predict(x_train)
    acc_train = np.mean(ypred_train == y_train)
    train_acc.append(acc_train * 100)

    ypred_test = svm_model.predict(x_val)
    acc_test = np.mean(ypred_test == y_val)
    val_acc.append(acc_test * 100)

    #When regularization parameter is 1 the model achieves best accuracy and␣
↪it does not overfit so storing the test accuracy when C = 1
    if i == 1:
      test_acc = svm_models_acc(svm_model, x_test, y_test)

  temp_df['Regularization Parameter'] = c
  temp_df['Training Accuracy'] = train_acc
  temp_df['Validation Accuracy'] = val_acc
```

```
    plt.plot(c, train_acc,'.-',color = 'red')
    plt.plot(c, val_acc,'.-',color = 'orange')
    plt.xlabel('c')
    plt.ylabel('Accuracy')
    plt.title("Accuracy vs c for training and test data without kernel")
    plt.legend(["train", "val"])
    plt.grid()
    plt.show()

    return test_acc, temp_df

  #If the kernel is linear or poly then defining the same model with different␣
↪kernel that is passed as parameters in the function.
  else:
    #Fitting the model for different values of regularization parameter
    for i in c:
      svm_model = svm.SVC(probability = False, kernel = kernel, C = i)
      svm_model.fit(x_train, y_train)

      ypred_train = svm_model.predict(x_train)
      acc_train = np.mean(ypred_train == y_train)
      train_acc.append(acc_train * 100)

      ypred_test = svm_model.predict(x_val)
      acc_test = np.mean(ypred_test == y_val)
      val_acc.append(acc_test * 100)

      #When regularization parameter is 1 the model achieves best accuracy and␣
↪it does not overfit so storing the test accuracy when C = 1
      if i == 1:
        test_acc = svm_models_acc(svm_model, x_test, y_test)

    temp_df['Regularization Parameter'] = c
    temp_df['Training Accuracy'] = train_acc
    temp_df['Validation Accuracy'] = val_acc

    plt.plot(c, train_acc, '.-', color = 'red')
    plt.plot(c, val_acc, '.-', color = 'orange')
    plt.xlabel('c')
    plt.ylabel('Accuracy')
    plt.title("Accuracy vs c for training and test data with " + str(kernel) +␣
↪" kernel")
    plt.legend(["train", "val"])
    plt.grid()
    plt.show()
```

```
    return test_acc, temp_df
```

Model - 1 SVM without Kernel

[9]:
```
c_svm = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100]
#Calling the svm model function with No kernel as a parameter to create a␣
↪simple svm model
test_acc_svm, temp_df = svm_models(x_train, y_train, x_val, y_val, x_test,␣
↪y_test, 'No kernel', c_svm)
```



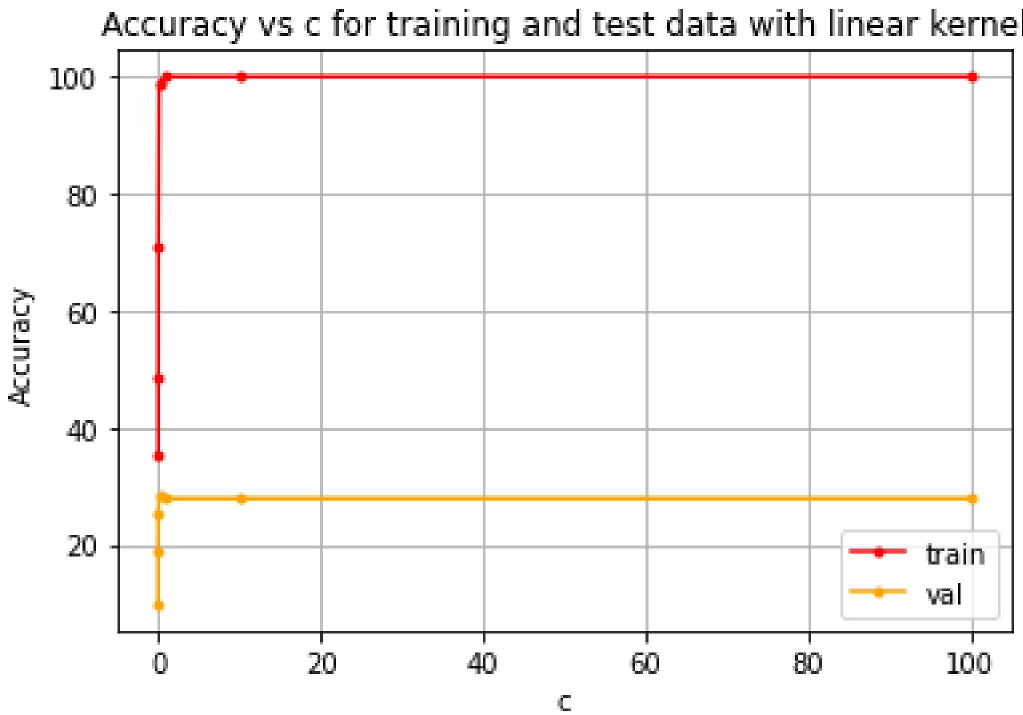
[10]:
```
#Printing the train and validation accuracy for different values of c
temp_df
```

[10]:

	Regularization Parameter	Training Accuracy	Validation Accuracy
0	0.0001	10.733333	7.9
1	0.0010	10.733333	7.9
2	0.0100	10.733333	7.9
3	0.1000	38.200000	11.9
4	1.0000	73.333333	11.9
5	10.0000	99.933333	11.9
6	100.0000	100.000000	11.9

Model - 2 SVM with Linear Kernel

[11]:
```
c_svm_linear = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100]
#Calling the svm model function and passing linear as parameter to create an␣
↪svm model with linear kernel and passing various regularization parameter.
test_acc_linear, temp_df = svm_models(x_train, y_train, x_val, y_val, x_test,␣
↪y_test, 'linear', c_svm_linear)
```



[12]:
```
#Printing the train and validation accuracy for different values of c
temp_df
```

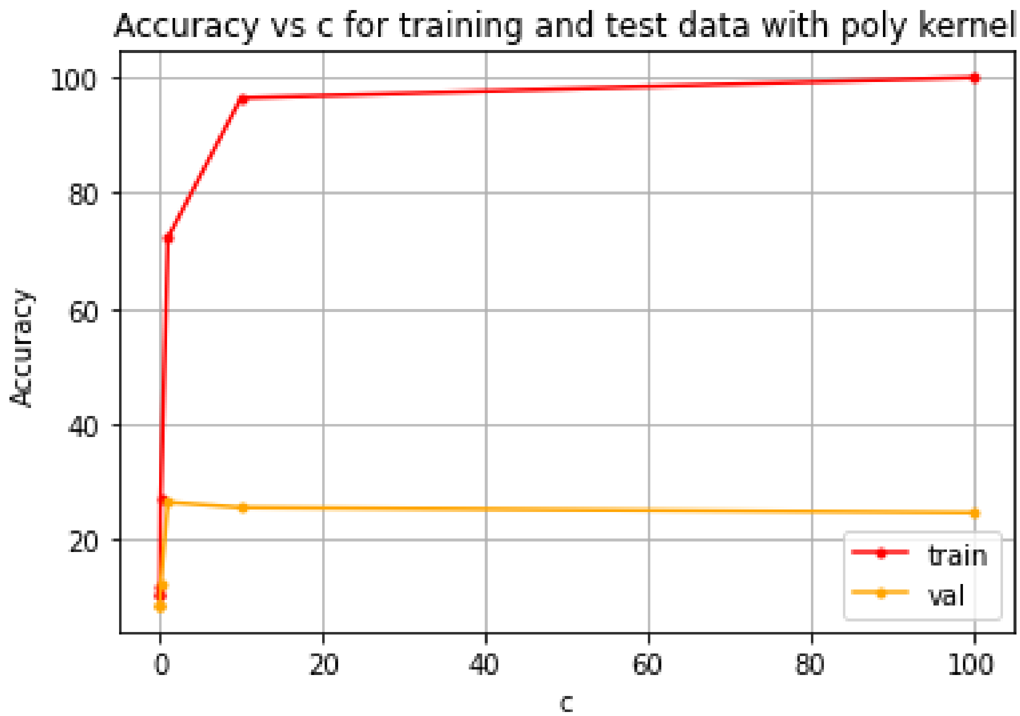
[12]:

	Regularization Parameter	Training Accuracy	Validation Accuracy
0	0.0001	35.466667	9.8
1	0.0010	48.466667	18.8
2	0.0100	70.933333	25.3
3	0.1000	98.966667	28.6
4	1.0000	100.000000	27.9
5	10.0000	100.000000	27.9
6	100.0000	100.000000	27.9

Model - 3 SVM with Polynomial Kernel

[13]:
```
c_svm_poly = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100]
#Calling the svm model function and passing poly as parameter to create an svm␣
↪model with linear kernel and passing various regularization parameter.
```

```
test_acc_poly, temp_df = svm_models(x_train, y_train, x_val, y_val, x_test,␣
↪y_test, 'poly', c_svm_poly)
```



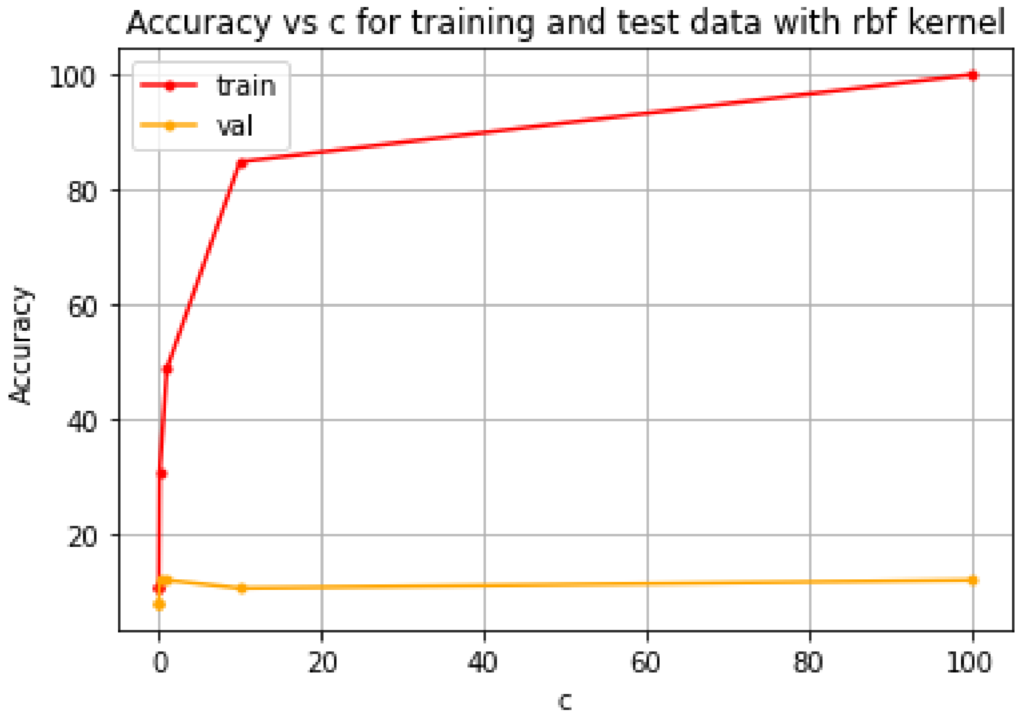
[14]:
```
#Printing the train and validation accuracy for different values of c
temp_df
```

[14]:

	Regularization Parameter	Training Accuracy	Validation Accuracy
0	0.0001	10.733333	8.7
1	0.0010	10.733333	8.7
2	0.0100	12.066667	8.7
3	0.1000	27.233333	12.5
4	1.0000	72.200000	26.5
5	10.0000	96.366667	25.6
6	100.0000	99.866667	24.7

Model - 4 SVM with RBF Kernel

[15]:
```
c_svm_rbf = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100]
#Calling the svm model function and passing rbf as parameter to create an svm␣
↪model with linear kernel and passing various regularization parameter.
test_acc_rbf, temp_df = svm_models(x_train, y_train, x_val, y_val, x_test,␣
↪y_test, 'rbf', c_svm_poly)
```



[16]:
```
#Printing the train and validation accuracy for different values of c
temp_df
```

[16]:

	Regularization Parameter	Training Accuracy	Validation Accuracy
0	0.0001	10.733333	7.9
1	0.0010	10.733333	7.9
2	0.0100	10.733333	7.9
3	0.1000	30.733333	11.9
4	1.0000	48.733333	11.9
5	10.0000	84.833333	10.5
6	100.0000	100.000000	11.9

0.2.2 Model - 5 DNN without CNN

[17]:
```
num_classes = 10

(x_train, y_train), (x_test, y_test) = cifar10.load_data()

print()
print('Training Data shape:', x_train.shape)
print("Number of Training Samples", x_train.shape[0])
print("Number of Testing Samples", x_test.shape[0])
```

```
# Converting to Categorical Classes
y_train = keras.utils.np_utils.to_categorical(y_train, num_classes)
y_test = keras.utils.np_utils.to_categorical(y_test, num_classes)
```

```
Training Data shape: (50000, 32, 32, 3)
Number of Training Samples 50000
Number of Testing Samples 10000
```

Pre - Processing

[18]:
```
#Splitting the data into train and validation
x_train, x_val, y_train, y_val = train_test_split(x_train, y_train, test_size =␣
↪0.25, random_state = 42)
```

[19]:
```
print("Number of Training Samples", x_train.shape[0])
print("Number of Validation Samples", x_val.shape[0])
print("Number of Testing Samples", x_test.shape[0])
```

```
Number of Training Samples 37500
Number of Validation Samples 12500
Number of Testing Samples 10000
```

[20]:
```
#Scaling the data for training and testing the model
X_train_scaled = x_train / 255
X_val_scaled = x_val / 255
X_test_scaled = x_test / 255
```

[21]:
```
# Creating Neural Network without CNN
model = keras.Sequential([
        keras.layers.Flatten(input_shape = (32, 32, 3)),
        keras.layers.Dense(3000, activation = 'relu'),
        keras.layers.Dense(1000, activation = 'relu'),
        keras.layers.Dense(10, activation = 'sigmoid')
    ])

#Compiling the model with Stochastic Gradient Descent as optimizer and␣
↪categorical cross entropy loss and metrics = accuracy
model.compile(optimizer = 'SGD', loss = 'categorical_crossentropy', metrics =␣
↪['accuracy'])
```

[22]:
```
#Training the model for 25 epochs along with validation data
history = model.fit(X_train_scaled, y_train, epochs = 25, validation_data =␣
↪(X_val_scaled, y_val))
```

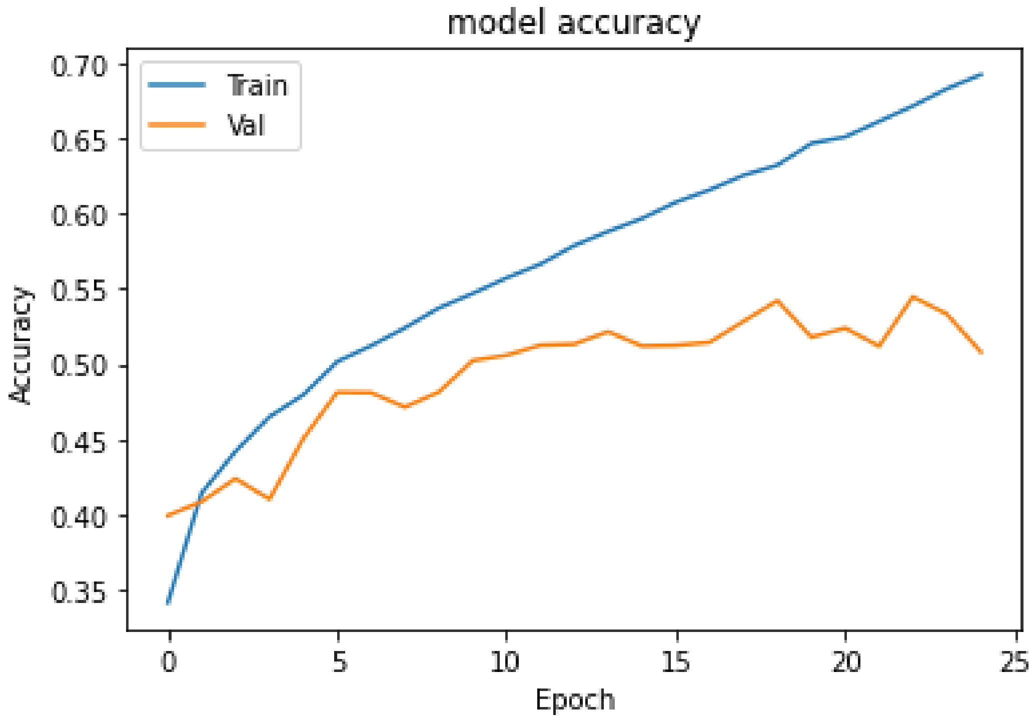
```
Epoch 1/25
1172/1172 [==============================] - 15s 11ms/step - loss: 1.8470 -
```

```
accuracy: 0.3418 - val_loss: 1.6987 - val_accuracy: 0.3996
Epoch 2/25
1172/1172 [==============================] - 12s 10ms/step - loss: 1.6598 -
accuracy: 0.4146 - val_loss: 1.6656 - val_accuracy: 0.4089
Epoch 3/25
1172/1172 [==============================] - 13s 11ms/step - loss: 1.5783 -
accuracy: 0.4421 - val_loss: 1.6007 - val_accuracy: 0.4242
Epoch 4/25
1172/1172 [==============================] - 13s 11ms/step - loss: 1.5210 -
accuracy: 0.4651 - val_loss: 1.6423 - val_accuracy: 0.4105
Epoch 5/25
1172/1172 [==============================] - 12s 10ms/step - loss: 1.4724 -
accuracy: 0.4797 - val_loss: 1.5445 - val_accuracy: 0.4506
Epoch 6/25
1172/1172 [==============================] - 12s 10ms/step - loss: 1.4288 -
accuracy: 0.5016 - val_loss: 1.4753 - val_accuracy: 0.4814
Epoch 7/25
1172/1172 [==============================] - 12s 10ms/step - loss: 1.3910 -
accuracy: 0.5122 - val_loss: 1.4660 - val_accuracy: 0.4811
Epoch 8/25
1172/1172 [==============================] - 12s 10ms/step - loss: 1.3570 -
accuracy: 0.5240 - val_loss: 1.5045 - val_accuracy: 0.4715
Epoch 9/25
1172/1172 [==============================] - 12s 10ms/step - loss: 1.3221 -
accuracy: 0.5373 - val_loss: 1.4478 - val_accuracy: 0.4815
Epoch 10/25
1172/1172 [==============================] - 12s 10ms/step - loss: 1.2952 -
accuracy: 0.5469 - val_loss: 1.4348 - val_accuracy: 0.5024
Epoch 11/25
1172/1172 [==============================] - 13s 11ms/step - loss: 1.2655 -
accuracy: 0.5572 - val_loss: 1.4029 - val_accuracy: 0.5058
Epoch 12/25
1172/1172 [==============================] - 13s 11ms/step - loss: 1.2395 -
accuracy: 0.5664 - val_loss: 1.3978 - val_accuracy: 0.5126
Epoch 13/25
1172/1172 [==============================] - 13s 11ms/step - loss: 1.2069 -
accuracy: 0.5786 - val_loss: 1.3817 - val_accuracy: 0.5133
Epoch 14/25
1172/1172 [==============================] - 12s 10ms/step - loss: 1.1833 -
accuracy: 0.5880 - val_loss: 1.3647 - val_accuracy: 0.5215
Epoch 15/25
1172/1172 [==============================] - 13s 11ms/step - loss: 1.1565 -
accuracy: 0.5966 - val_loss: 1.3860 - val_accuracy: 0.5120
Epoch 16/25
1172/1172 [==============================] - 13s 11ms/step - loss: 1.1274 -
accuracy: 0.6074 - val_loss: 1.4032 - val_accuracy: 0.5125
Epoch 17/25
1172/1172 [==============================] - 12s 10ms/step - loss: 1.1024 -
```

```
accuracy: 0.6157 - val_loss: 1.3868 - val_accuracy: 0.5145
Epoch 18/25
1172/1172 [==============================] - 12s 10ms/step - loss: 1.0753 -
accuracy: 0.6253 - val_loss: 1.3494 - val_accuracy: 0.5284
Epoch 19/25
1172/1172 [==============================] - 13s 11ms/step - loss: 1.0514 -
accuracy: 0.6321 - val_loss: 1.3344 - val_accuracy: 0.5422
Epoch 20/25
1172/1172 [==============================] - 12s 10ms/step - loss: 1.0246 -
accuracy: 0.6464 - val_loss: 1.3840 - val_accuracy: 0.5179
Epoch 21/25
1172/1172 [==============================] - 13s 11ms/step - loss: 1.0007 -
accuracy: 0.6507 - val_loss: 1.3815 - val_accuracy: 0.5239
Epoch 22/25
1172/1172 [==============================] - 12s 10ms/step - loss: 0.9767 -
accuracy: 0.6610 - val_loss: 1.4213 - val_accuracy: 0.5119
Epoch 23/25
1172/1172 [==============================] - 12s 10ms/step - loss: 0.9496 -
accuracy: 0.6713 - val_loss: 1.3250 - val_accuracy: 0.5446
Epoch 24/25
1172/1172 [==============================] - 12s 10ms/step - loss: 0.9243 -
accuracy: 0.6826 - val_loss: 1.3513 - val_accuracy: 0.5333
Epoch 25/25
1172/1172 [==============================] - 12s 10ms/step - loss: 0.9019 -
accuracy: 0.6921 - val_loss: 1.4430 - val_accuracy: 0.5082
```

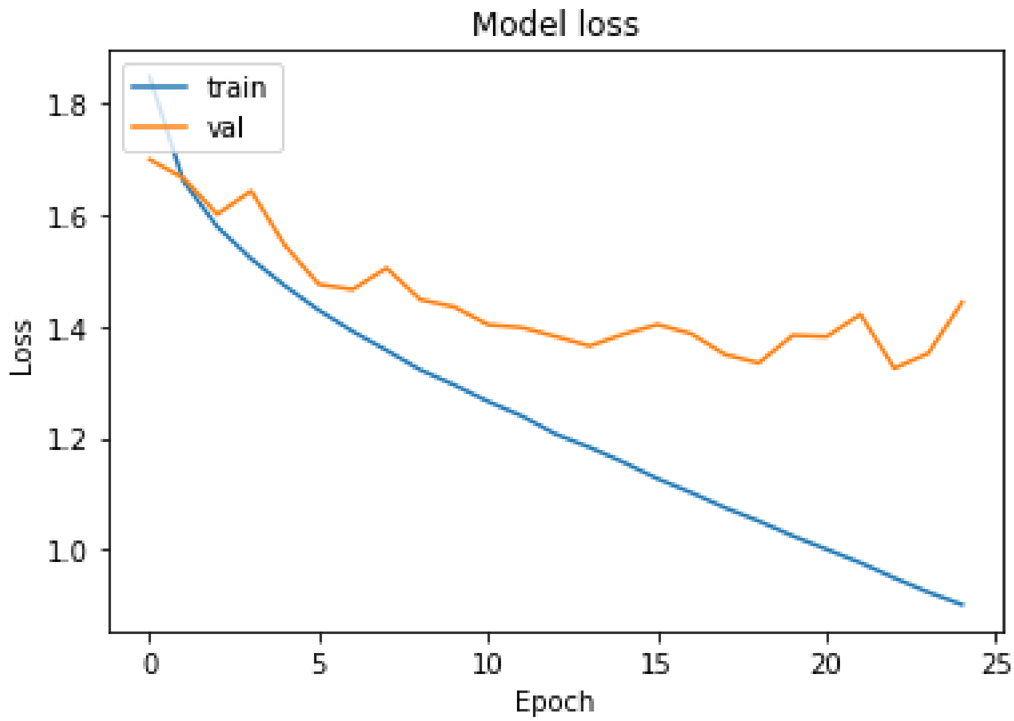
[23]:

```
#Plotting the Training and Validation Accuracy vs # of epochs
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc = 'upper left')
plt.show()
```



[24]:

```
#Plotting the Training and Validation Loss vs # of epochs
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['train', 'val'], loc = 'upper left')
plt.show()
```



[25]:
```
#Testing the model on the test data
test_loss_wo_cnn, test_accuracy_wo_cnn = model.evaluate(X_test_scaled, y_test)
```

```
313/313 [==============================] - 2s 5ms/step - loss: 1.4368 -
accuracy: 0.5066
```

0.2.3 Model - 6 DNN with CNN

[26]:
```
import tensorflow as tf
```

[27]:
```
num_classes = 10

(x_train, y_train), (x_test, y_test) = cifar10.load_data()

print()
print('Training Data shape:', x_train.shape)
print("Number of Training Samples", x_train.shape[0])
print("Number of Testing Samples", x_test.shape[0])
```

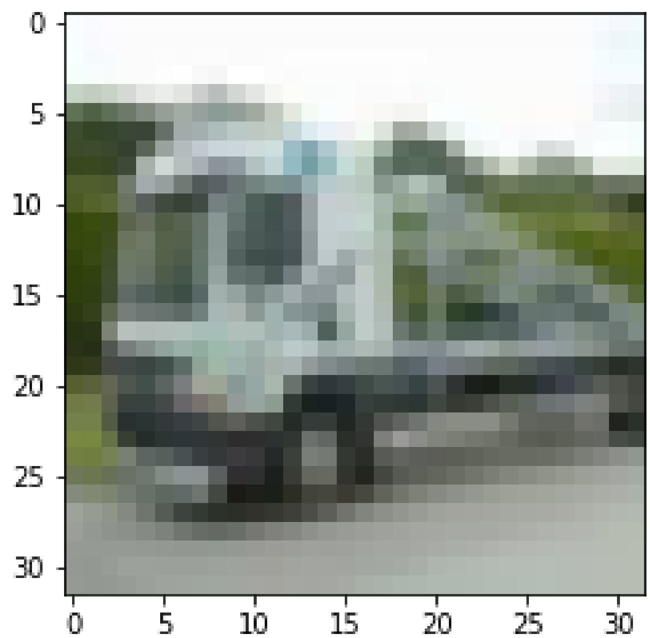
```
Training Data shape: (50000, 32, 32, 3)
Number of Training Samples 50000
Number of Testing Samples 10000
```

[28]:
```
#Splitting the data into train and validation
x_train, x_val, y_train, y_val = train_test_split(x_train, y_train, test_size =␣
↪0.25, random_state = 42)
```

[29]:
```
#Scaling the data for training the model
X_train_scaled = x_train / 255
X_val_scaled = x_val / 255
X_test_scaled = x_test / 255
```

[30]:
```
#Plotting a random test image
plt.imshow(x_test[217])
```

[30]: <matplotlib.image.AxesImage at 0x7f4291498750>



[31]:
```
#Creating a neural network with Convolution Layers
model_cnn = tf.keras.models.Sequential()
model_cnn.add(tf.keras.layers.Conv2D(filters=32,kernel_size=3,padding="same",␣
↪activation="relu", input_shape=[32,32,3]))
model_cnn.add(tf.keras.layers.Conv2D(filters=32,kernel_size=3,padding="same",␣
↪activation="relu"))
model_cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2,padding='valid'))
model_cnn.add(tf.keras.layers.Conv2D(filters=64,kernel_size=3,padding="same",␣
↪activation="relu"))
model_cnn.add(tf.keras.layers.Conv2D(filters=64,kernel_size=3,padding="same",␣
↪activation="relu"))
```

```
model_cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2,padding='valid'))
model_cnn.add(tf.keras.layers.Flatten())
model_cnn.add(tf.keras.layers.Dropout(0.5,noise_shape=None,seed=None))
model_cnn.add(tf.keras.layers.Dense(units = 128,activation='relu'))
model_cnn.add(tf.keras.layers.Dense(units = 10,activation='softmax'))
```

[32]:
```
#Printing the model architecture
model_cnn.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 32, 32, 32)        896

 conv2d_1 (Conv2D)           (None, 32, 32, 32)        9248

 max_pooling2d (MaxPooling2D  (None, 16, 16, 32)       0
 )

 conv2d_2 (Conv2D)           (None, 16, 16, 64)        18496

 conv2d_3 (Conv2D)           (None, 16, 16, 64)        36928

 max_pooling2d_1 (MaxPooling  (None, 8, 8, 64)         0
 2D)

 flatten_1 (Flatten)         (None, 4096)              0

 dropout (Dropout)           (None, 4096)              0

 dense_3 (Dense)             (None, 128)               524416

 dense_4 (Dense)             (None, 10)                1290

=================================================================
Total params: 591,274
Trainable params: 591,274
Non-trainable params: 0
_________________________________________________________________
```

[33]:
```
#Compiling the model with Adam as optimizer and sparse categorical cross␣
↪entropy loss and metrics = sparse categorical accuracy
model_cnn.compile(loss = "sparse_categorical_crossentropy", optimizer = "Adam",␣
↪metrics = ["sparse_categorical_accuracy"])
```

[34]:
```
#Training the model for 25 epochs along with validation data
history1 = model_cnn.fit(X_train_scaled, y_train, epochs = 25, validation_data␣
↪= (X_val_scaled, y_val))
```

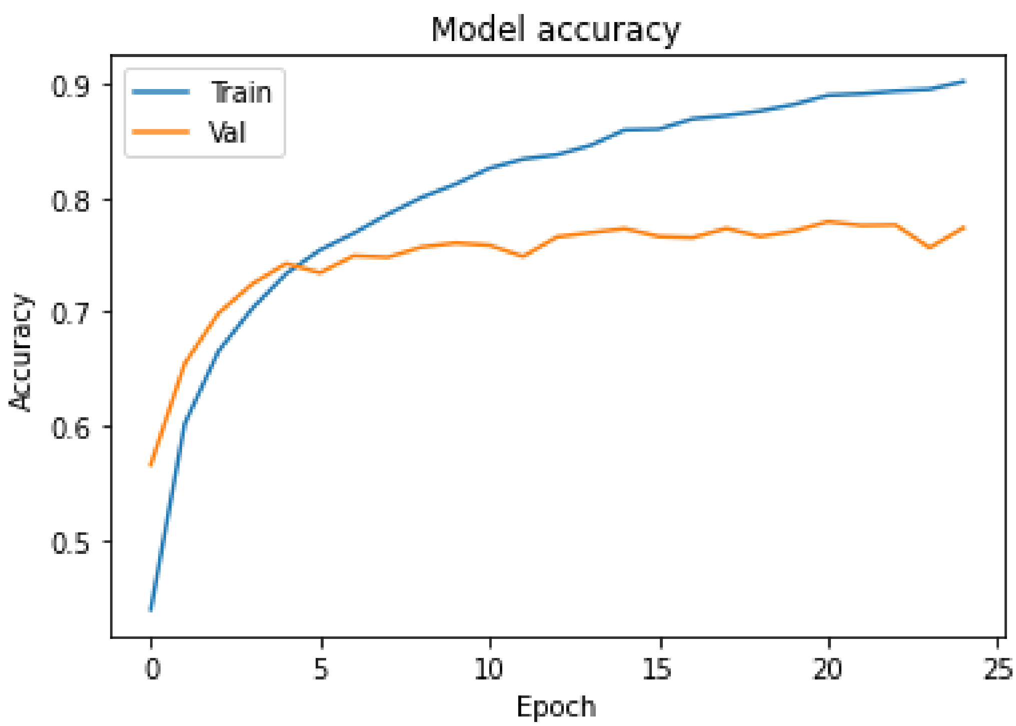
```
Epoch 1/25
1172/1172 [==============================] - 30s 17ms/step - loss: 1.5332 -
sparse_categorical_accuracy: 0.4387 - val_loss: 1.2095 -
val_sparse_categorical_accuracy: 0.5660
Epoch 2/25
1172/1172 [==============================] - 18s 15ms/step - loss: 1.1192 -
sparse_categorical_accuracy: 0.6017 - val_loss: 0.9728 -
val_sparse_categorical_accuracy: 0.6546
Epoch 3/25
1172/1172 [==============================] - 19s 16ms/step - loss: 0.9403 -
sparse_categorical_accuracy: 0.6657 - val_loss: 0.8558 -
val_sparse_categorical_accuracy: 0.6990
Epoch 4/25
1172/1172 [==============================] - 19s 16ms/step - loss: 0.8351 -
sparse_categorical_accuracy: 0.7032 - val_loss: 0.7831 -
val_sparse_categorical_accuracy: 0.7248
Epoch 5/25
1172/1172 [==============================] - 20s 17ms/step - loss: 0.7543 -
sparse_categorical_accuracy: 0.7337 - val_loss: 0.7419 -
val_sparse_categorical_accuracy: 0.7426
Epoch 6/25
1172/1172 [==============================] - 19s 17ms/step - loss: 0.6988 -
sparse_categorical_accuracy: 0.7544 - val_loss: 0.7663 -
val_sparse_categorical_accuracy: 0.7344
Epoch 7/25
1172/1172 [==============================] - 19s 16ms/step - loss: 0.6461 -
sparse_categorical_accuracy: 0.7691 - val_loss: 0.7270 -
val_sparse_categorical_accuracy: 0.7494
Epoch 8/25
1172/1172 [==============================] - 19s 16ms/step - loss: 0.5968 -
sparse_categorical_accuracy: 0.7859 - val_loss: 0.7268 -
val_sparse_categorical_accuracy: 0.7480
Epoch 9/25
1172/1172 [==============================] - 19s 16ms/step - loss: 0.5631 -
sparse_categorical_accuracy: 0.8006 - val_loss: 0.7120 -
val_sparse_categorical_accuracy: 0.7570
Epoch 10/25
1172/1172 [==============================] - 19s 16ms/step - loss: 0.5263 -
sparse_categorical_accuracy: 0.8123 - val_loss: 0.6909 -
val_sparse_categorical_accuracy: 0.7606
Epoch 11/25
1172/1172 [==============================] - 20s 17ms/step - loss: 0.4911 -
sparse_categorical_accuracy: 0.8262 - val_loss: 0.7274 -
```

```
val_sparse_categorical_accuracy: 0.7586
Epoch 12/25
1172/1172 [==============================] - 20s 17ms/step - loss: 0.4682 -
sparse_categorical_accuracy: 0.8343 - val_loss: 0.7558 -
val_sparse_categorical_accuracy: 0.7487
Epoch 13/25
1172/1172 [==============================] - 19s 17ms/step - loss: 0.4511 -
sparse_categorical_accuracy: 0.8381 - val_loss: 0.6974 -
val_sparse_categorical_accuracy: 0.7659
Epoch 14/25
1172/1172 [==============================] - 20s 17ms/step - loss: 0.4285 -
sparse_categorical_accuracy: 0.8465 - val_loss: 0.7383 -
val_sparse_categorical_accuracy: 0.7697
Epoch 15/25
1172/1172 [==============================] - 20s 17ms/step - loss: 0.3964 -
sparse_categorical_accuracy: 0.8599 - val_loss: 0.7052 -
val_sparse_categorical_accuracy: 0.7732
Epoch 16/25
1172/1172 [==============================] - 20s 17ms/step - loss: 0.3868 -
sparse_categorical_accuracy: 0.8606 - val_loss: 0.7419 -
val_sparse_categorical_accuracy: 0.7663
Epoch 17/25
1172/1172 [==============================] - 20s 17ms/step - loss: 0.3662 -
sparse_categorical_accuracy: 0.8696 - val_loss: 0.7623 -
val_sparse_categorical_accuracy: 0.7653
Epoch 18/25
1172/1172 [==============================] - 20s 17ms/step - loss: 0.3531 -
sparse_categorical_accuracy: 0.8726 - val_loss: 0.7193 -
val_sparse_categorical_accuracy: 0.7734
Epoch 19/25
1172/1172 [==============================] - 20s 17ms/step - loss: 0.3433 -
sparse_categorical_accuracy: 0.8766 - val_loss: 0.7771 -
val_sparse_categorical_accuracy: 0.7663
Epoch 20/25
1172/1172 [==============================] - 19s 17ms/step - loss: 0.3268 -
sparse_categorical_accuracy: 0.8823 - val_loss: 0.7767 -
val_sparse_categorical_accuracy: 0.7710
Epoch 21/25
1172/1172 [==============================] - 19s 17ms/step - loss: 0.3084 -
sparse_categorical_accuracy: 0.8904 - val_loss: 0.7362 -
val_sparse_categorical_accuracy: 0.7794
Epoch 22/25
1172/1172 [==============================] - 19s 17ms/step - loss: 0.3057 -
sparse_categorical_accuracy: 0.8917 - val_loss: 0.7355 -
val_sparse_categorical_accuracy: 0.7760
Epoch 23/25
1172/1172 [==============================] - 19s 16ms/step - loss: 0.2988 -
sparse_categorical_accuracy: 0.8940 - val_loss: 0.7616 -
```

```
val_sparse_categorical_accuracy: 0.7765
Epoch 24/25
1172/1172 [==============================] - 19s 16ms/step - loss: 0.2894 -
sparse_categorical_accuracy: 0.8955 - val_loss: 0.8389 -
val_sparse_categorical_accuracy: 0.7564
Epoch 25/25
1172/1172 [==============================] - 20s 17ms/step - loss: 0.2768 -
sparse_categorical_accuracy: 0.9023 - val_loss: 0.7878 -
val_sparse_categorical_accuracy: 0.7738
```

[38]:

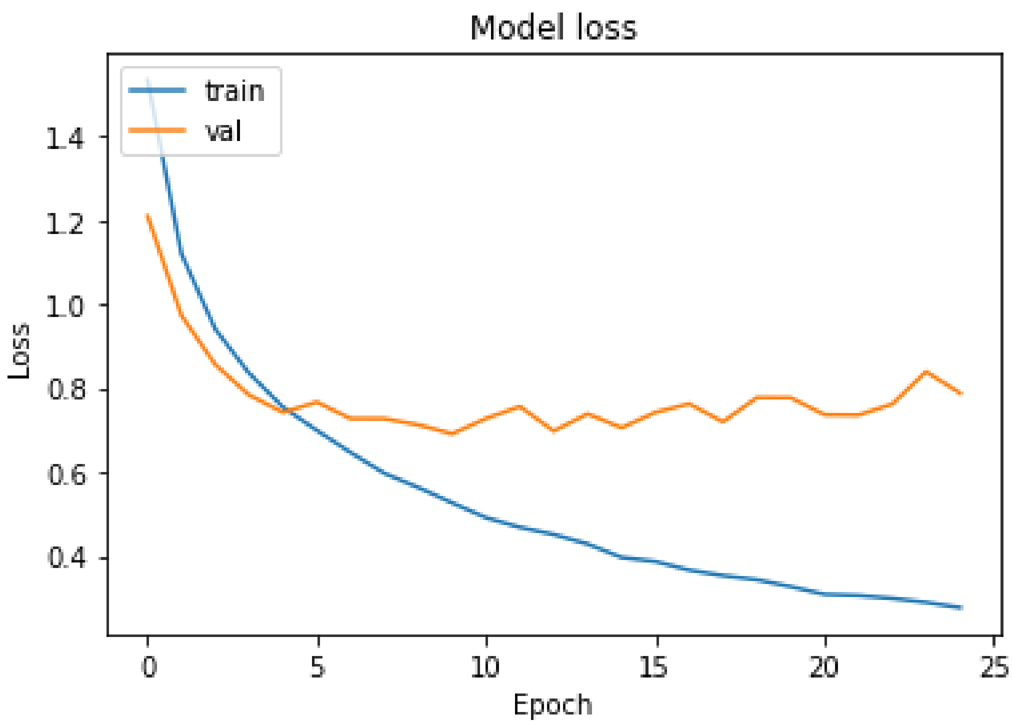
```
#Plotting the Training and Validation Accuracy vs # of epochs
plt.plot(history1.history['sparse_categorical_accuracy'])
plt.plot(history1.history['val_sparse_categorical_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc = 'upper left')
plt.show()
```



[39]:

```
#Plotting the Training and Validation Loss vs # of epochs
plt.plot(history1.history['loss'])
plt.plot(history1.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
```

```
plt.xlabel('Epoch')
plt.legend(['train', 'val'], loc = 'upper left')
plt.show()
```



[40]:
```
#Testing the model on the test data
test_loss_cnn, test_accuracy_cnn = model_cnn.evaluate(X_test_scaled, y_test)
```

```
313/313 [==============================] - 2s 8ms/step - loss: 0.8099 -
sparse_categorical_accuracy: 0.7700
```

1 Model Evalution

[41]:
```
#Creating an empty dataframe to compare the results of all models
df = pd.DataFrame()
```

[42]:
```
#Creating Model Name Column and appending all the proposed model names
df['Model Name'] = ['SVM without Kernel', 'SVM With Linear Kernel', 'SVM With␣
↪Poly Kernel', 'SVM With RBF Kernel', 'Neural Network without CNN', 'Neural␣
↪Network with CNN']
```

[43]:
```
#Creating the Test Accuracy column and storing the accuracy on test data for␣
↪all the 6 proposed models
```

```
df['Test Accuracy'] = [test_acc_svm * 100, test_acc_linear * 100, test_acc_poly␣
↪* 100, test_acc_rbf * 100, test_accuracy_wo_cnn * 100,  test_accuracy_cnn *␣
↪100 ]
```

[44]:
```
df
```

[44]:
```
                    Model Name  Test Accuracy
0           SVM without Kernel      10.000000
1       SVM With Linear Kernel      26.090000
2         SVM With Poly Kernel      25.560000
3          SVM With RBF Kernel      10.000000
4   Neural Network without CNN      50.660002
5      Neural Network with CNN      76.999998
```

Conclusion : From the above dataframe we can see that the Supervised Model such as SVM with different kernels give low accuracy ranging from 10 to 26% on test data which is low compared to neural networks with and without CNN. Moreover, the best model is the model with CNN layer having an accuracy of 77% on the test data.

[ ]:
```
!wget -nc https://raw.githubusercontent.com/brpy/colab-pdf/master/colab_pdf.py
from colab_pdf import colab_pdf
colab_pdf('Simran_Goindani_Ashir_Mehta_DS5220_Final_Project.ipynb')
```

```
--2022-05-06 10:17:32--  https://raw.githubusercontent.com/brpy/colab-
pdf/master/colab_pdf.py
Resolving raw.githubusercontent.com (raw.githubusercontent.com)…
185.199.108.133, 185.199.109.133, 185.199.110.133, …
Connecting to raw.githubusercontent.com
(raw.githubusercontent.com)|185.199.108.133|:443… connected.
HTTP request sent, awaiting response… 200 OK
Length: 1864 (1.8K) [text/plain]
Saving to: ‘colab_pdf.py’

colab_pdf.py        100%[===================>]   1.82K  --.-KB/s    in 0s

2022-05-06 10:17:32 (18.1 MB/s) - ‘colab_pdf.py’ saved [1864/1864]

Mounted at /content/drive/

WARNING: apt does not have a stable CLI interface. Use with caution in scripts.


WARNING: apt does not have a stable CLI interface. Use with caution in scripts.

Extracting templates from packages: 100%
```

[ ]: