Experiment - 1

Bank Churn ANN

```
import numpy as np
import pandas as pd
```

```
churn_data = pd.read_csv('/workspace/FDP/Day3/Churn_Modelling.csv', delimiter = ',')
churn_data.head(5)
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1

```
churn_data.columns
```

```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

```
churn_data = churn_data.set_index('RowNumber')
churn_data.head()
```

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Es
RowNumber												
1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	
2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	
3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	
4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	
5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	

```
churn_data.shape
```

```
(10000, 13)
```

```
churn_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10000 entries, 1 to 10000
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   CustomerId       10000 non-null  int64  
 1   Surname          10000 non-null  object 
 2   CreditScore      10000 non-null  int64  
 3   Geography        10000 non-null  object 
 4   Gender           10000 non-null  object 
 5   Age              10000 non-null  int64  
 6   Tenure           10000 non-null  int64  
 7   Balance          10000 non-null  float64
 8   NumOfProducts    10000 non-null  int64  
 9   HasCrCard        10000 non-null  int64  
 10  IsActiveMember   10000 non-null  int64  
 11  EstimatedSalary  10000 non-null  float64
 12  Exited           10000 non-null  int64  
dtypes: float64(2), int64(8), object(3)
memory usage: 1.1+ MB
```

```
churn_data.isna().sum()
```

```
churn_data.isna().sum()
```

```
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

```
churn_data.nunique()
```

```
CustomerId         10000
Surname             2932
CreditScore          460
Geography              3
Gender                 2
Age                   70
Tenure                11
Balance             6382
NumOfProducts          4
HasCrCard              2
IsActiveMember         2
EstimatedSalary     9999
Exited                 2
dtype: int64
```

```
churn_data.drop(['CustomerId','Surname'],axis=1,inplace=True)
```

```
churn_data.head()
```

RowNumber	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
1	619	France	Female	42	2	0.00	1	1	1	101348.88	1
2	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
3	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
4	699	France	Female	39	1	0.00	2	0	0	93826.63	0
5	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

```
churn_data.shape
```

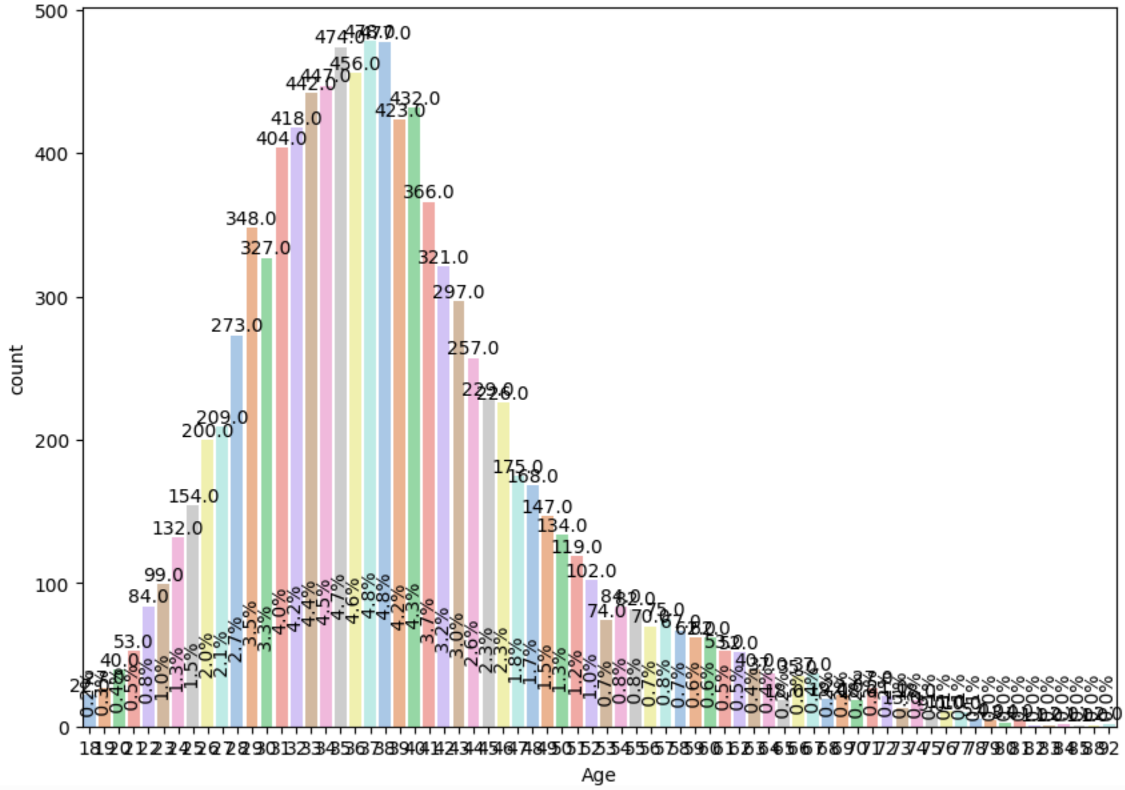
```
(10000, 11)
```

```
from matplotlib import pyplot as plt
import seaborn as sns
from scipy import stats
df = churn_data.copy()


def plot_univariate(col):
    if(df[col].nunique()>2):
        plt.figure(figsize=(10,7))
        h = 0.15
        rot=90
    else:
        plt.figure(figsize=(6,6))
        h = 0.5
        rot=0
    plot = sns.countplot(x = df[col], palette='pastel')

    for bars in plot.containers:
        for p in bars:
            plot.annotate(format(p.get_height()), (p.get_x() + p.get_width()*0.5, p.get_height()),
                    ha = 'center', va = 'bottom')
            plot.annotate(f'{p.get_height()*100/df[col].shape[0] : .1f}%', (p.get_x() + p.get_width()*0.5, h*p.get_height()),
                    ha = 'center', va = 'bottom', rotation=rot)


def spearman(df,hue):
    feature = []
    correlation = []
```

```
    result = []
    for col in df.columns:
        corr, p = stats.spearmanr(df[col], df[hue])
        feature.append(col)
        correlation.append(corr)
        alpha = 0.05
        if p > alpha:
            result.append('No correlation (fail to reject H0)')
        else:
            result.append('Some correlation (reject H0)')
    c = pd.DataFrame({'Feature Name':feature,'correlation coefficient':correlation, 'Inference':result})
    display(c)
```

```
plot_univariate('Age')
```

```
/tmp/ipykernel_6944/4200767248.py:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `le

  plot = sns.countplot(x = df[col], palette='pastel')
```




```
spearman(churn_data,'Age')
```

	Feature Name	correlation coefficient	Inference
0	CreditScore	-0.007974	No correlation (fail to reject H0)
1	Geography	0.035351	Some correlation (reject H0)
2	Gender	-0.029785	Some correlation (reject H0)
3	Age	1.000000	Some correlation (reject H0)
4	Tenure	-0.010405	No correlation (fail to reject H0)
5	Balance	0.033304	Some correlation (reject H0)
6	NumOfProducts	-0.058566	Some correlation (reject H0)
7	HasCrCard	-0.015278	No correlation (fail to reject H0)
8	IsActiveMember	0.039839	Some correlation (reject H0)
9	EstimatedSalary	-0.002431	No correlation (fail to reject H0)
10	Exited	0.323968	Some correlation (reject H0)

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
churn_data[['Geography', 'Gender']] = churn_data[['Geography', 'Gender']].apply(le.fit_transform)
```

```
churn_data.head()
```

RowNumber	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
1	619	0	0	42	2	0.00	1	1	1	101348.88	1
2	608	2	0	41	1	83807.86	1	0	1	112542.58	0
3	502	0	0	42	8	159660.80	3	1	0	113931.57	1
4	699	0	0	39	1	0.00	2	0	0	93826.63	0
5	850	2	0	43	2	125510.82	1	1	1	79084.10	0

```
y = churn_data.Exited
X = churn_data.drop(['Exited'],axis=1)
```

```
X.columns
```

```
Index(['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance',
       'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary'],
      dtype='object')
```

```
y
```

```
RowNumber
1        1
2        0
3        1
4        0
5        0
        ..
9996     0
9997     0
9998     1
9999     1
10000    0
Name: Exited, Length: 10000, dtype: int64
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 2)
```

```
print("Shape of the X_train", X_train.shape)
print("Shape of the X_test", X_test.shape)
print("Shape of the y_train", y_train.shape)
print("Shape of the y_test", y_test.shape)
```

```
Shape of the X_train (7000, 10)
Shape of the X_test (3000, 10)
Shape of the y_train (7000,)
Shape of the y_test (3000,)
```

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

```
# sequential model to initialise our ann and dense module to build the layers
from keras.models import Sequential
from keras.layers import Dense
```

```
2024-05-21 08:34:06.981674: E external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9373] Unable to register cuDNN factory: Attemp
2024-05-21 08:34:06.981725: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:607] Unable to register cuFFT factory: Attempt
2024-05-21 08:34:06.982807: E external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1534] Unable to register cuBLAS factory: Atte
2024-05-21 08:34:06.989509: I tensorflow/core/platform/cpu_feature_guard.cc:183] This TensorFlow binary is optimized to use availabl
To enable the following instructions: SSE3 SSE4.1 SSE4.2 AVX, in other operations, rebuild TensorFlow with the appropriate compiler
```

```
classifier = Sequential()
# Adding the input layer and the first hidden layer
classifier.add(Dense(units = 8, kernel_initializer = 'uniform', activation = 'relu', input_dim = 10))

# Adding the second hidden layer
classifier.add(Dense(units = 16, kernel_initializer = 'uniform', activation = 'relu'))

# Adding the output layer
classifier.add(Dense(units = 1, kernel_initializer = 'uniform', activation = 'sigmoid'))
```

```
2024-05-21 08:34:10.706731: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1926] Created device /job:localhost/replica:0/task:0/
```

```
classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])

# Fitting the ANN to the Training set
classifier.fit(X_train, y_train, batch_size = 10, epochs = 100, verbose = 1)
```

```
Epoch 1/100
2024-05-21 08:34:30.051165: I external/local_xla/xla/service/service.cc:168] XLA service 0x7fc261d536a0 initialized for platform
2024-05-21 08:34:30.051210: I external/local_xla/xla/service/service.cc:176]   StreamExecutor device (0): NVIDIA A100-SXM4-40GB M
2024-05-21 08:34:30.056612: I tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_util.cc:269] disabling MLIR crash reproducer, s
2024-05-21 08:34:30.108404: I external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:467] Loaded cuDNN version 90000
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
I0000 00:00:1716280470.197288    7745 device_compiler.h:186] Compiled cluster using XLA!  This line is logged at most once for th
700/700 [==============================] - 3s 1ms/step - loss: 0.4773 - accuracy: 0.7924
Epoch 2/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4296 - accuracy: 0.7926
Epoch 3/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4231 - accuracy: 0.8116
Epoch 4/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4188 - accuracy: 0.8240
Epoch 5/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4158 - accuracy: 0.8297
Epoch 6/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4134 - accuracy: 0.8314
Epoch 7/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4120 - accuracy: 0.8291
Epoch 8/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4107 - accuracy: 0.8336
Epoch 9/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4093 - accuracy: 0.8321
Epoch 10/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4089 - accuracy: 0.8327
Epoch 11/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4075 - accuracy: 0.8324
Epoch 12/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4071 - accuracy: 0.8320
Epoch 13/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4064 - accuracy: 0.8320
Epoch 14/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4050 - accuracy: 0.8336
Epoch 15/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4053 - accuracy: 0.8346
Epoch 16/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4045 - accuracy: 0.8326
Epoch 17/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4035 - accuracy: 0.8353
Epoch 18/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4041 - accuracy: 0.8359
Epoch 19/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4030 - accuracy: 0.8340
Epoch 20/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4020 - accuracy: 0.8344
Epoch 21/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4015 - accuracy: 0.8357
Epoch 22/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4015 - accuracy: 0.8331
Epoch 23/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4013 - accuracy: 0.8331
Epoch 24/100
700/700 [==============================] - 1s 1ms/step - loss: 0.4010 - accuracy: 0.8356
Epoch 25/100
700/700 [==============================] - 1s 1ms/step - loss: 0.3994 - accuracy: 0.8371
Epoch 26/100
```

```
score, acc = classifier.evaluate(X_train, y_train,
                            batch_size=10)
print('Train score:', score)
print('Train accuracy:', acc)

# Predicting the Test set results
y_pred = classifier.predict(X_test)
y_pred = (y_pred > 0.5)

print('*'*20)
score, acc = classifier.evaluate(X_test, y_test,
                            batch_size=10)
print('Test score:', score)
print('Test accuracy:', acc)
```

```
700/700 [==============================] - 1s 884us/step - loss: 0.3388 - accuracy: 0.8609
Train score: 0.33875057101249695
Train accuracy: 0.8608571290969849
94/94 [==============================] - 0s 667us/step
```

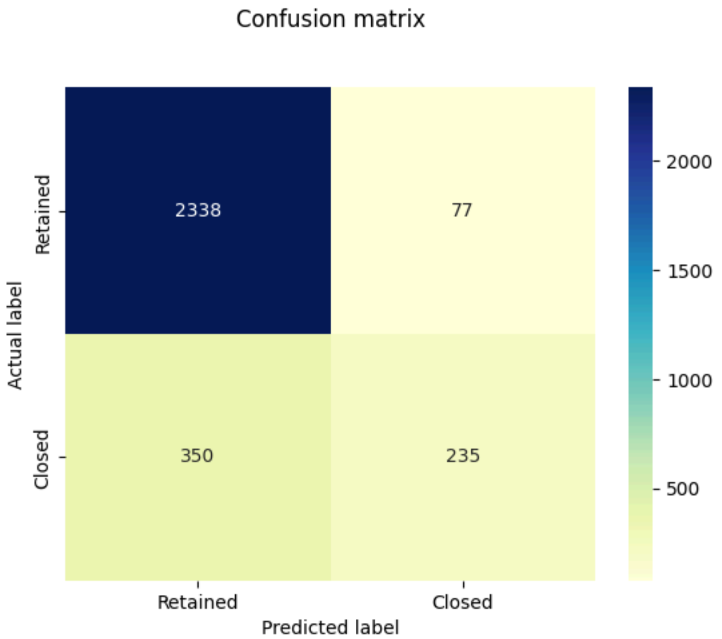
```
********************
300/300 [==============================] - 0s 910us/step - loss: 0.3567 - accuracy: 0.8577
Test score: 0.3566587269306183
Test accuracy: 0.8576666712760925
```

```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
target_names = ['Retained', 'Closed']
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[2338   77]
 [ 350  235]]
```

```
import matplotlib.pyplot as plt
import seaborn as sns


p = sns.heatmap(pd.DataFrame(cm), annot=True, xticklabels=target_names, yticklabels=target_names, cmap="YlGnBu" ,fmt='g')
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

```
Text(0.5, 23.52222222222222, 'Predicted label')
```

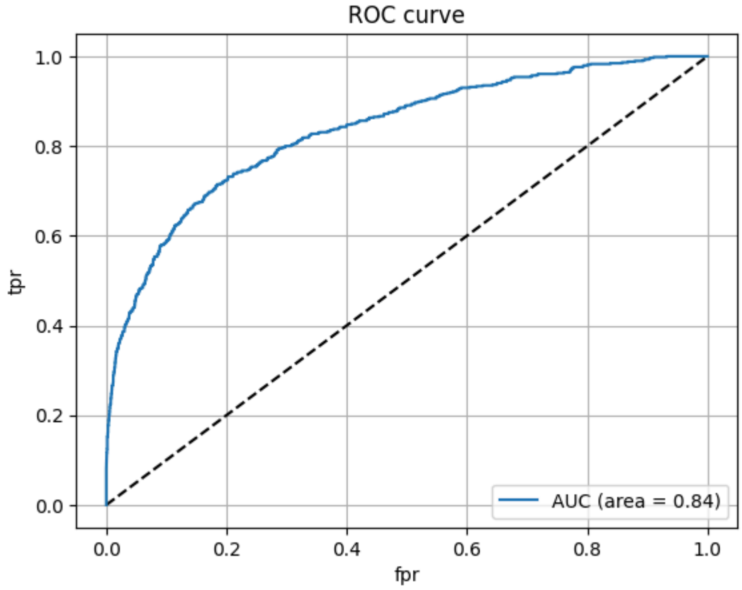



```
#import classification_report
from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred, target_names=target_names))
```

```
              precision    recall  f1-score   support

    Retained       0.87      0.97      0.92      2415
      Closed       0.75      0.40      0.52       585

    accuracy                           0.86      3000
   macro avg       0.81      0.68      0.72      3000
weighted avg       0.85      0.86      0.84      3000
```

```
from sklearn.metrics import roc_curve, auc
y_pred_proba = classifier.predict(X_test)
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
roc_auc = auc(fpr, tpr)
plt.plot([0,1],[0,1],'k--')
plt.plot(fpr,tpr, label='AUC (area = %0.2f)' % roc_auc)
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.grid()
plt.legend(loc="lower right")
plt.title('ROC curve')
plt.show()
```

```
94/94 [==============================] - 0s 667us/step
```




```
#Area under ROC curve
from sklearn.metrics import roc_auc_score
roc_auc_score(y_test,y_pred_proba)
```

```
0.8357169400647662
```

Experiment - 2

ANN using Bird data

```
import numpy as np
import pandas as pd
```

```
bird_data = pd.read_csv('/workspace/FDP/Day3/bird.csv', delimiter = ',')
bird_data.head(5)
```

	id	huml	humw	ulnal	ulnaw	feml	femw	tibl	tibw	tarl	tarw	type
0	0	80.78	6.68	72.01	4.88	41.81	3.70	5.50	4.03	38.70	3.84	SW
1	1	88.91	6.63	80.53	5.59	47.04	4.30	80.22	4.51	41.50	4.01	SW
2	2	79.97	6.37	69.26	5.28	43.07	3.90	75.35	4.04	38.31	3.34	SW
3	3	77.65	5.70	65.76	4.77	40.04	3.52	69.17	3.40	35.78	3.41	SW
4	4	62.80	4.84	52.09	3.73	33.95	2.72	56.27	2.96	31.88	3.13	SW

```
bird_data.columns
```

```
Index(['id', 'huml', 'humw', 'ulnal', 'ulnaw', 'feml', 'femw', 'tibl', 'tibw',
       'tarl', 'tarw', 'type'],
      dtype='object')
```

```
bird_data = bird_data.set_index('id')
bird_data.head()
```

	huml	humw	ulnal	ulnaw	feml	femw	tibl	tibw	tarl	tarw	type
id											
0	80.78	6.68	72.01	4.88	41.81	3.70	5.50	4.03	38.70	3.84	SW
1	88.91	6.63	80.53	5.59	47.04	4.30	80.22	4.51	41.50	4.01	SW
2	79.97	6.37	69.26	5.28	43.07	3.90	75.35	4.04	38.31	3.34	SW
3	77.65	5.70	65.76	4.77	40.04	3.52	69.17	3.40	35.78	3.41	SW
4	62.80	4.84	52.09	3.73	33.95	2.72	56.27	2.96	31.88	3.13	SW

```
bird_data.shape
```

```
(420, 11)
```

```
bird_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 420 entries, 0 to 419
Data columns (total 11 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   huml    419 non-null    float64
 1   humw    419 non-null    float64
 2   ulnal   417 non-null    float64
 3   ulnaw   418 non-null    float64
 4   feml    418 non-null    float64
 5   femw    419 non-null    float64
 6   tibl    418 non-null    float64
 7   tibw    419 non-null    float64
 8   tarl    419 non-null    float64
 9   tarw    419 non-null    float64
 10  type    420 non-null    object
dtypes: float64(10), object(1)
memory usage: 39.4+ KB
```

```
bird_data.isna().sum()
```

```
huml     1
humw     1
ulnal    3
ulnaw    2
feml     2
femw     1
```

```
tibl     2
tibw     1
tarl     1
tarw     1
type     0
dtype: int64
```

```
bird_data.dropna(how='any', inplace=True)
```

```
bird_data.isna().sum()
```

```
huml     0
humw     0
ulnal    0
ulnaw    0
feml     0
femw     0
tibl     0
tibw     0
tarl     0
tarw     0
type     0
dtype: int64
```

```
bird_data.shape
```

```
(413, 11)
```

```
bird_data.nunique()
```

```
huml     403
humw     319
ulnal    394
ulnaw    305
feml     397
femw     287
tibl     401
tibw     283
tarl     403
tarw     277
type       6
dtype: int64
```

```
bird_data['type'].unique()
```

```
array(['SW', 'W', 'T', 'R', 'P', 'SO'], dtype=object)
```

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
bird_data[['type']] = bird_data[['type']].apply(le.fit_transform)
```

```
bird_data.head()
```

id	huml	humw	ulnal	ulnaw	feml	femw	tibl	tibw	tarl	tarw	type
0	80.78	6.68	72.01	4.88	41.81	3.70	5.50	4.03	38.70	3.84	3
1	88.91	6.63	80.53	5.59	47.04	4.30	80.22	4.51	41.50	4.01	3
2	79.97	6.37	69.26	5.28	43.07	3.90	75.35	4.04	38.31	3.34	3
3	77.65	5.70	65.76	4.77	40.04	3.52	69.17	3.40	35.78	3.41	3
4	62.80	4.84	52.09	3.73	33.95	2.72	56.27	2.96	31.88	3.13	3

```
y = bird_data['type']
X = bird_data.drop(['type'],axis=1)
```

```
X.columns
```

```
Index(['huml', 'humw', 'ulnal', 'ulnaw', 'feml', 'femw', 'tibl', 'tibw',
       'tarl', 'tarw'],
      dtype='object')
```

```
y
```

```
id
0      3
```

```
1      3
2      3
3      3
4      3
      ..
415    2
416    2
417    2
418    2
419    2
Name: type, Length: 413, dtype: int64
```

```
y.shape
```

```
(413,)
```

```
# from tensorflow.keras.utils import np_utils
# num_classes = 6
# y = np_utils.to_categorical(y, num_classes)
# y
```

```
from tensorflow.keras.utils import to_categorical

num_classes = 6
y = to_categorical(y, num_classes)
print(y)
```

```
[[0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 ...
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]]
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 2)
```

```
print("Shape of the X_train", X_train.shape)
print("Shape of the X_test", X_test.shape)
print("Shape of the y_train", y_train.shape)
print("Shape of the y_test", y_test.shape)
```

```
Shape of the X_train (330, 10)
Shape of the X_test (83, 10)
Shape of the y_train (330, 6)
Shape of the y_test (83, 6)
```

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

```
# sequential model to initialise our ann and dense module to build the layers
from keras.models import Sequential
from keras.layers import Dense
```

```
classifier = Sequential()
# Adding the input layer and the first hidden layer
classifier.add(Dense(units = 8, kernel_initializer = 'uniform', activation = 'relu', input_dim = 10))

# Adding the second hidden layer
classifier.add(Dense(units = 16, kernel_initializer = 'uniform', activation = 'relu'))

# Adding the third hidden layer
classifier.add(Dense(units = 32, kernel_initializer = 'uniform', activation = 'relu'))

# Adding the output layer
classifier.add(Dense(units = 6, kernel_initializer = 'uniform', activation = 'softmax'))
```

```
2024-05-21 08:54:03.283163: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1926] Created device /job:localhost/replica:0/task:0/
```

```
classifier.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics = ['accuracy'])

# Fitting the ANN to the Training set
classifier.fit(X_train, y_train, batch_size = 16, epochs = 800, verbose = 1)
```

```
Epoch 1/800
2024-05-21 08:54:07.013668: I external/local_xla/xla/service/service.cc:168] XLA service 0x7fd5fd374770 initialized for platform
2024-05-21 08:54:07.013710: I external/local_xla/xla/service/service.cc:176]   StreamExecutor device (0): NVIDIA A100-SXM4-40GB M
2024-05-21 08:54:07.019479: I tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_util.cc:269] disabling MLIR crash reproducer, s
2024-05-21 08:54:07.057513: I external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:467] Loaded cuDNN version 90000
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
I0000 00:00:1716281647.144364   13834 device_compiler.h:186] Compiled cluster using XLA!  This line is logged at most once for th
21/21 [==============================] - 2s 2ms/step - loss: 1.7886 - accuracy: 0.2364
Epoch 2/800
21/21 [==============================] - 0s 2ms/step - loss: 1.7772 - accuracy: 0.3364
Epoch 3/800
21/21 [==============================] - 0s 2ms/step - loss: 1.7505 - accuracy: 0.4364
Epoch 4/800
21/21 [==============================] - 0s 2ms/step - loss: 1.6777 - accuracy: 0.4818
Epoch 5/800
21/21 [==============================] - 0s 2ms/step - loss: 1.5472 - accuracy: 0.4909
Epoch 6/800
21/21 [==============================] - 0s 2ms/step - loss: 1.4310 - accuracy: 0.4970
Epoch 7/800
21/21 [==============================] - 0s 2ms/step - loss: 1.3724 - accuracy: 0.5000
Epoch 8/800
21/21 [==============================] - 0s 2ms/step - loss: 1.3375 - accuracy: 0.5030
Epoch 9/800
21/21 [==============================] - 0s 2ms/step - loss: 1.3134 - accuracy: 0.5030
Epoch 10/800
21/21 [==============================] - 0s 2ms/step - loss: 1.2927 - accuracy: 0.5061
Epoch 11/800
21/21 [==============================] - 0s 2ms/step - loss: 1.2780 - accuracy: 0.5091
Epoch 12/800
21/21 [==============================] - 0s 2ms/step - loss: 1.2687 - accuracy: 0.5091
Epoch 13/800
21/21 [==============================] - 0s 2ms/step - loss: 1.2571 - accuracy: 0.5121
Epoch 14/800
21/21 [==============================] - 0s 2ms/step - loss: 1.2445 - accuracy: 0.5212
Epoch 15/800
21/21 [==============================] - 0s 2ms/step - loss: 1.2328 - accuracy: 0.5242
Epoch 16/800
21/21 [==============================] - 0s 2ms/step - loss: 1.2212 - accuracy: 0.5273
Epoch 17/800
21/21 [==============================] - 0s 2ms/step - loss: 1.2172 - accuracy: 0.5273
Epoch 18/800
21/21 [==============================] - 0s 2ms/step - loss: 1.2037 - accuracy: 0.5303
Epoch 19/800
21/21 [==============================] - 0s 2ms/step - loss: 1.1877 - accuracy: 0.5303
Epoch 20/800
21/21 [==============================] - 0s 2ms/step - loss: 1.1763 - accuracy: 0.5333
Epoch 21/800
21/21 [==============================] - 0s 2ms/step - loss: 1.1673 - accuracy: 0.5364
Epoch 22/800
21/21 [==============================] - 0s 2ms/step - loss: 1.1575 - accuracy: 0.5394
Epoch 23/800
21/21 [==============================] - 0s 2ms/step - loss: 1.1437 - accuracy: 0.5424
Epoch 24/800
21/21 [==============================] - 0s 2ms/step - loss: 1.1276 - accuracy: 0.5424
Epoch 25/800
21/21 [==============================] - 0s 2ms/step - loss: 1.1143 - accuracy: 0.5455
Epoch 26/800
```

```
score, acc = classifier.evaluate(X_train, y_train,
                               batch_size=10)
print('Train score:', score)
print('Train accuracy:', acc)

print('*'*20)
score, acc = classifier.evaluate(X_test, y_test,
                               batch_size=10)
print('Test score:', score)
print('Test accuracy:', acc)
```

```
33/33 [==============================] - 0s 999us/step - loss: 0.1421 - accuracy: 0.9545
Train score: 0.14205241203308105
Train accuracy: 0.9545454382896423
********************
9/9 [==============================] - 0s 1ms/step - loss: 0.4386 - accuracy: 0.8916
Test score: 0.4385785162448883
Test accuracy: 0.891566276550293
```

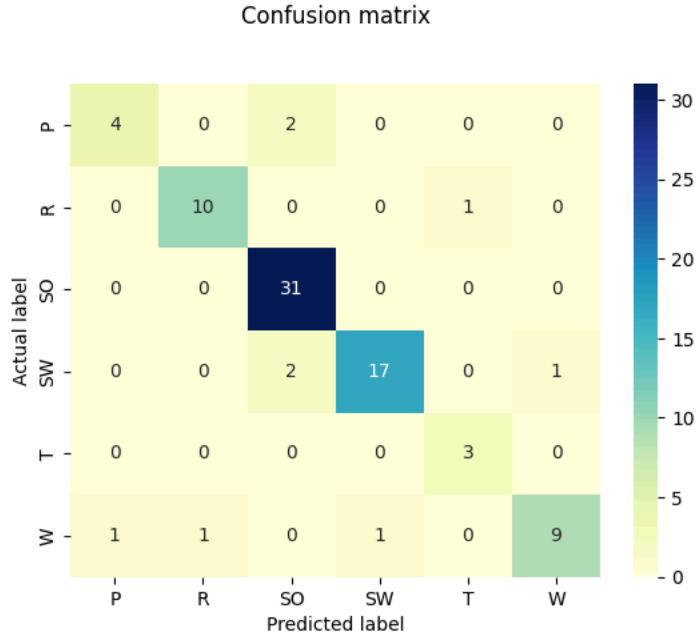
```
# Predicting the Test set results
pred = classifier.predict(X_test)
print("Y_pred:", pred)
print("*****************")
y_pred = np.argmax(pred, axis = 1)
print("Y_pred:", y_pred)
print("*****************")
print("Y_test:", y_test)
y_true = np.argmax(y_test, axis = 1)
```

```
print("*****************")
print("Y_test:", y_true)
```

```
 [0. 0. 0. 0. 0. 1.]
 [0. 1. 0. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 0. 1.]
 [0. 0. 0. 0. 0. 1.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 1. 0. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 1. 0. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 1. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 1.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 0. 0. 1. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 0. 0. 0. 1.]
 [0. 1. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 1.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 1. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 1.]
 [0. 0. 0. 1. 0. 0.]
 [0. 1. 0. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 0. 1.]
 [0. 0. 0. 0. 0. 1.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]]
*****************
Y_test: [2 1 4 0 5 3 1 5 1 1 2 3 2 0 2 2 5 3 3 4 2 3 2 3 2 3 2 2 2 5 1 2 3 5 5 3 3
 2 2 2 0 3 3 1 2 3 3 1 2 0 3 2 3 1 5 2 2 2 2 2 4 2 5 1 0 2 2 0 5 3 2 1 5 3
 1 3 5 5 2 3 2 2 2]
```

```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_true, y_pred)
target_names = ['P', 'R', 'SO', 'SW', 'T', 'W']


import matplotlib.pyplot as plt
import seaborn as sns


p = sns.heatmap(pd.DataFrame(cm), annot=True,xticklabels=target_names, yticklabels=target_names, cmap="YlGnBu" ,fmt='g')
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

```
Text(0.5, 23.52222222222222, 'Predicted label')
```

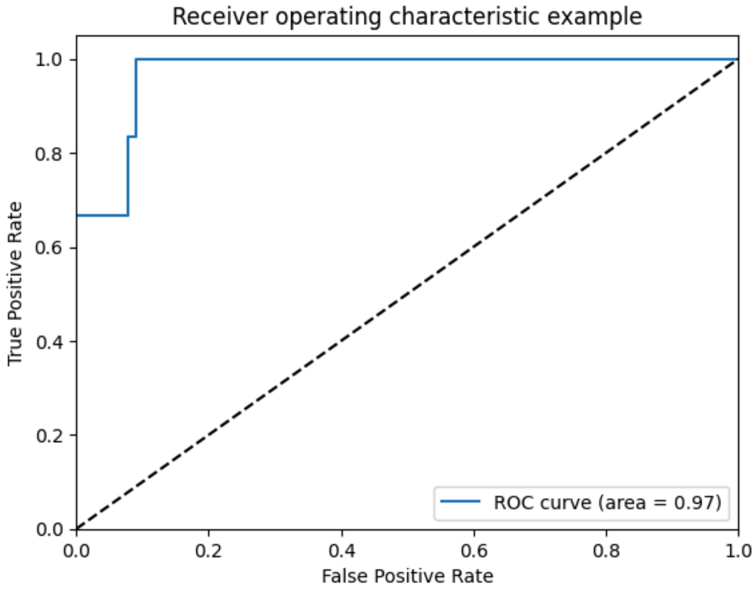


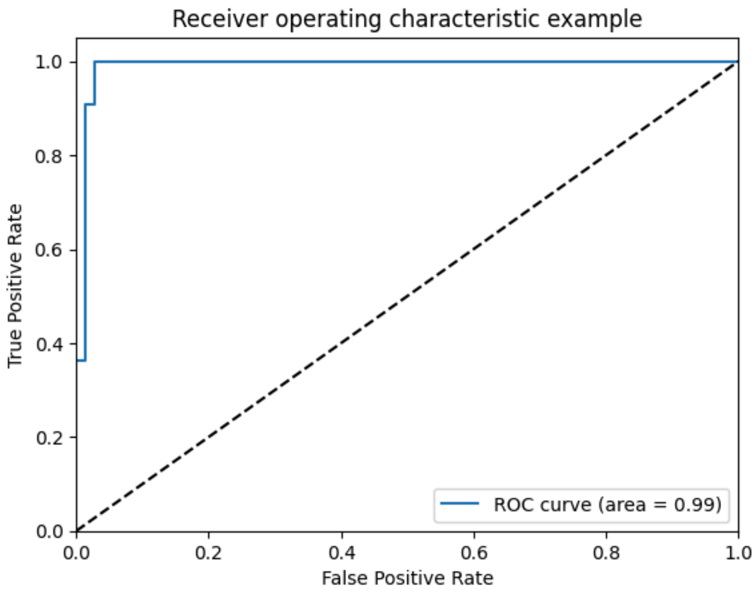

```
#import classification_report
from sklearn.metrics import classification_report
print(classification_report(y_true,y_pred, target_names = target_names))
```

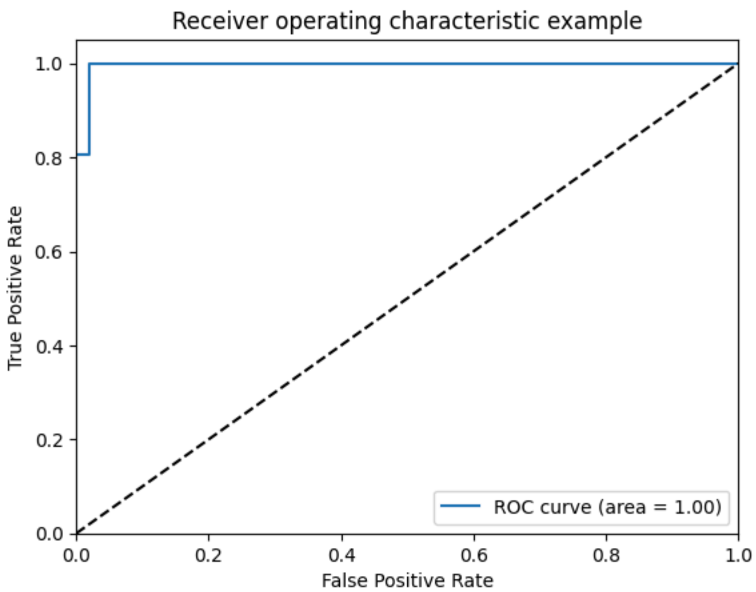
```
              precision    recall  f1-score   support

           P       0.80      0.67      0.73         6
           R       0.91      0.91      0.91        11
          SO       0.89      1.00      0.94        31
          SW       0.94      0.85      0.89        20
           T       0.75      1.00      0.86         3
           W       0.90      0.75      0.82        12

    accuracy                           0.89        83
   macro avg       0.86      0.86      0.86        83
weighted avg       0.89      0.89      0.89        83
```

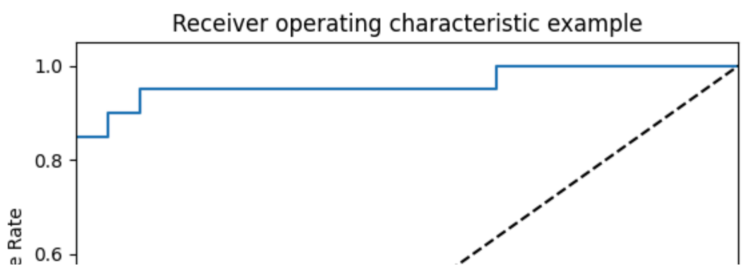
ROC curve

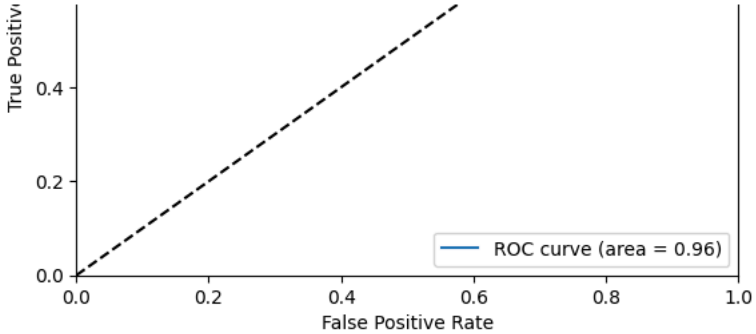
```
from sklearn.metrics import roc_curve, auc
from itertools import cycle
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(6):
    fpr[i], tpr[i], _ = roc_curve(y_test[:, i], pred[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Plot of a ROC curve for a specific class
for i in range(6):
    plt.figure()
    plt.plot(fpr[i], tpr[i], label='ROC curve (area = %0.2f)' % roc_auc[i])
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()
```

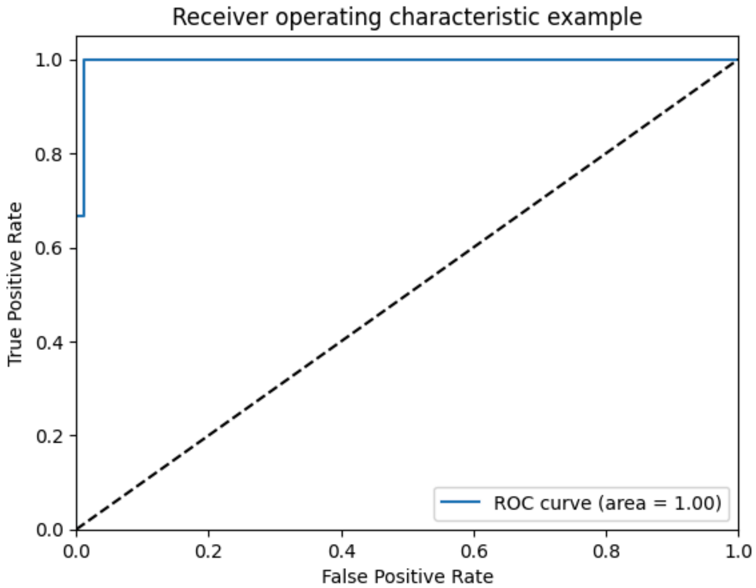

Receiver operating characteristic example
True Positive Rate
False Positive Rate
ROC curve (area = 0.97)

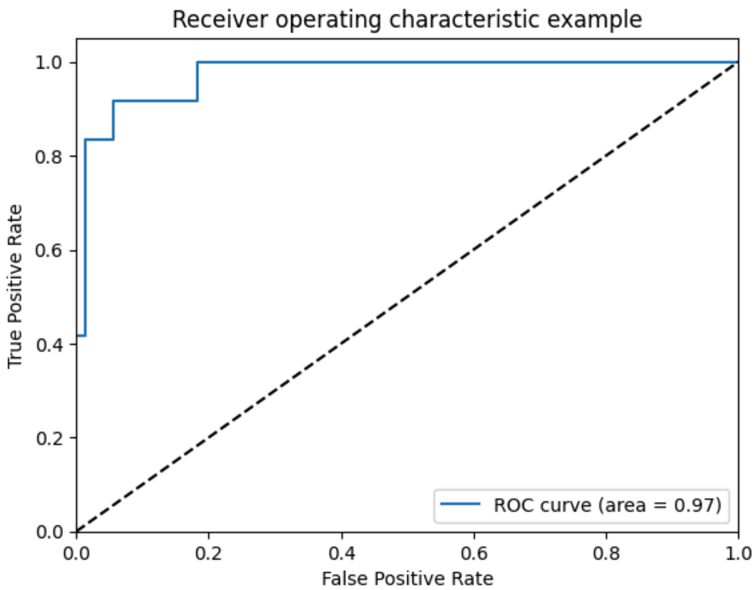

Receiver operating characteristic example
True Positive Rate
False Positive Rate
ROC curve (area = 0.99)


Receiver operating characteristic example
True Positive Rate
False Positive Rate
ROC curve (area = 1.00)


Receiver operating characteristic example


True Positive
0.4
0.2
0.0
ROC curve (area = 0.96)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate


Receiver operating characteristic example
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
ROC curve (area = 1.00)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate


Receiver operating characteristic example
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
ROC curve (area = 0.97)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate

```
fpr = dict()
tpr = dict()
roc_auc = dict()
lw=2
for i in range(6):
    fpr[i], tpr[i], _ = roc_curve(y_test[:, i], pred[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])
colors =cycle(['blue', 'green', 'red','darkorange','olive','purple'])
for i, color in zip(range(6), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label='AUC = {1:0.4f}'
             ''.format(i, roc_auc[i]))
plt.plot([0, 1], [0, 1], 'k--', lw=lw)
plt.xlim([-0.05, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate',fontsize=15)
plt.ylabel('True Positive Rate',fontsize=15)
# plt.title('Receiver operating characteristic for multi-class data')
plt.legend(loc="lower right")
plt.show()
```

Experiment - 3

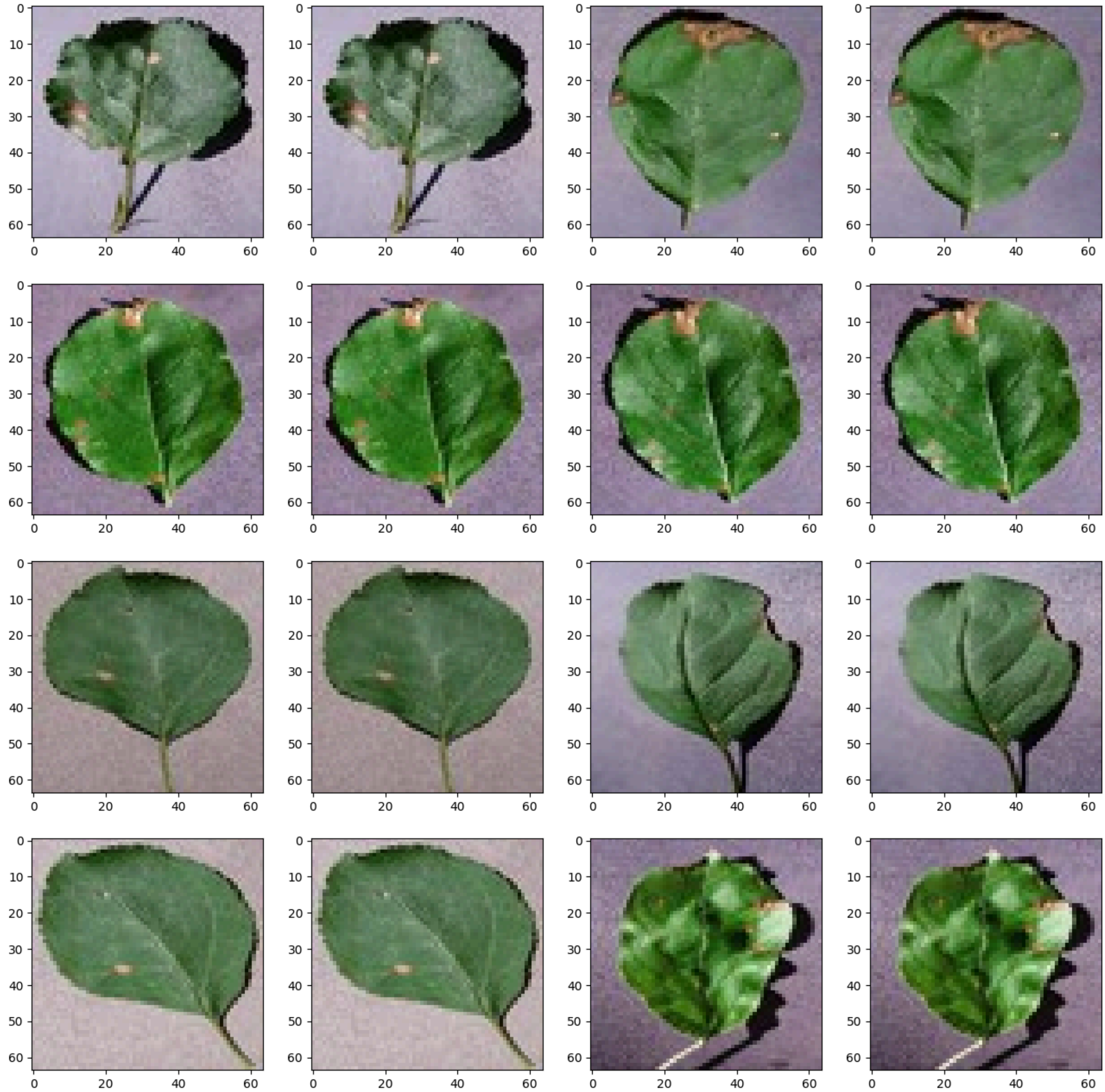
```
from tensorflow.keras import applications
from tensorflow.keras import optimizers
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Dropout, Flatten, Dense, GlobalAveragePooling2D
from tensorflow.keras import backend as k
from tensorflow.keras.callbacks import ModelCheckpoint, LearningRateScheduler, TensorBoard, EarlyStopping
```

```
import numpy as np
from tensorflow.keras import models
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Model
from tensorflow.keras import layers
from tensorflow.keras.layers import  Dense, Flatten, Conv2D, MaxPooling2D
from tensorflow.keras import Input
```

```
# Normalize training and validation data in the range of 0 to 1
train_datagen = ImageDataGenerator(rescale=1./255) # vertical_flip=True,
                                                   # horizontal_flip=True,
                                                   # height_shift_range=0.1,
                                                   # width_shift_range=0.1
validation_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

# Read the training sample and set the batch size
train_generator = train_datagen.flow_from_directory(
        'C://Users//abhia//Downloads//plant_village (1)//plant_village/t/rain',
        target_size=(64, 64),
        batch_size=16,
        class_mode='categorical')

# Read Validation data from directory and define target size with batch size
validation_generator = validation_datagen.flow_from_directory(
        '/workspace/Bootcamp/Data/plant_village/val/',
        target_size=(64, 64),
        batch_size=16,
        class_mode='categorical',
        shuffle=False)

test_generator = test_datagen.flow_from_directory(
        '/workspace/Bootcamp/Data/plant_village/test/',
        target_size=(64, 64),
        batch_size=1,
        class_mode='categorical',
        shuffle=False)
```

Visualization of few images

```
plt.figure(figsize=(16, 16))
for i in range(1, 17):
  plt.subplot(4, 4, i)
  img, label = test_generator.next()
  # print(img.shape)
  # print(label)
  plt.imshow(img[0])
plt.show()
```



```
img, label = test_generator.next()
img[0].shape
```

```
(64, 64, 3)
```

```
# Create the model
model = models.Sequential()
# Add new layers
model.add(Conv2D(128, kernel_size=(3,3), activation = 'relu', input_shape=(64,64,3)))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(64, kernel_size=(3,3), activation = 'relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(64, kernel_size=(3,3), activation = 'relu'))
```

```
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(32, activation='relu'))
model.add(layers.Dense(4, activation='softmax'))
model.summary()
```

Compiling and Training the Model

```
# We are going to use accuracy metrics and cross entropy loss as performance parameters
model.compile(optimizer = optimizers.Adam(learning_rate = 0.0001), loss='categorical_crossentropy', metrics=['acc'])
# Train the model
history = model.fit(train_generator,
      steps_per_epoch=train_generator.samples/train_generator.batch_size,
      epochs=30,
      validation_data=validation_generator,
      validation_steps=validation_generator.samples/validation_generator.batch_size,
      verbose=2)
```

```
Epoch 1/30
Epoch 1/30
188/187 - 2s - loss: 0.0354 - acc: 0.9893 - val_loss: 0.2115 - val_acc: 0.9402
Epoch 2/30
Epoch 1/30
188/187 - 2s - loss: 0.0313 - acc: 0.9890 - val_loss: 0.2183 - val_acc: 0.9339
Epoch 3/30
Epoch 1/30
188/187 - 2s - loss: 0.0292 - acc: 0.9903 - val_loss: 0.2038 - val_acc: 0.9465
Epoch 4/30
Epoch 1/30
188/187 - 2s - loss: 0.0314 - acc: 0.9907 - val_loss: 0.2843 - val_acc: 0.9181
Epoch 5/30
Epoch 1/30
188/187 - 2s - loss: 0.0213 - acc: 0.9940 - val_loss: 0.3160 - val_acc: 0.9181
Epoch 6/30
Epoch 1/30
188/187 - 2s - loss: 0.0276 - acc: 0.9923 - val_loss: 0.2019 - val_acc: 0.9449
Epoch 7/30
Epoch 1/30
188/187 - 2s - loss: 0.0184 - acc: 0.9960 - val_loss: 0.2326 - val_acc: 0.9307
Epoch 8/30
Epoch 1/30
188/187 - 2s - loss: 0.0161 - acc: 0.9970 - val_loss: 0.2079 - val_acc: 0.9386
Epoch 9/30
Epoch 1/30
188/187 - 2s - loss: 0.0145 - acc: 0.9980 - val_loss: 0.2025 - val_acc: 0.9465
Epoch 10/30
Epoch 1/30
188/187 - 2s - loss: 0.0180 - acc: 0.9953 - val_loss: 0.2236 - val_acc: 0.9386
Epoch 11/30
Epoch 1/30
188/187 - 2s - loss: 0.0152 - acc: 0.9970 - val_loss: 0.2413 - val_acc: 0.9339
Epoch 12/30
Epoch 1/30
188/187 - 2s - loss: 0.0245 - acc: 0.9913 - val_loss: 0.1965 - val_acc: 0.9465
Epoch 13/30
Epoch 1/30
188/187 - 2s - loss: 0.0202 - acc: 0.9940 - val_loss: 0.3189 - val_acc: 0.9228
Epoch 14/30
Epoch 1/30
188/187 - 2s - loss: 0.0136 - acc: 0.9970 - val_loss: 0.1991 - val_acc: 0.9449
Epoch 15/30
Epoch 1/30
188/187 - 2s - loss: 0.0083 - acc: 0.9983 - val_loss: 0.2098 - val_acc: 0.9402
Epoch 16/30
Epoch 1/30
188/187 - 2s - loss: 0.0081 - acc: 0.9993 - val_loss: 0.2170 - val_acc: 0.9496
Epoch 17/30
Epoch 1/30
188/187 - 2s - loss: 0.0104 - acc: 0.9980 - val_loss: 0.2084 - val_acc: 0.9480
Epoch 18/30
Epoch 1/30
188/187 - 2s - loss: 0.0070 - acc: 0.9993 - val_loss: 0.1953 - val_acc: 0.9480
Epoch 19/30
Epoch 1/30
188/187 - 2s - loss: 0.0578 - acc: 0.9804 - val_loss: 0.4641 - val_acc: 0.8898
Epoch 20/30
```

Saving the model

```
model.save("CONV_plant_deseas.h5")
print("Saved model to disk")
```

```
Saved model to disk
```

Loading the model

```
model = models.load_model('CONV_plant_deseas.h5')
```

Visualization of Accuracy and Loss Curves

```
train_acc = history.history['acc']
val_acc = history.history['val_acc']
train_loss = history.history['loss']
val_loss = history.history['val_loss']


epochs = range(len(train_acc))
plt.plot(epochs, train_acc, 'b', label='Training Accuracy')
plt.plot(epochs, val_acc, 'g', label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.grid()
plt.legend()
plt.figure()
plt.show()

plt.plot(epochs, train_loss, 'b', label='Training Loss')
plt.plot(epochs, val_loss, 'g', label='Validation Loss')
plt.title('Training and Validation Loss')
plt.grid()
plt.legend()
plt.show()
```

Prediction

```
# Get the filenames from the generator
fnames = test_generator.filenames

# Get the ground truth from generator
ground_truth = test_generator.classes

# Get the label to class mapping from the generator
label2index = test_generator.class_indices

# Getting the mapping from class index to class label
idx2label = dict((v,k) for k,v in label2index.items())

# Get the predictions from the model using the generator
predictions = model.predict_generator(test_generator, steps=test_generator.samples/test_generator.batch_size,verbose=1)
predicted_classes = np.argmax(predictions,axis=1)

errors = np.where(predicted_classes != ground_truth)[0]
print("No of errors = {}/{}".format(len(errors),test_generator.samples))
```

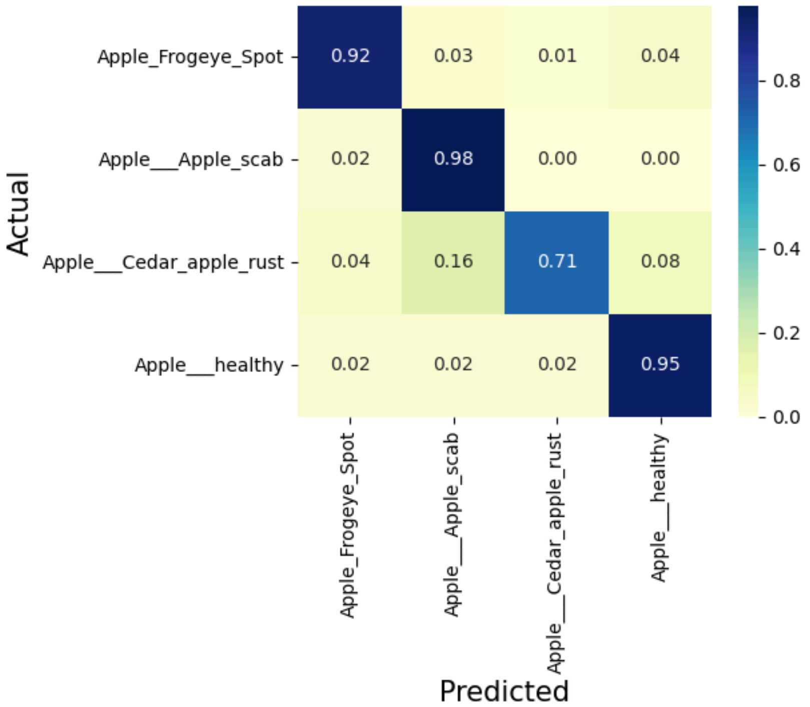
```
546/546 [==============================] - 1s 1ms/step
No of errors = 38/546
```

```
accuracy = ((test_generator.samples-len(errors))/test_generator.samples) * 100
accuracy
```

```
93.04029304029304
```

Confusion Matrix

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import numpy as np
from matplotlib import pyplot as plt
cm = confusion_matrix(y_true=ground_truth, y_pred=predicted_classes)
cm = np.array(cm)
# Normalise
cmn = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
fig, ax = plt.subplots(figsize=(5,4))
sns.heatmap(cmn, annot=True, fmt='.2f', xticklabels=label2index, yticklabels=label2index, cmap="YlGnBu")
plt.ylabel('Actual', fontsize=15)
plt.xlabel('Predicted', fontsize=15)
plt.show(block=False)
```



Classification Report

```
from sklearn.metrics import classification_report
print(classification_report(ground_truth, predicted_classes, target_names=label2index))
```

```
                          precision    recall  f1-score   support

      Apple_Frogeye_Spot       0.91      0.92      0.92       103
      Apple___Apple_scab       0.90      0.98      0.94       134
Apple___Cedar_apple_rust       0.85      0.71      0.78        49
         Apple___healthy       0.97      0.95      0.96       260

                accuracy                           0.93       546
               macro avg       0.91      0.89      0.90       546
            weighted avg       0.93      0.93      0.93       546
```

Experiment - 4

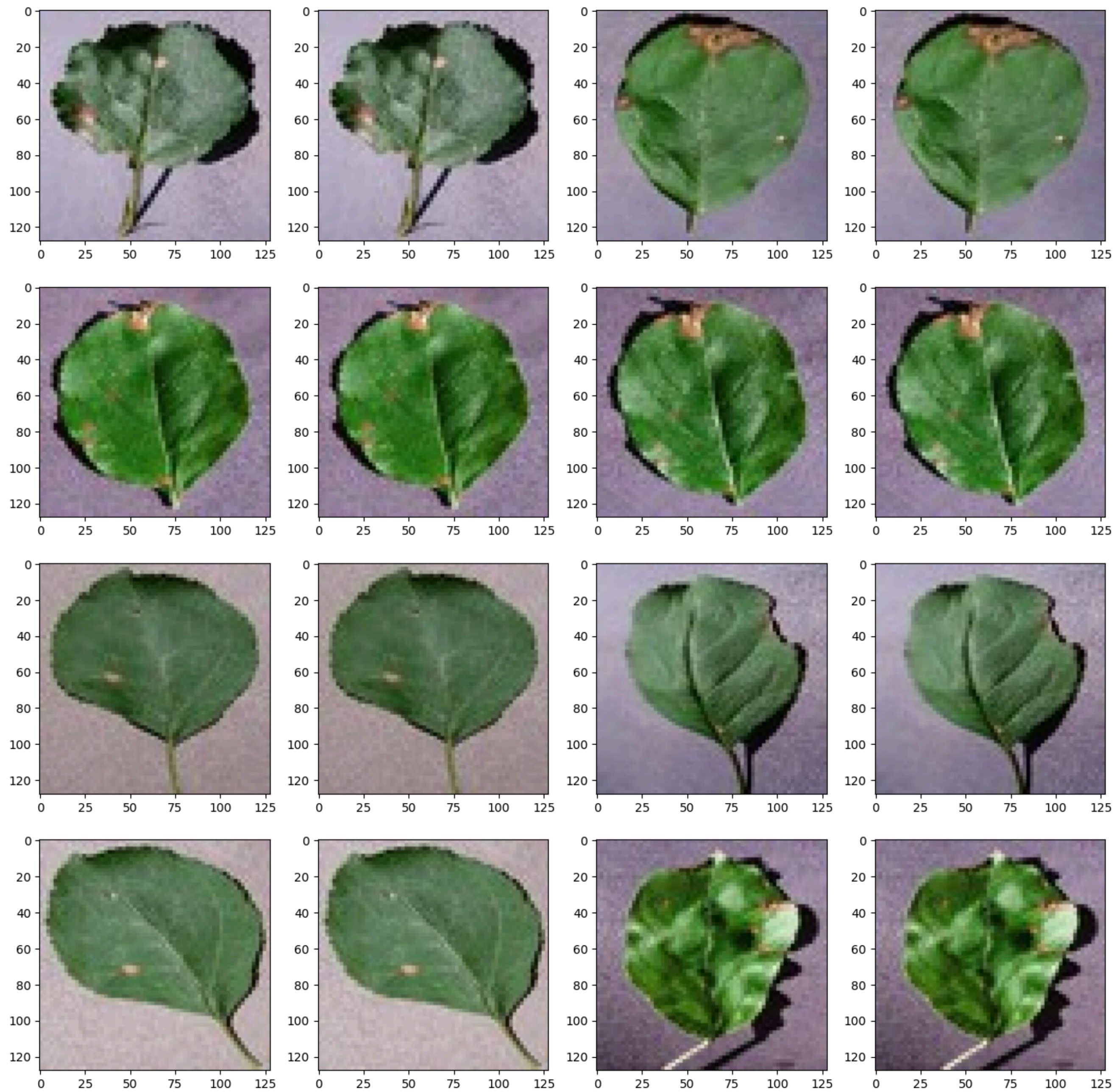
Deep Learning Training and Architecture, Feature Extraction, Models training with some pretrained models.

```
import numpy as np
from tensorflow.keras import Input
from tensorflow.keras import models
from tensorflow.keras import layers
from tensorflow.keras import optimizers
from tensorflow.keras.models import Model
from tensorflow.keras import applications
from tensorflow.keras import backend as k
import matplotlib.pyplot as plt
from tensorflow.keras.optimizers import SGD, Adam
from tensorflow.keras.layers import  Dense, Flatten, Conv2D, MaxPooling2D
from tensorflow.keras.preprocessing import image
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Dropout, Flatten, Dense, GlobalAveragePooling2D
from tensorflow.keras.callbacks import ModelCheckpoint, LearningRateScheduler, TensorBoard, EarlyStopping
```

```
# Normalize training and validation data in the range of 0 to 1
train_datagen = ImageDataGenerator(rescale=1./255) # vertical_flip=True,
                                                   # horizontal_flip=True,
                                                   # height_shift_range=0.1,
                                                   # width_shift_range=0.1
validation_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

# Read the training sample and set the batch size
train_generator = train_datagen.flow_from_directory(
        '/workspace/Bootcamp/Data/plant_village/train/',
        target_size=(128, 128),
        batch_size=16,
        class_mode='categorical')

# Read Validation data from directory and define target size with batch size
validation_generator = validation_datagen.flow_from_directory(
        '/workspace/Bootcamp/Data/plant_village/val/',
        target_size=(128, 128),
        batch_size=16,
        class_mode='categorical',
        shuffle=False)

test_generator = test_datagen.flow_from_directory(
        '/workspace/Bootcamp/Data/plant_village/test/',
        target_size=(128, 128),
        batch_size=1,
        class_mode='categorical',
        shuffle=False)
```

```
Found 3004 images belonging to 4 classes.
Found 635 images belonging to 4 classes.
Found 547 images belonging to 4 classes.
```

```
plt.figure(figsize=(16, 16))
for i in range(1, 17):
  plt.subplot(4, 4, i)
  img, label = test_generator.next()
  # print(img.shape)
  # print(label)
  plt.imshow(img[0])
plt.show()
```



```
img, label = test_generator.next()
img[0].shape
```

```
(128, 128, 3)
```

VGG16

```
from tensorflow.keras.applications.vgg16 import VGG16

## Loading VGG16 model
```

```
base_model = VGG16(weights="imagenet", include_top=False, input_shape= (128, 128, 3))
# Include_top = False means excluding the model fully connected layers
base_model.trainable = False ## Not trainable weights,
#weights of the VGG16 model will not be updated during training
base_model.summary()
```

```
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_2 (InputLayer)         [(None, 128, 128, 3)]     0         
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 128, 128, 64)      1792      
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 128, 128, 64)      36928     
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 64, 64, 64)        0         
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 64, 64, 128)       73856     
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 64, 64, 128)       147584    
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 32, 32, 128)       0         
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 32, 32, 256)       295168    
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 32, 32, 256)       590080    
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 32, 32, 256)       590080    
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 16, 16, 256)       0         
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 16, 16, 512)       1180160   
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 16, 16, 512)       2359808   
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 16, 16, 512)       2359808   
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 8, 8, 512)         0         
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 8, 8, 512)         2359808   
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 8, 8, 512)         2359808   
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 8, 8, 512)         2359808   
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 4, 4, 512)         0         
=================================================================
Total params: 14,714,688
Trainable params: 0
Non-trainable params: 14,714,688
_________________________________________________________________
```

```
flatten_layer = layers.GlobalAveragePooling2D()
# dense_layer_1 = layers.Dense(64, activation='relu')
# dense_layer_2 = layers.Dense(32, activation='relu')
prediction_layer = layers.Dense(4, activation='softmax')

model = models.Sequential([
    base_model,
    flatten_layer,
    prediction_layer
])
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
vgg16 (Model)                (None, 4, 4, 512)         14714688  
_________________________________________________________________
global_average_pooling2d (Gl (None, 512)               0         
_________________________________________________________________
dense (Dense)                (None, 4)                 2052      
=================================================================
Total params: 14,716,740
Trainable params: 2,052
Non-trainable params: 14,714,688
_________________________________________________________________
```

Training

```
# sgd = SGD(lr=0.001,decay=1e-6, momentum=0.9, nesterov=True)
# We are going to use accuracy metrics and cross entropy loss as performance parameters
```

```
model.compile(optimizer = Adam(learning_rate = 0.0001), loss='categorical_crossentropy', metrics=['acc'])
# Train the model
history = model.fit(train_generator,
      steps_per_epoch=train_generator.samples/train_generator.batch_size,
      epochs=30,
      validation_data=validation_generator,
      validation_steps=validation_generator.samples/validation_generator.batch_size,
      verbose=1)
```

```
188/187 [==============================] - 6s 32ms/step - loss: 0.1155 - acc: 0.9710 - val_loss: 0.1342 - val_acc: 0.9591
Epoch 12/30
186/187 [============================>.] - ETA: 0s - loss: 0.1159 - acc: 0.9701Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1150 - acc: 0.9704 - val_loss: 0.1345 - val_acc: 0.9559
Epoch 13/30
186/187 [============================>.] - ETA: 0s - loss: 0.1138 - acc: 0.9707Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1149 - acc: 0.9704 - val_loss: 0.1343 - val_acc: 0.9559
Epoch 14/30
186/187 [============================>.] - ETA: 0s - loss: 0.1142 - acc: 0.9717Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1145 - acc: 0.9710 - val_loss: 0.1334 - val_acc: 0.9559
Epoch 15/30
186/187 [============================>.] - ETA: 0s - loss: 0.1147 - acc: 0.9707Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1143 - acc: 0.9710 - val_loss: 0.1335 - val_acc: 0.9591
Epoch 16/30
186/187 [============================>.] - ETA: 0s - loss: 0.1138 - acc: 0.9714Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1139 - acc: 0.9714 - val_loss: 0.1339 - val_acc: 0.9575
Epoch 17/30
186/187 [============================>.] - ETA: 0s - loss: 0.1135 - acc: 0.9717Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1138 - acc: 0.9714 - val_loss: 0.1343 - val_acc: 0.9575
Epoch 18/30
186/187 [============================>.] - ETA: 0s - loss: 0.1135 - acc: 0.9704Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1134 - acc: 0.9704 - val_loss: 0.1340 - val_acc: 0.9591
Epoch 19/30
186/187 [============================>.] - ETA: 0s - loss: 0.1134 - acc: 0.9714Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1137 - acc: 0.9714 - val_loss: 0.1339 - val_acc: 0.9559
Epoch 20/30
186/187 [============================>.] - ETA: 0s - loss: 0.1134 - acc: 0.9717Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1130 - acc: 0.9717 - val_loss: 0.1322 - val_acc: 0.9575
Epoch 21/30
186/187 [============================>.] - ETA: 0s - loss: 0.1124 - acc: 0.9711Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1126 - acc: 0.9710 - val_loss: 0.1325 - val_acc: 0.9559
Epoch 22/30
186/187 [============================>.] - ETA: 0s - loss: 0.1127 - acc: 0.9714Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1123 - acc: 0.9717 - val_loss: 0.1333 - val_acc: 0.9591
Epoch 23/30
186/187 [============================>.] - ETA: 0s - loss: 0.1108 - acc: 0.9714Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1120 - acc: 0.9707 - val_loss: 0.1331 - val_acc: 0.9591
Epoch 24/30
186/187 [============================>.] - ETA: 0s - loss: 0.1117 - acc: 0.9717Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1117 - acc: 0.9714 - val_loss: 0.1324 - val_acc: 0.9559
Epoch 25/30
186/187 [============================>.] - ETA: 0s - loss: 0.1111 - acc: 0.9711Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1114 - acc: 0.9710 - val_loss: 0.1318 - val_acc: 0.9559
Epoch 26/30
186/187 [============================>.] - ETA: 0s - loss: 0.1114 - acc: 0.9707Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1113 - acc: 0.9710 - val_loss: 0.1314 - val_acc: 0.9559
Epoch 27/30
186/187 [============================>.] - ETA: 0s - loss: 0.1093 - acc: 0.9727Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1109 - acc: 0.9717 - val_loss: 0.1318 - val_acc: 0.9559
Epoch 28/30
186/187 [============================>.] - ETA: 0s - loss: 0.1108 - acc: 0.9721Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1106 - acc: 0.9720 - val_loss: 0.1307 - val_acc: 0.9575
Epoch 29/30
186/187 [============================>.] - ETA: 0s - loss: 0.1104 - acc: 0.9711Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1104 - acc: 0.9710 - val_loss: 0.1322 - val_acc: 0.9575
Epoch 30/30
186/187 [============================>.] - ETA: 0s - loss: 0.1096 - acc: 0.9738Epoch 1/30
188/187 [==============================] - 6s 32ms/step - loss: 0.1101 - acc: 0.9734 - val_loss: 0.1305 - val_acc: 0.9559
```

```
model.save("VGG16_plant_deseas.h5")
print("Saved model to disk")
```

```
Saved model to disk
```

```
model = models.load_model('VGG16_plant_deseas.h5')
print("Model is loaded")
```

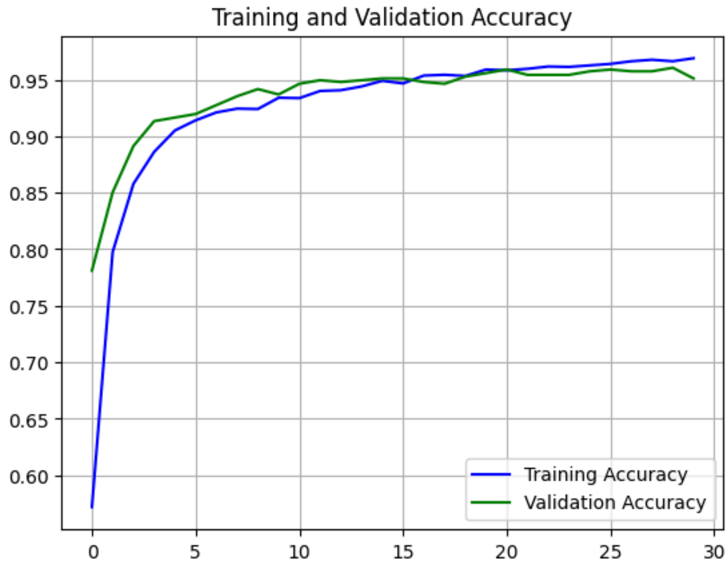
```
Model is loaded
```

```
model.save_weights('cnn_classification.h5')
```

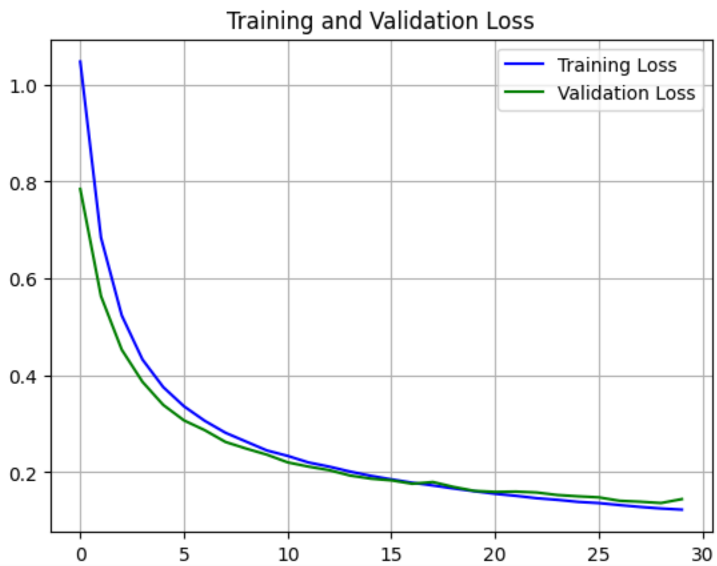
```
model.load_weights('cnn_classification.h5')
```

```
train_acc = history.history['acc']
val_acc = history.history['val_acc']
train_loss = history.history['loss']
```

```
val_loss = history.history['val_loss']


epochs = range(len(train_acc))
plt.plot(epochs, train_acc, 'b', label='Training Accuracy')
plt.plot(epochs, val_acc, 'g', label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.grid()
plt.legend()
plt.figure()
plt.show()

plt.plot(epochs, train_loss, 'b', label='Training Loss')
plt.plot(epochs, val_loss, 'g', label='Validation Loss')
plt.title('Training and Validation Loss')
plt.grid()
plt.legend()
plt.show()
```




```
<Figure size 640x480 with 0 Axes>
```




```
# Get the filenames from the generator
fnames = test_generator.filenames

# Get the ground truth from generator
ground_truth = test_generator.classes

# Get the label to class mapping from the generator
label2index = test_generator.class_indices

# Getting the mapping from class index to class label
idx2label = dict((v,k) for k,v in label2index.items())

# Get the predictions from the model using the generator
predictions = model.predict_generator(test_generator, steps=test_generator.samples/test_generator.batch_size,verbose=1)
predicted_classes = np.argmax(predictions,axis=1)
```

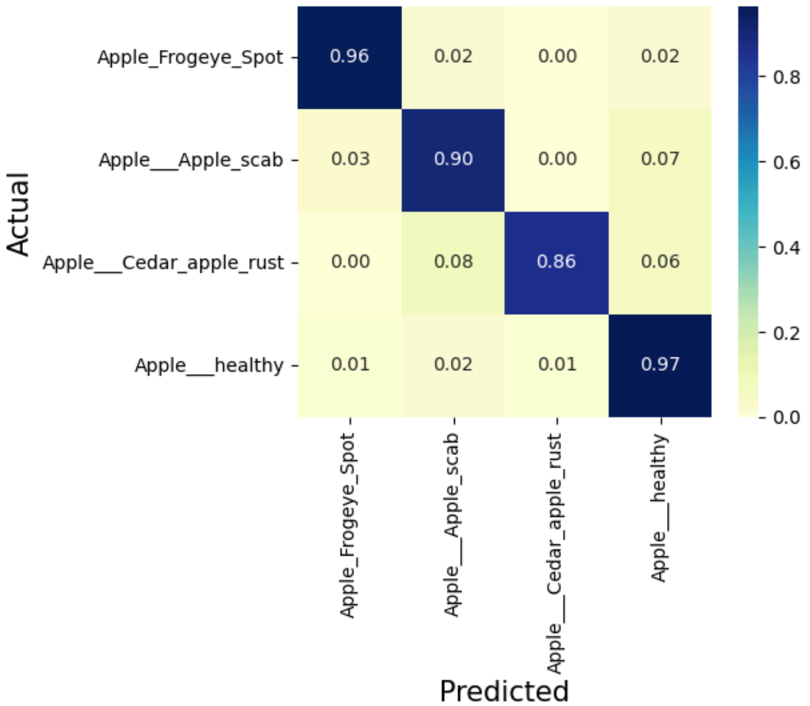
```
errors = np.where(predicted_classes != ground_truth)[0]
print("No of errors = {}/{}".format(len(errors),test_generator.samples))
```

```
547/547 [==============================] - 3s 6ms/step
No of errors = 33/547
```

```
accuracy = ((test_generator.samples-len(errors))/test_generator.samples) * 100
accuracy
```

```
93.96709323583181
```

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import numpy as np
from matplotlib import pyplot as plt
cm = confusion_matrix(y_true=ground_truth, y_pred=predicted_classes)
cm = np.array(cm)
# Normalise
cmn = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
fig, ax = plt.subplots(figsize=(5,4))
sns.heatmap(cmn, annot=True, fmt='.2f', xticklabels=label2index, yticklabels=label2index, cmap="YlGnBu")
plt.ylabel('Actual', fontsize=15)
plt.xlabel('Predicted', fontsize=15)
plt.show(block=False)
```




```
from sklearn.metrics import classification_report
print(classification_report(ground_truth, predicted_classes, target_names=label2index))
```

```
                          precision    recall  f1-score   support

      Apple_Frogeye_Spot       0.94      0.96      0.95       104
      Apple___Apple_scab       0.92      0.90      0.91       134
Apple___Cedar_apple_rust       0.95      0.86      0.90        49
         Apple___healthy       0.95      0.97      0.96       260

                accuracy                           0.94       547
               macro avg       0.94      0.92      0.93       547
            weighted avg       0.94      0.94      0.94       547
```

Start coding or generate with AI.

```
from tensorflow.keras import applications

## Loading InceptionV3 model
base_model = applications.InceptionV3(weights="imagenet", include_top=False, input_shape= (128, 128, 3))
base_model.trainable = False ## Not trainable weights

base_model.summary()
```

```
base_model.summary()
```

```
Downloading data from https://github.com/fchollet/deep-learning-models/releases/download/v0.5/inception_v3_weights_tf_dim_orderin
87916544/87910968 [==============================] - 15s 0us/step
Model: "inception_v3"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_3 (InputLayer)            [(None, 128, 128, 3) 0
__________________________________________________________________________________________________
conv2d (Conv2D)                 (None, 63, 63, 32)   864         input_3[0][0]
__________________________________________________________________________________________________
batch_normalization (BatchNorma (None, 63, 63, 32)   96          conv2d[0][0]
__________________________________________________________________________________________________
activation (Activation)         (None, 63, 63, 32)   0           batch_normalization[0][0]
__________________________________________________________________________________________________
conv2d_1 (Conv2D)               (None, 61, 61, 32)   9216        activation[0][0]
__________________________________________________________________________________________________
batch_normalization_1 (BatchNor (None, 61, 61, 32)   96          conv2d_1[0][0]
__________________________________________________________________________________________________
activation_1 (Activation)       (None, 61, 61, 32)   0           batch_normalization_1[0][0]
__________________________________________________________________________________________________
conv2d_2 (Conv2D)               (None, 61, 61, 64)   18432       activation_1[0][0]
__________________________________________________________________________________________________
batch_normalization_2 (BatchNor (None, 61, 61, 64)   192         conv2d_2[0][0]
__________________________________________________________________________________________________
activation_2 (Activation)       (None, 61, 61, 64)   0           batch_normalization_2[0][0]
__________________________________________________________________________________________________
max_pooling2d (MaxPooling2D)    (None, 30, 30, 64)   0           activation_2[0][0]
__________________________________________________________________________________________________
conv2d_3 (Conv2D)               (None, 30, 30, 80)   5120        max_pooling2d[0][0]
__________________________________________________________________________________________________
batch_normalization_3 (BatchNor (None, 30, 30, 80)   240         conv2d_3[0][0]
__________________________________________________________________________________________________
activation_3 (Activation)       (None, 30, 30, 80)   0           batch_normalization_3[0][0]
__________________________________________________________________________________________________
conv2d_4 (Conv2D)               (None, 28, 28, 192)  138240      activation_3[0][0]
__________________________________________________________________________________________________
batch_normalization_4 (BatchNor (None, 28, 28, 192)  576         conv2d_4[0][0]
__________________________________________________________________________________________________
activation_4 (Activation)       (None, 28, 28, 192)  0           batch_normalization_4[0][0]
__________________________________________________________________________________________________
max_pooling2d_1 (MaxPooling2D)  (None, 13, 13, 192)  0           activation_4[0][0]
__________________________________________________________________________________________________
conv2d_8 (Conv2D)               (None, 13, 13, 64)   12288       max_pooling2d_1[0][0]
__________________________________________________________________________________________________
batch_normalization_8 (BatchNor (None, 13, 13, 64)   192         conv2d_8[0][0]
__________________________________________________________________________________________________
activation_8 (Activation)       (None, 13, 13, 64)   0           batch_normalization_8[0][0]
__________________________________________________________________________________________________
conv2d_6 (Conv2D)               (None, 13, 13, 48)   9216        max_pooling2d_1[0][0]
__________________________________________________________________________________________________
conv2d_9 (Conv2D)               (None, 13, 13, 96)   55296       activation_8[0][0]
__________________________________________________________________________________________________
batch_normalization_6 (BatchNor (None, 13, 13, 48)   144         conv2d_6[0][0]
__________________________________________________________________________________________________
batch_normalization_9 (BatchNor (None, 13, 13, 96)   288         conv2d_9[0][0]
__________________________________________________________________________________________________
activation_6 (Activation)       (None, 13, 13, 48)   0           batch_normalization_6[0][0]
```

```
flatten_layer = layers.GlobalAveragePooling2D()
dense_layer_1 = layers.Dense(64, activation='relu')
dense_layer_2 = layers.Dense(32, activation='relu')
prediction_layer = layers.Dense(4, activation='softmax')

model = models.Sequential([
    base_model,
    flatten_layer,
    dense_layer_1,
    dense_layer_2,
    prediction_layer
])

model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
inception_v3 (Model)         (None, 2, 2, 2048)        21802784
_________________________________________________________________
global_average_pooling2d_2 ( (None, 2048)              0
_________________________________________________________________
dense_2 (Dense)              (None, 64)                131136
_________________________________________________________________
dense_3 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_4 (Dense)              (None, 4)                 132
```

```
=================================================================
Total params: 21,936,132
Trainable params: 133,348
Non-trainable params: 21,802,784
_________________________________________________________________
```

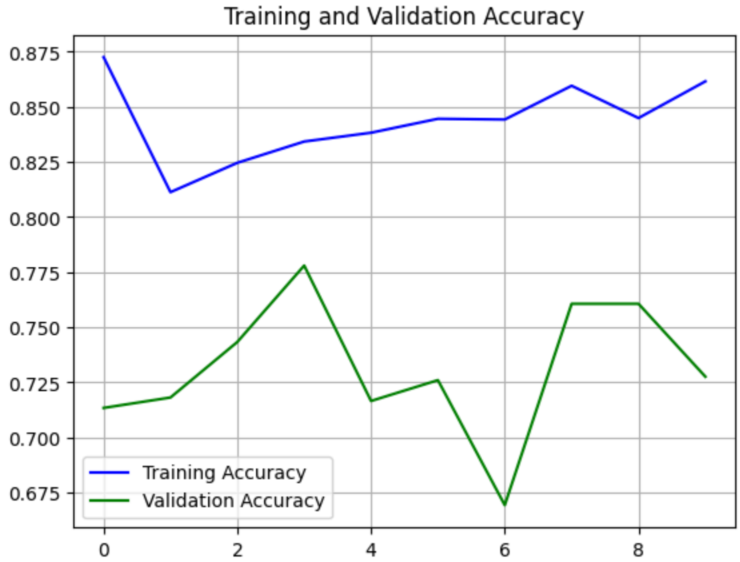
```
model.compile(optimizer = Adam(learning_rate = 0.001), loss='categorical_crossentropy', metrics=['acc'])
# Train the model
history = model.fit(train_generator,
      steps_per_epoch=train_generator.samples/train_generator.batch_size,
      epochs=10,
      validation_data=validation_generator,
      validation_steps=validation_generator.samples/validation_generator.batch_size,
      verbose=2)
```

```
Epoch 1/10
Epoch 1/10
188/187 - 9s - loss: 0.3544 - acc: 0.8725 - val_loss: 1.8910 - val_acc: 0.7134
Epoch 2/10
Epoch 1/10
188/187 - 5s - loss: 0.4988 - acc: 0.8113 - val_loss: 1.5254 - val_acc: 0.7181
Epoch 3/10
Epoch 1/10
188/187 - 5s - loss: 0.4549 - acc: 0.8246 - val_loss: 1.2376 - val_acc: 0.7433
Epoch 4/10
Epoch 1/10
188/187 - 5s - loss: 0.4242 - acc: 0.8342 - val_loss: 1.2466 - val_acc: 0.7780
Epoch 5/10
Epoch 1/10
188/187 - 5s - loss: 0.4462 - acc: 0.8382 - val_loss: 1.6309 - val_acc: 0.7165
Epoch 6/10
Epoch 1/10
188/187 - 5s - loss: 0.4180 - acc: 0.8445 - val_loss: 1.3079 - val_acc: 0.7260
Epoch 7/10
Epoch 1/10
188/187 - 5s - loss: 0.4094 - acc: 0.8442 - val_loss: 2.0786 - val_acc: 0.6693
Epoch 8/10
Epoch 1/10
188/187 - 5s - loss: 0.3816 - acc: 0.8595 - val_loss: 1.5253 - val_acc: 0.7606
Epoch 9/10
Epoch 1/10
188/187 - 5s - loss: 0.4081 - acc: 0.8449 - val_loss: 1.1693 - val_acc: 0.7606
Epoch 10/10
Epoch 1/10
188/187 - 5s - loss: 0.3675 - acc: 0.8615 - val_loss: 1.4619 - val_acc: 0.7276
```

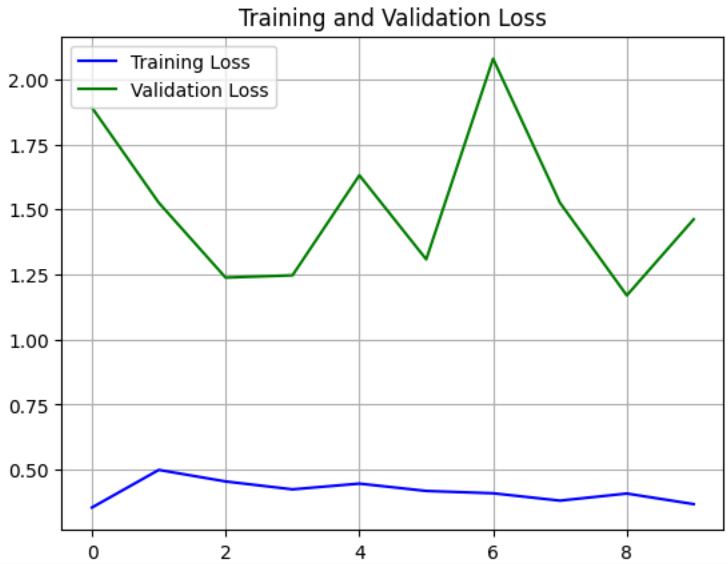
```
model.save("InceptionNet_plant_deseas.h5")
print("Saved model to disk")
```

```
Saved model to disk
```

```
train_acc = history.history['acc']
val_acc = history.history['val_acc']
train_loss = history.history['loss']
val_loss = history.history['val_loss']


epochs = range(len(train_acc))
plt.plot(epochs, train_acc, 'b', label='Training Accuracy')
plt.plot(epochs, val_acc, 'g', label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.grid()
plt.legend()
plt.figure()
plt.show()

plt.plot(epochs, train_loss, 'b', label='Training Loss')
plt.plot(epochs, val_loss, 'g', label='Validation Loss')
plt.title('Training and Validation Loss')
plt.grid()
plt.legend()
plt.show()
```




```
<Figure size 640x480 with 0 Axes>
```




```
# Get the filenames from the generator
fnames = test_generator.filenames

# Get the ground truth from generator
ground_truth = test_generator.classes

# Get the label to class mapping from the generator
label2index = test_generator.class_indices

# Getting the mapping from class index to class label
idx2label = dict((v,k) for k,v in label2index.items())

# Get the predictions from the model using the generator
predictions = model.predict_generator(test_generator, steps=test_generator.samples/test_generator.batch_size,verbose=1)
predicted_classes = np.argmax(predictions,axis=1)

errors = np.where(predicted_classes != ground_truth)[0]
print("No of errors = {}/{}".format(len(errors),test_generator.samples))
```

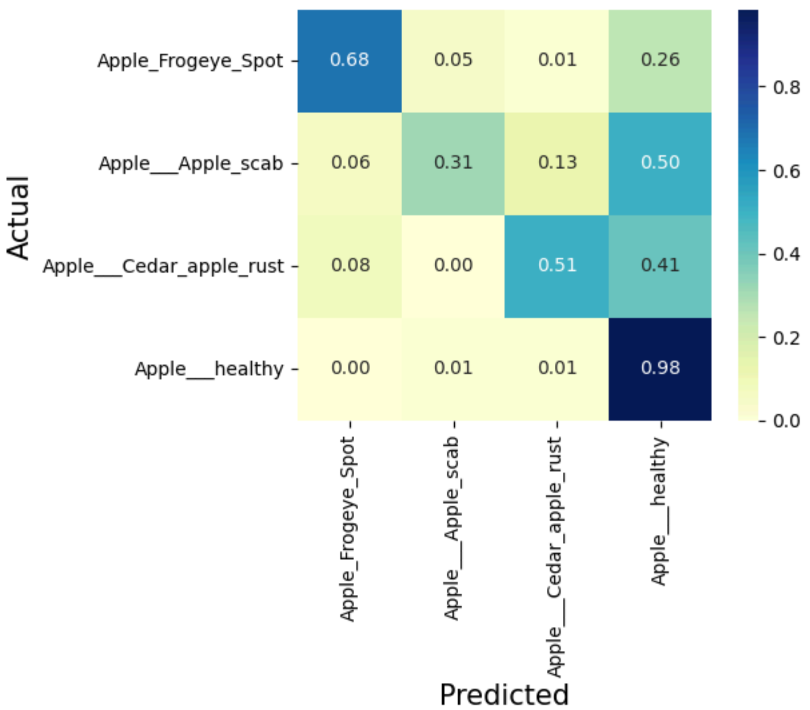
```
547/547 [==============================] - 9s 17ms/step
No of errors = 153/547
```

```
accuracy = ((test_generator.samples-len(errors))/test_generator.samples) * 100
accuracy
```

```
72.0292504570384
```

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import numpy as np
from matplotlib import pyplot as plt
```

```
cm = confusion_matrix(y_true=ground_truth, y_pred=predicted_classes)
cm = np.array(cm)
# Normalise
cmn = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
fig, ax = plt.subplots(figsize=(5,4))
sns.heatmap(cmn, annot=True, fmt='.2f', xticklabels=label2index, yticklabels=label2index, cmap="YlGnBu")
plt.ylabel('Actual', fontsize=15)
plt.xlabel('Predicted', fontsize=15)
plt.show(block=False)
```




```
from sklearn.metrics import classification_report
print(classification_report(ground_truth, predicted_classes, target_names=label2index))
```

```
                          precision    recall  f1-score   support

      Apple_Frogeye_Spot       0.86      0.68      0.76       104
      Apple___Apple_scab       0.86      0.31      0.46       134
Apple___Cedar_apple_rust       0.56      0.51      0.53        49
         Apple___healthy       0.69      0.98      0.81       260

                accuracy                           0.72       547
               macro avg       0.74      0.62      0.64       547
            weighted avg       0.75      0.72      0.69       547
```

Start coding or generate with AI.

ResNet

```
from keras import applications

## Loading VGG16 model
base_model = applications.ResNet50(weights="imagenet", include_top=False, input_shape= (128, 128, 3))
base_model.trainable = False ## Not trainable weights

base_model.summary()


flatten_layer = layers.GlobalAveragePooling2D()
# dense_layer_1 = layers.Dense(63, activation='relu')
# dense_layer_2 = layers.Dense(32, activation='relu')
prediction_layer = layers.Dense(4, activation='softmax'

model = models.Sequential([
    base_model,
    flatten_layer,
    # dense_layer_1,
    # dense_layer_2,
    prediction_layer
])
```

```
model.summary()


model.compile(optimizer = Adam(learning_rate = 0.001), loss='categorical_crossentropy', metrics=['acc'])
# Train the model
history = model.fit(train_generator,
      steps_per_epoch=train_generator.samples/train_generator.batch_size,
      epochs=30,
      validation_data=validation_generator,
      validation_steps=validation_generator.samples/validation_generator.batch_size,
      verbose=1)


model.save("ResNet_plant_deseas.h5")
print("Saved model to disk")


train_acc = history.history['acc']
val_acc = history.history['val_acc']
train_loss = history.history['loss']
val_loss = history.history['val_loss']


epochs = range(len(train_acc))
plt.plot(epochs, train_acc, 'b', label='Training Accuracy')
plt.plot(epochs, val_acc, 'g', label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.grid()
plt.legend()
plt.figure()
plt.show()

plt.plot(epochs, train_loss, 'b', label='Training Loss')
plt.plot(epochs, val_loss, 'g', label='Validation Loss')
plt.title('Training and Validation Loss')
plt.grid()
plt.legend()
plt.show()


# Get the filenames from the generator
fnames = test_generator.filenames

# Get the ground truth from generator
ground_truth = test_generator.classes

# Get the label to class mapping from the generator
label2index = test_generator.class_indices

# Getting the mapping from class index to class label
idx2label = dict((v,k) for k,v in label2index.items())

# Get the predictions from the model using the generator
predictions = model.predict_generator(test_generator, steps=test_generator.samples/test_generator.batch_size,verbose=1)
predicted_classes = np.argmax(predictions,axis=1)

errors = np.where(predicted_classes != ground_truth)[0]
print("No of errors = {}/{}".format(len(errors),test_generator.samples))



accuracy = ((test_generator.samples-len(errors))/test_generator.samples) * 100
accuracy


from sklearn.metrics import confusion_matrix
import seaborn as sns
import numpy as np
from matplotlib import pyplot as plt
cm = confusion_matrix(y_true=ground_truth, y_pred=predicted_classes)
cm = np.array(cm)
# Normalise
cmn = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
fig, ax = plt.subplots(figsize=(5,4))
sns.heatmap(cmn, annot=True, fmt='.2f', xticklabels=label2index, yticklabels=label2index, cmap="YlGnBu")
plt.ylabel('Actual', fontsize=15)
plt.xlabel('Predicted', fontsize=15)
plt.show(block=False)


from sklearn.metrics import classification_report
print(classification_report(ground_truth, predicted_classes, target_names=label2index))
```

Experiment - 5

Text data handling with RNN for sentiment analysis

```
import pandas as pd    # to load dataset
import numpy as np     # for mathematic equation
from nltk.corpus import stopwords   # to get collection of stopwords
from sklearn.model_selection import train_test_split       # for splitting dataset
from tensorflow.keras.preprocessing.text import Tokenizer  # to encode text to int
from tensorflow.keras.preprocessing.sequence import pad_sequences   # to do padding or truncating
from tensorflow.keras.models import Sequential     # the model
from tensorflow.keras.layers import Embedding, LSTM, Dense # layers of the architecture
from tensorflow.keras.callbacks import ModelCheckpoint   # save model
from tensorflow.keras.models import load_model   # load saved model
import re
from keras.layers import SimpleRNN
```

```
data = pd.read_csv('/content/drive/MyDrive/AMITY/Deep Learning (codes)/Data/IMDB Dataset.csv')
print(data)
```

```
                                                  review sentiment
0      One of the other reviewers has mentioned that ...  positive
1      A wonderful little production. <br /><br />The...  positive
2      I thought this was a wonderful way to spend ti...  positive
3      Basically there's a family where a little boy ...  negative
4      Petter Mattei's "Love in the Time of Money" is...  positive
...                                                  ...       ...
49995  I thought this movie did a down right good job...  positive
49996  Bad plot, bad dialogue, bad acting, idiotic di...  negative
49997  I am a Catholic taught in parochial elementary...  negative
49998  I'm going to have to disagree with the previou...  negative
49999  No one expects the Star Trek movies to be high...  negative

[50000 rows x 2 columns]
```

Stop Word is a commonly used words in a sentence, usually a search engine is programmed to ignore this words (i.e. "the", "a", "an", "of", etc.)
Declaring the english stop words

```
import nltk
nltk.download("stopwords")
english_stops = set(stopwords.words('english'))
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
def load_dataset():
    df = pd.read_csv('/content/drive/MyDrive/AMITY/Deep Learning (codes)/Data/IMDB Dataset.csv')
    x_data = df['review']       # Reviews/Input
    y_data = df['sentiment']    # Sentiment/Output

    # PRE-PROCESS REVIEW
    x_data = x_data.replace({'<.*?>': ''}, regex = True)          # remove html tag
    x_data = x_data.replace({'[^A-Za-z]': ' '}, regex = True)     # remove non alphabet
    x_data = x_data.apply(lambda review: [w for w in review.split() if w not in english_stops])  # remove stop words
    x_data = x_data.apply(lambda review: [w.lower() for w in review])   # lower case

    # ENCODE SENTIMENT -> 0 & 1
    y_data = y_data.replace('positive', 1)
    y_data = y_data.replace('negative', 0)

    return x_data, y_data

x_data, y_data = load_dataset()

print('Reviews')
print(x_data, '\n')
print('Sentiment')
print(y_data)
```

```
Reviews
0        [one, reviewers, mentioned, watching, oz, epis...
1        [a, wonderful, little, production, the, filmin...
2        [i, thought, wonderful, way, spend, time, hot,...
3        [basically, family, little, boy, jake, thinks,...
4        [petter, mattei, love, time, money, visually, ...
```

```
                                   ...
49995    [i, thought, movie, right, good, job, it, crea...
49996    [bad, plot, bad, dialogue, bad, acting, idioti...
49997    [i, catholic, taught, parochial, elementary, s...
49998    [i, going, disagree, previous, comment, side, ...
49999    [no, one, expects, star, trek, movies, high, a...
Name: review, Length: 50000, dtype: object

Sentiment
0        1
1        1
2        1
3        0
4        1
        ..
49995    1
49996    0
49997    0
49998    0
49999    0
Name: sentiment, Length: 50000, dtype: int64
```

```
x_train, x_test, y_train, y_test = train_test_split(x_data, y_data, test_size = 0.2)

print('Train Set')
print(x_train, '\n')
print(x_test, '\n')
print('Test Set')
print(y_train, '\n')
print(y_test)
```

```
Train Set
22596    [boring, badly, written, italian, exploitation...
5353     [the, other, supposed, horror, movie, made, it...
42152    [a, tough, life, gets, tougher, three, childre...
15434    [why, earth, colin, firth, pointless, film, ha...
7280     [this, far, worst, movie, i, ever, seen, cinem...
                                   ...
39945    [this, show, lasted, moments, plots, usually, ...
13858    [i, rented, thinking, would, pretty, good, cov...
25266    [having, pleasantly, surprised, sandra, bulloc...
10659    [the, difficulty, i, musical, version, les, mi...
39372    [this, movie, proof, film, noire, enduring, st...
Name: review, Length: 40000, dtype: object

2006     [this, movie, time, favorite, you, really, see...
33575    [this, british, film, version, stage, play, i,...
6808     [alexander, nevsky, brilliant, piece, cinemati...
32330    [found, old, vhs, version, film, parents, hous...
3777     [i, went, see, movie, daughter, i, insisted, g...
                                   ...
40255    [what, heck, people, expect, horror, films, da...
5864     [especially, time, much, science, fiction, fil...
44604    [nicole, eggert, listed, star, despite, michea...
42481    [a, thief, night, got, best, end, times, thril...
31671    [i, enjoy, national, anthem, i, enjoy, nationa...
Name: review, Length: 10000, dtype: object

Test Set
22596    0
5353     0
42152    1
15434    0
7280     0
        ..
39945    0
13858    0
25266    0
10659    0
39372    1
Name: sentiment, Length: 40000, dtype: int64

2006     1
33575    1
6808     1
32330    0
3777     0
        ..
40255    1
5864     1
44604    0
42481    1
31671    1
Name: sentiment, Length: 10000, dtype: int64
```

Function for getting the average review length, by calculating the mean of all the reviews length (using numpy.mean)

```
def get_max_length():
    review_length = []
    for review in x_train:
        review_length.append(len(review))

    return int(np.ceil(np.mean(review_length)))


# ENCODE REVIEW
token = Tokenizer(lower=False)    # no need lower, because already lowered the data in load_data()
token.fit_on_texts(x_train)
x_train = token.texts_to_sequences(x_train)
x_test = token.texts_to_sequences(x_test)

max_length = get_max_length()

x_train = pad_sequences(x_train, maxlen=max_length, padding='post', truncating='post')
x_test = pad_sequences(x_test, maxlen=max_length, padding='post', truncating='post')

total_words = len(token.word_index) + 1   # add 1 because of 0 padding
print('Total Words:', total_words)

print('Encoded X Train\n', x_train, '\n')
print('Encoded X Test\n', x_test, '\n')
print('Maximum review length: ', max_length)
```

```
Total Words: 92636
Encoded X Train
 [[  257   863   310 ...     0     0     0]
 [    2  1340   350 ...    28   282   409]
 [   39  1138    40 ...     0     0     0]
 ...
 [ 1587  3903   660 ...    62 14457  1006]
 [    2  6090     1 ...  4973  5675   406]
 [    8     3  2912 ...     0     0     0]]

Encoded X Test
 [[    8     3    10 ...     0     0     0]
 [    8   603     4 ...   278 10278  2289]
 [ 3551 11276   417 ...     0     0     0]
 ...
 [ 3908 20405  3718 ...     0     0     0]
 [   39  2984   218 ...  3947     3   765]
 [    1   260  1833 ...     0     0     0]]

Maximum review length:  130
```

```
rnn = Sequential()

rnn.add(Embedding(total_words,32,input_length =max_length))
rnn.add(SimpleRNN(64,input_shape = (total_words, max_length), return_sequences=False,activation="relu"))
rnn.add(Dense(1, activation = 'sigmoid')) #flatten

print(rnn.summary())
rnn.compile(loss="binary_crossentropy",optimizer='adam',metrics=["accuracy"])
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 130, 32)           2964352

 simple_rnn (SimpleRNN)      (None, 64)                6208

 dense (Dense)               (None, 1)                 65

=================================================================
Total params: 2,970,625
Trainable params: 2,970,625
Non-trainable params: 0
_________________________________________________________________
None
```

```
history = rnn.fit(x_train,y_train,epochs = 20,batch_size=128,verbose = 1)
```

```
Epoch 1/20
313/313 [==============================] - 96s 286ms/step - loss: 0.6915 - accuracy: 0.5184
Epoch 2/20
313/313 [==============================] - 68s 218ms/step - loss: 0.6616 - accuracy: 0.5879
Epoch 3/20
313/313 [==============================] - 63s 202ms/step - loss: 0.6626 - accuracy: 0.5762
Epoch 4/20
313/313 [==============================] - 56s 180ms/step - loss: 0.5900 - accuracy: 0.6328
Epoch 5/20
313/313 [==============================] - 51s 162ms/step - loss: 0.4166 - accuracy: 0.8135
```

```
Epoch 6/20
313/313 [==============================] - 51s 161ms/step - loss: 0.3511 - accuracy: 0.8806
Epoch 7/20
313/313 [==============================] - 47s 149ms/step - loss: 0.2362 - accuracy: 0.9194
Epoch 8/20
313/313 [==============================] - 46s 148ms/step - loss: 0.1676 - accuracy: 0.9421
Epoch 9/20
313/313 [==============================] - 45s 144ms/step - loss: 0.3168 - accuracy: 0.8689
Epoch 10/20
313/313 [==============================] - 46s 148ms/step - loss: 0.5571 - accuracy: 0.6458
Epoch 11/20
313/313 [==============================] - 44s 141ms/step - loss: 0.4791 - accuracy: 0.7574
Epoch 12/20
313/313 [==============================] - 45s 144ms/step - loss: 0.2817 - accuracy: 0.9088
Epoch 13/20
313/313 [==============================] - 43s 139ms/step - loss: 0.4030 - accuracy: 0.8431
Epoch 14/20
313/313 [==============================] - 45s 142ms/step - loss: 0.2630 - accuracy: 0.9154
Epoch 15/20
313/313 [==============================] - 43s 138ms/step - loss: 0.2351 - accuracy: 0.9260
Epoch 16/20
313/313 [==============================] - 43s 138ms/step - loss: 0.2000 - accuracy: 0.9385
Epoch 17/20
313/313 [==============================] - 45s 143ms/step - loss: 0.1599 - accuracy: 0.9498
Epoch 18/20
313/313 [==============================] - 44s 140ms/step - loss: 0.1374 - accuracy: 0.9577
Epoch 19/20
313/313 [==============================] - 44s 141ms/step - loss: 0.1331 - accuracy: 0.9611
Epoch 20/20
313/313 [==============================] - 43s 136ms/step - loss: 0.2814 - accuracy: 0.8869
```

```
model = rnn.save('rnn.h5')
loaded_model = load_model('rnn.h5')
```

```
y_pred = rnn.predict(x_test, batch_size = 128)
print(y_pred)
print(y_test)
for i in range(len(y_pred)):
  if y_pred[i]>0.5:
    y_pred[i] = 1
  else:
    y_pred[i] = 0

true = 0
for i, y in enumerate(y_test):
    if y == y_pred[i]:
        true += 1

print('Correct Prediction: {}'.format(true))
print('Wrong Prediction: {}'.format(len(y_pred) - true))
print('Accuracy: {}'.format(true/len(y_pred)*100))
```

```
79/79 [==============================] - 1s 12ms/step
[[0.78446704]
 [0.02569966]
 [0.78301245]
 ...
 [0.2700789 ]
 [0.72713566]
 [0.78446704]]
2006     1
33575    1
6808     1
32330    0
3777     0
        ..
40255    1
5864     1
44604    0
42481    1
31671    1
Name: sentiment, Length: 10000, dtype: int64
Correct Prediction: 6918
Wrong Prediction: 3082
Accuracy: 69.17999999999999
```

Message: **Nothing was typical about this. Everything was beautifully done in this movie, the story, the flow, the scenario, everything. I highly recommend it for mystery lovers, for anyone who wants to watch a good movie!**

```
review = str(input('Movie Review: '))
```

```
Movie Review: Nothing was typical about this. Everything was beautifully done in this movie, the story, the flow, the scenario, ever
```

Pre-processing of entered review

```
# Pre-process input
regex = re.compile(r'[^a-zA-Z\s]')
review = regex.sub('', review)
print('Cleaned: ', review)

words = review.split(' ')
filtered = [w for w in words if w not in english_stops]
filtered = ' '.join(filtered)
filtered = [filtered.lower()]

print('Filtered: ', filtered)
```

```
Cleaned:  Nothing was typical about this Everything was beautifully done in this movie the story the flow the scenario everything I
Filtered:  ['nothing typical everything beautifully done movie story flow scenario everything i highly recommend mystery lovers anyo
```

```
tokenize_words = token.texts_to_sequences(filtered)
tokenize_words = pad_sequences(tokenize_words, maxlen=max_length, padding='post', truncating='post')
print(tokenize_words)
```

```
[[  76  705  174 1210  126    3   13 2692 2596  174    1  442  280  701
  1771  155  400   33    9    3    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0]]
```

Prediction

```
result = rnn.predict(tokenize_words)
print(result)
```

```
1/1 [==============================] - 0s 40ms/step
[[0.78446704]]
```

```
if result >= 0.7:
    print('positive')
else:
    print('negative')
```

```
positive
```

Start coding or generate with AI.

Experiment - 6

Sentiment analysis using RNN-LSTM on tweets data

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
df = pd.read_csv('/content/drive/MyDrive/AMITY/Deep Learning (codes)/Data/data.csv')
df.head()
```

	Unnamed: 0	count	hate_speech	offensive_language	neither	class	tweet
0	0	3	0	0	3	2	!!! RT @mayasolovely: As a woman you shouldn't...
1	1	3	0	3	0	1	!!!!! RT @mleew17: boy dats cold...tyga dwn ba...
2	2	3	0	3	0	1	!!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...
3	3	3	0	2	1	1	!!!!!!!!! RT @C_G_Anderson: @viva_based she lo...
4	4	6	0	6	0	1	!!!!!!!!!!!!! RT @ShenikaRoberts: The shit you...

```
classes = ['Hate Speech','Offensive Language','None']
```

```
df.drop(['count','hate_speech','offensive_language','neither','Unnamed: 0'],axis=1,inplace=True)
```

```
df.head()
```

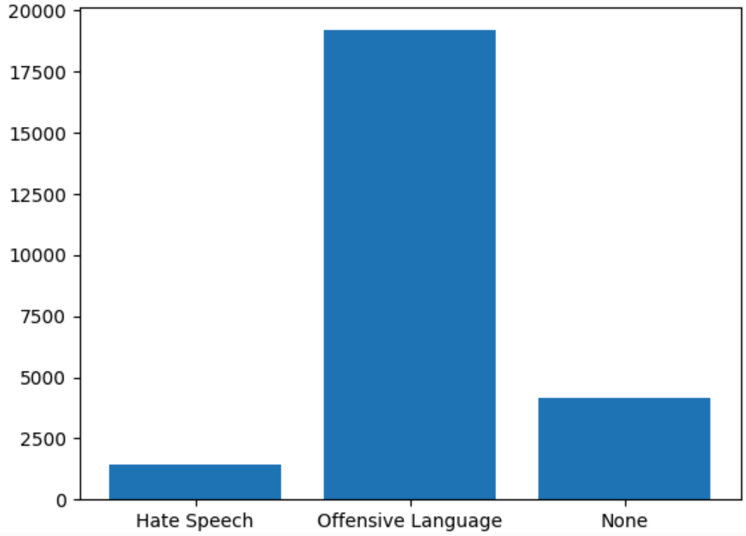
	class	tweet
0	2	!!! RT @mayasolovely: As a woman you shouldn't...
1	1	!!!!! RT @mleew17: boy dats cold...tyga dwn ba...
2	1	!!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...
3	1	!!!!!!!!! RT @C_G_Anderson: @viva_based she lo...
4	1	!!!!!!!!!!!!! RT @ShenikaRoberts: The shit you...

```
df.shape
```

```
(24783, 2)
```

```
labels = df['class']
unique, counts = np.unique(labels, return_counts=True)
values = list(zip(unique, counts))
plt.bar(classes,counts)
for i in values:
    print(classes[i[0]],' : ',i[1])
plt.show()
```

```
Hate Speech  :  1430
Offensive Language  :  19190
None  :  4163
```




```
hate_tweets = df[df['class']==0]
offensive_tweets = df[df['class']==1]
neither = df[df['class']==2]
print(hate_tweets.shape)
print(offensive_tweets.shape)
print(neither.shape)
```

```
(1430, 2)
(19190, 2)
(4163, 2)
```

```
for i in range(3):
    hate_tweets = pd.concat([hate_tweets,hate_tweets],ignore_index = True)
neither = pd.concat([neither,neither,neither], ignore_index = True)
offensive_tweets = offensive_tweets.iloc[0:12000,:]
print(hate_tweets.shape)
print(offensive_tweets.shape)
print(neither.shape)
```

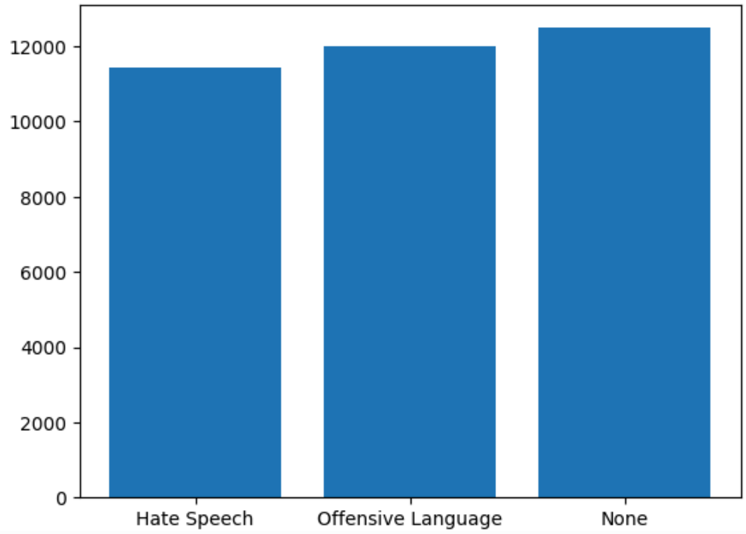
```
(11440, 2)
(12000, 2)
(12489, 2)
```

```
df = pd.concat([hate_tweets,offensive_tweets,neither],ignore_index = True)
df.shape
```

```
(35929, 2)
```

```
labels = df['class']
unique, counts = np.unique(labels, return_counts=True)
values = list(zip(unique, counts))
plt.bar(classes,counts)
for i in values:
    print(classes[i[0]],' : ',i[1])
plt.show()
```

```
Hate Speech  :  11440
Offensive Language  :  12000
None  :  12489
```




```
df.head()
```

	class	tweet
0	0	"@Blackman38Tide: @WhaleLookyHere @HowdyDowdy1...
1	0	"@CB_Baby24: @white_thunduh alsarabsss" hes a ...
2	0	"@DevilGrimz: @VigxRArts you're fucking gay, b...
3	0	"@MarkRoundtreeJr: LMFAOOOO I HATE BLACK PEOPL...
4	0	"@NoChillPaz: "At least I'm not a nigger" http...

```
import nltk
from nltk.stem import WordNetLemmatizer
from nltk.corpus import stopwords
import re
nltk.download('wordnet')
nltk.download('stopwords')
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
True
```

```
# dealing with Slangs
d = {'luv':'love','wud':'would','lyk':'like','wateva':'whatever','ttyl':'talk to you later',
               'kul':'cool','fyn':'fine','omg':'oh my god!','fam':'family','bruh':'brother',
               'cud':'could','fud':'food', 'u': 'you',
     'ur':'your', 'bday' : 'birthday', 'bihday' : 'birthday'}


stop_words = set(stopwords.words("english"))
stop_words.add('rt')
stop_words.remove('not')
lemmatizer = WordNetLemmatizer()
giant_url_regex = ('http[s]?://(?:[a-zA-Z]|[0-9]|[$-_@.&+]|' '[!*\(\),]|(?:%[0-9a-fA-F][0-9a-fA-F]))+')
mention_regex = '@[\w\-]+'

def clean_text(text):
    text = re.sub('"', "", text)
    text = re.sub(mention_regex, ' ',text) #removing all user names
    text = re.sub(giant_url_regex, ' ', text)  #remocing the urls
    text = text.lower()
    text = re.sub("hm+", "", text) #removing variants of hmmm
    text = re.sub("[^a-z]+", " ", text) #removing all numbers, special chars like @,#,? etc
    text = text.split()
    text = [word for word in text if not word in stop_words]
    text = [d[word] if word in d else word for word in text]  #replacing some slangs
    text = [lemmatizer.lemmatize(token) for token in text]
    text = [lemmatizer.lemmatize(token, "v") for token in text]
    text = " ".join(text)
    return text
```

```
df['processed_tweets'] = df.tweet.apply(lambda x: clean_text(x))   # df.review.map(clean_text) Also can be used
df.head()
```

	class	tweet	processed_tweets
0	0	"@Blackman38Tide: @WhaleLookyHere @HowdyDowdy1...	queer gaywad
1	0	"@CB_Baby24: @white_thunduh alsarabsss" hes a ...	alsarabsss he beaner smh tell he mexican
2	0	"@DevilGrimz: @VigxRArts you're fucking gay, b...	fuck gay blacklist hoe hold tehgodclan anyway
3	0	"@MarkRoundtreeJr: LMFAOOOO I HATE BLACK PEOPL...	lmfaoooo hate black people black people nigger
4	0	"@NoChillPaz: "At least I'm not a nigger" http...	least not nigger lmfao

```
x = df.processed_tweets
y = df['class']
print(x.shape)
print(y.shape)
```

```
(35929,)
(35929,)
```

```
# finding unique words
word_unique = []
for i in x:
    for j in i.split():
        word_unique.append(j)
unique, counts = np.unique(word_unique, return_counts=True)
print("The total words in the tweets are : ", len(word_unique))
print("The total UNIQUE words in the tweets are : ", len(unique))
```

```
The total words in the tweets are :  275540
The total UNIQUE words in the tweets are :  14146
```

```
# finding length of tweets
tweets_length = []
for i in x:
    tweets_length.append(len(i.split()))
print("The Average Length tweets are : ",np.mean(tweets_length))
print("The max length of tweets is : ", np.max(tweets_length))
print("The min length of tweets is : ", np.min(tweets_length))
```

```
The Average Length tweets are :  7.669013888502324
The max length of tweets is :  28
The min length of tweets is :  0
```

```
tweets_length = pd.DataFrame(tweets_length)
# tweets_length.describe()
```

	0
count	35929.000000
mean	7.669014
std	3.989625
min	0.000000
25%	4.000000
50%	7.000000
75%	11.000000
max	28.000000

```
#Sorting the Unique words based on their Frequency
col = list(zip(unique, counts))
col = sorted(col, key = lambda x: x[1],reverse=True)
col=pd.DataFrame(col)
print("Top 20 Occuring Words with their frequency are:")
col.iloc[:20,:]
```

```
Top 20 Occuring Words with their frequency are:
```

	0	1
0	bitch	9066
1	like	3817
2	get	3636
3	hoe	3426
4	trash	3217
5	fuck	3103
6	nigga	2819
7	faggot	2239
8	as	2073
9	you	1851
10	pussy	1847
11	go	1773
12	not	1764
13	bird	1515
14	lol	1494
15	nigger	1459
16	say	1456
17	make	1373
18	amp	1329
19	white	1328

```
from sklearn.feature_extraction.text import TfidfVectorizer


vectorizer = TfidfVectorizer(max_features = 8000 )
# tokenize and build vocab

vectorizer.fit(x)
# summarize

print(len(vectorizer.vocabulary_))
print(vectorizer.idf_.shape)
```

```
8000
(8000,)
```

```
x_tfidf = vectorizer.transform(x).toarray()
print(x_tfidf.shape)
```

```
(35929, 8000)
```

```
from keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences


num_words = 8000
embed_dim = 32
tokenizer = Tokenizer(num_words=num_words,oov_token = "<oov>" )
tokenizer.fit_on_texts(x)
word_index=tokenizer.word_index
sequences = tokenizer.texts_to_sequences(x)
length=[]
for i in sequences:
    length.append(len(i))
print(len(length))
print("Mean is: ",np.mean(length))
print("Max is: ",np.max(length))
print("Min is: ",np.min(length))
```

```
35929
Mean is:  7.669013888502324
Max is:  28
Min is:  0
```

```
pad_length = 24
sequences = pad_sequences(sequences, maxlen = pad_length, truncating = 'pre', padding = 'post')
sequences.shape
```

```
(35929, 24)
```

Splitting the Data

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(sequences,y,test_size = 0.05)
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(34132, 24)
(1797, 24)
(34132,)
(1797,)
```

RNN Model

```
from keras.layers import Dense, Embedding, Dropout , Activation, Flatten, SimpleRNN
from keras.layers import GlobalMaxPool1D
from keras.models import Model, Sequential
import tensorflow as tf


recall = tf.keras.metrics.Recall()
precision = tf.keras.metrics.Precision()

model = Sequential([Embedding(num_words, embed_dim, input_length = pad_length),
                   SimpleRNN(8, return_sequences = True),
                   GlobalMaxPool1D(),
                   Dense(20,activation = 'relu',kernel_initializer='he_uniform'),
                   Dropout(0.25),
                   Dense(3,activation = 'softmax')])
model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
# model.name = 'Twitter Hate Text Classification'
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_1 (Embedding)     (None, 24, 32)            256000

 simple_rnn_1 (SimpleRNN)    (None, 24, 8)             328

 global_max_pooling1d_1 (Glo  (None, 8)                0
 balMaxPooling1D)

 dense_2 (Dense)             (None, 20)                180

 dropout_1 (Dropout)         (None, 20)                0

 dense_3 (Dense)             (None, 3)                 63

=================================================================
Total params: 256,571
Trainable params: 256,571
Non-trainable params: 0
_________________________________________________________________
```

```
history = model.fit(x = x_train, y = y_train, epochs = 5,validation_split = 0.05)
```

```
Epoch 1/5
1014/1014 [==============================] - 12s 12ms/step - loss: 0.2029 - accuracy: 0.9373 - val_loss: 0.1583 - val_accuracy: 0.94
Epoch 2/5
1014/1014 [==============================] - 11s 11ms/step - loss: 0.1271 - accuracy: 0.9624 - val_loss: 0.1521 - val_accuracy: 0.94
Epoch 3/5
1014/1014 [==============================] - 12s 11ms/step - loss: 0.0906 - accuracy: 0.9754 - val_loss: 0.1479 - val_accuracy: 0.95
Epoch 4/5
1014/1014 [==============================] - 12s 12ms/step - loss: 0.0714 - accuracy: 0.9801 - val_loss: 0.1644 - val_accuracy: 0.95
Epoch 5/5
1014/1014 [==============================] - 12s 12ms/step - loss: 0.0588 - accuracy: 0.9839 - val_loss: 0.1541 - val_accuracy: 0.95
```

```
evaluate = model.evaluate(x_test,y_test)
```

```
57/57 [==============================] - 0s 3ms/step - loss: 0.1112 - accuracy: 0.9688
```

```
print("Test Acuracy is : {:.2f} %".format(evaluate[1]*100))
print("Test Loss is : {:.4f}".format(evaluate[0]))
```

```
Test Acuracy is : 96.88 %
Test Loss is : 0.1112
```

```
predictions = model.predict(x_test)
```

```
57/57 [==============================] - 0s 2ms/step
```

```
predict = []
for i in predictions:
    predict.append(np.argmax(i))
```

```
from sklearn import metrics
cm = metrics.confusion_matrix(predict,y_test)
acc = metrics.accuracy_score(predict,y_test)
```

```
print("The Confusion matrix is: \n",cm)
```

```
The Confusion matrix is:
 [[548  22   1]
 [  6 572   8]
 [  0  19 621]]
```

```
print(acc*100)
```

```
96.88369504730106
```

```
from sklearn import metrics
print(metrics.classification_report(y_test, predict))
```

```
              precision    recall  f1-score   support

           0       0.96      0.99      0.97       554
           1       0.98      0.93      0.95       613
           2       0.97      0.99      0.98       630

    accuracy                           0.97      1797
   macro avg       0.97      0.97      0.97      1797
weighted avg       0.97      0.97      0.97      1797
```

```
from tensorflow.keras.layers import Embedding, LSTM, Dense
# ARCHITECTURE
EMBED_DIM = 32
LSTM_OUT = 64

model = Sequential()
model.add(Embedding(num_words, EMBED_DIM, input_length = pad_length))
model.add(LSTM(LSTM_OUT))
model.add(Dense(3, activation='softmax'))
model.compile(optimizer = 'adam', loss = 'sparse_categorical_crossentropy', metrics = ['accuracy'])

print(model.summary())
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_4 (Embedding)     (None, 24, 32)            256000

 lstm_1 (LSTM)               (None, 64)                24832

 dense_5 (Dense)             (None, 3)                 195

=================================================================
Total params: 281,027
Trainable params: 281,027
Non-trainable params: 0
_________________________________________________________________
None
```

```
history = model.fit(x = x_train, y = y_train, epochs = 10,validation_split = 0.05)
```

```
Epoch 1/10
1014/1014 [==============================] - 26s 24ms/step - loss: 0.4328 - accuracy: 0.8246 - val_loss: 0.2531 - val_accuracy: 0.9:
```

```
Epoch 2/10
1014/1014 [==============================] - 22s 22ms/step - loss: 0.1874 - accuracy: 0.9405 - val_loss: 0.1876 - val_accuracy: 0.93
Epoch 3/10
1014/1014 [==============================] - 23s 23ms/step - loss: 0.1426 - accuracy: 0.9554 - val_loss: 0.1991 - val_accuracy: 0.93
Epoch 4/10
1014/1014 [==============================] - 24s 23ms/step - loss: 0.1188 - accuracy: 0.9626 - val_loss: 0.1991 - val_accuracy: 0.93
Epoch 5/10
1014/1014 [==============================] - 23s 23ms/step - loss: 0.0999 - accuracy: 0.9688 - val_loss: 0.2142 - val_accuracy: 0.94
Epoch 6/10
1014/1014 [==============================] - 23s 22ms/step - loss: 0.0835 - accuracy: 0.9730 - val_loss: 0.1820 - val_accuracy: 0.95
Epoch 7/10
1014/1014 [==============================] - 24s 23ms/step - loss: 0.0735 - accuracy: 0.9767 - val_loss: 0.2202 - val_accuracy: 0.94
Epoch 8/10
1014/1014 [==============================] - 24s 23ms/step - loss: 0.0670 - accuracy: 0.9783 - val_loss: 0.2666 - val_accuracy: 0.94
Epoch 9/10
1014/1014 [==============================] - 22s 22ms/step - loss: 0.0577 - accuracy: 0.9815 - val_loss: 0.1988 - val_accuracy: 0.94
Epoch 10/10
1014/1014 [==============================] - 24s 23ms/step - loss: 0.0537 - accuracy: 0.9823 - val_loss: 0.2313 - val_accuracy: 0.94
```

```
evaluate = model.evaluate(x_test,y_test)
```

```
57/57 [==============================] - 0s 8ms/step - loss: 0.1719 - accuracy: 0.9594
```

```
print("Test Acuracy is : {:.2f} %".format(evaluate[1]*100))
print("Test Loss is : {:.4f}".format(evaluate[0]))
```

```
Test Acuracy is : 95.94 %
Test Loss is : 0.1719
```

```
predictions = model.predict(x_test)
```

```
57/57 [==============================] - 1s 8ms/step
```

```
predict = []
for i in predictions:
    predict.append(np.argmax(i))
```

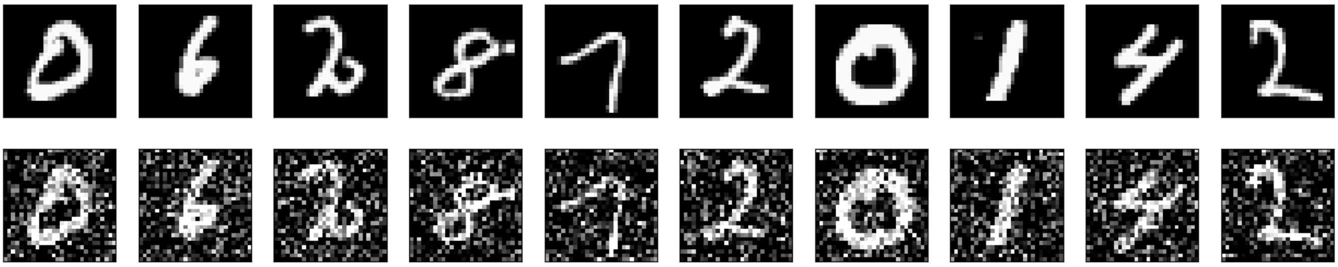
Experiment - 7

Auto encoders using MNIST data

```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt

from tensorflow.keras import layers
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Model


def preprocess(array):
    """
    Normalizes the supplied array and reshapes it into the appropriate format.
    """

    array = array.astype("float32") / 255.0
    array = np.reshape(array, (len(array), 28, 28, 1))
    return array


def noise(array):
    """
    Adds random noise to each image in the supplied array.
    """

    noise_factor = 0.4 #amount of noise to add
    noisy_array = array + noise_factor * np.random.normal(
        loc=0.0, scale=1.0, size=array.shape
    )

    return np.clip(noisy_array, 0.0, 1.0)


def display(array1, array2):
    """
    Displays ten random images from each one of the supplied arrays.
    """

    n = 10

    indices = np.random.randint(len(array1), size=n)
    images1 = array1[indices, :]
    images2 = array2[indices, :]

    plt.figure(figsize=(20, 4))
    for i, (image1, image2) in enumerate(zip(images1, images2)):
        ax = plt.subplot(2, n, i + 1)
        plt.imshow(image1.reshape(28, 28))
        plt.gray()
        ax.get_xaxis().set_visible(False)
        ax.get_yaxis().set_visible(False)

        ax = plt.subplot(2, n, i + 1 + n)
        plt.imshow(image2.reshape(28, 28))
        plt.gray()
        ax.get_xaxis().set_visible(False)
        ax.get_yaxis().set_visible(False)

    plt.show()


# Since we only need images from the dataset to encode and decode, we
# won't use the labels.
(train_data, _), (test_data, _) = mnist.load_data()

# Normalize and reshape the data
train_data = preprocess(train_data)
test_data = preprocess(test_data)

# Create a copy of the data with added noise
noisy_train_data = noise(train_data)
noisy_test_data = noise(test_data)

# Display the train data and a version of it with added noise
display(train_data, noisy_train_data)
```

```
display(train_data, noisy_train_data)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 ━━━━━━━━━━━━━━━━━━━━ 2s 0us/step
```



```
input = layers.Input(shape=(28, 28, 1))

# Encoder
x = layers.Conv2D(32, (3, 3), activation="relu", padding="same")(input)
x = layers.MaxPooling2D((2, 2), padding="same")(x)
x = layers.Conv2D(32, (3, 3), activation="relu", padding="same")(x)
x = layers.MaxPooling2D((2, 2), padding="same")(x)

# Decoder
x = layers.Conv2DTranspose(32, (3, 3), strides=2, activation="relu", padding="same")(x)
x = layers.Conv2DTranspose(32, (3, 3), strides=2, activation="relu", padding="same")(x)
x = layers.Conv2D(1, (3, 3), activation="sigmoid", padding="same")(x)

# Autoencoder
autoencoder = Model(input, x)
autoencoder.compile(optimizer="adam", loss="binary_crossentropy")
autoencoder.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 28, 28, 1)	0
conv2d (Conv2D)	(None, 28, 28, 32)	320
max_pooling2d (MaxPooling2D)	(None, 14, 14, 32)	0
conv2d_1 (Conv2D)	(None, 14, 14, 32)	9,248
max_pooling2d_1 (MaxPooling2D)	(None, 7, 7, 32)	0
conv2d_transpose (Conv2DTranspose)	(None, 14, 14, 32)	9,248
conv2d_transpose_1 (Conv2DTranspose)	(None, 28, 28, 32)	9,248
conv2d_2 (Conv2D)	(None, 28, 28, 1)	289

Total params: 28,353 (110.75 KB)

```
autoencoder.fit(
    x=train_data,
    y=train_data,
    epochs=50,
    batch_size=128,
    shuffle=True,
    validation_data=(test_data, test_data),
)
```

```
Epoch 1/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 10s 12ms/step - loss: 0.2439 - val_loss: 0.0743
Epoch 2/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0736 - val_loss: 0.0701
Epoch 3/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0704 - val_loss: 0.0685
Epoch 4/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0689 - val_loss: 0.0676
Epoch 5/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0679 - val_loss: 0.0669
Epoch 6/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0672 - val_loss: 0.0663
Epoch 7/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0667 - val_loss: 0.0659
Epoch 8/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0663 - val_loss: 0.0656
```

```
Epoch 9/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0659 - val_loss: 0.0652
Epoch 10/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0656 - val_loss: 0.0649
Epoch 11/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0654 - val_loss: 0.0647
Epoch 12/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0650 - val_loss: 0.0644
Epoch 13/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0648 - val_loss: 0.0644
Epoch 14/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0645 - val_loss: 0.0641
Epoch 15/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - loss: 0.0643 - val_loss: 0.0639
Epoch 16/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0642 - val_loss: 0.0637
Epoch 17/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0641 - val_loss: 0.0636
Epoch 18/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0640 - val_loss: 0.0634
Epoch 19/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0638 - val_loss: 0.0634
Epoch 20/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0637 - val_loss: 0.0633
Epoch 21/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - loss: 0.0636 - val_loss: 0.0632
Epoch 22/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0634 - val_loss: 0.0631
Epoch 23/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0635 - val_loss: 0.0630
Epoch 24/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - loss: 0.0634 - val_loss: 0.0629
Epoch 25/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0634 - val_loss: 0.0629
Epoch 26/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0633 - val_loss: 0.0629
Epoch 27/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - loss: 0.0632 - val_loss: 0.0628
Epoch 28/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0630 - val_loss: 0.0627
Epoch 29/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0630 - val_loss: 0.0626
```

```
predictions = autoencoder.predict(test_data)
display(test_data, predictions)
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```

Experiment - 8

variational-autoencoders

```
# For working with and visualizing the data
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

# For training the VAE
import tensorflow as tf

# For creating interactive widgets
import ipywidgets as widgets
from IPython.display import display
```

```
2024-05-22 06:28:22.848294: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use availab]
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
```

```
# Load the data from a .csv file
pixel_data = pd.read_csv('/workspace/Bootcamp/data/age_gender.csv')['pixels']
```

```
# Shuffle the data
pixel_data = pixel_data.sample(frac=1.0, random_state=1)
# Convert the data into a NumPy array
pixel_data = pixel_data.apply(lambda x: np.array(x.split(" "), dtype=np.int))
pixel_data = np.stack(np.array(pixel_data), axis=0)
# Rescale pixel values to be between 0 and 1
pixel_data = pixel_data * (1./255)
```

```
/tmp/ipykernel_92174/3099532490.py:4: DeprecationWarning: `np.int` is a deprecated alias for the builtin `int`. To silence this warn
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  pixel_data = pixel_data.apply(lambda x: np.array(x.split(" "), dtype=np.int))
```

```
# The data is now a NumPy array of 23705 images.
# we are working with 48x48x1 images)
pixel_data.shape
```

```
(23705, 2304)
```

```
class Sampling(tf.keras.layers.Layer):
    def call(self, inputs):
        z_mean, z_log_var = inputs  # Unpack the inputs into mean and log-variance
        batch = tf.shape(z_mean)[0]  # Get the batch size
        dim = tf.shape(z_mean)[1]  # Get the dimensionality of the latent space
        epsilon = tf.keras.backend.random_normal(shape=(batch, dim))  # Sample from standard normal distribution
        return epsilon * tf.exp(z_log_var * 0.5) + z_mean  # Apply the reparameterization trick
```

```
def build_vae(num_pixels, num_latent_vars=3):

    # Encoder
    encoder_inputs = tf.keras.Input(shape=(num_pixels,))  # Input layer for the encoder
    x = tf.keras.layers.Dense(512, activation='relu')(encoder_inputs)  # First dense layer with 512 units and ReLU activation
    x = tf.keras.layers.Dense(128, activation='relu')(x)  # Second dense layer with 128 units and ReLU activation
    x = tf.keras.layers.Dense(32, activation='relu')(x)  # Third dense layer with 32 units and ReLU activation
    z_mean = tf.keras.layers.Dense(num_latent_vars)(x)  # Dense layer for the mean of the latent variables
    z_log_var = tf.keras.layers.Dense(num_latent_vars)(z_mean)  # Dense layer for the log-variance of the latent variables
    z = Sampling()([z_mean, z_log_var])  # Sampling layer to sample the latent variables using the reparameterization trick

    encoder = tf.keras.Model(inputs=encoder_inputs, outputs=z)  # Define the encoder model

    # Decoder
    decoder_inputs = tf.keras.Input(shape=(num_latent_vars,))  # Input layer for the decoder
    x = tf.keras.layers.Dense(32, activation='relu')(decoder_inputs)  # First dense layer with 32 units and ReLU activation
    x = tf.keras.layers.Dense(128, activation='relu')(x)  # Second dense layer with 128 units and ReLU activation
    x = tf.keras.layers.Dense(512, activation='relu')(x)  # Third dense layer with 512 units and ReLU activation
    reconstruction = tf.keras.layers.Dense(num_pixels, activation='linear')(x)  # Output dense layer with 'num_pixels' units and linear

    decoder = tf.keras.Model(inputs=decoder_inputs, outputs=reconstruction)  # Define the decoder model

    # Full model
```

```
    model_inputs = encoder.input  # Inputs of the full VAE model are the inputs of the encoder
    model_outputs = decoder(encoder.output)  # Outputs of the full VAE model are the outputs of the decoder, given the encoder's output

    model = tf.keras.Model(inputs=model_inputs, outputs=model_outputs)  # Define the full VAE model

    # Compile model for training
    model.compile(
        optimizer='adam',  # Adam optimizer
        loss='mse'  # Mean Squared Error (MSE) loss function
    )

    # Return all three models
    return encoder, decoder, model  # Return the encoder, decoder, and full VAE models
```

```
face_encoder, face_decoder, face_model = build_vae(num_pixels=2304, num_latent_vars=3)
```

```
2024-05-22 06:28:31.067844: W tensorflow/core/common_runtime/gpu/gpu_device.cc:1960] Cannot dlopen some GPU libraries. Please make s
Skipping registering GPU devices...
```

```
print(face_encoder.summary())
```

```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                Output Shape                 Param #   Connected to
==================================================================================================
 input_1 (InputLayer)        [(None, 2304)]               0         []

 dense (Dense)               (None, 512)                  1180160   ['input_1[0][0]']

 dense_1 (Dense)             (None, 128)                  65664     ['dense[0][0]']

 dense_2 (Dense)             (None, 32)                   4128      ['dense_1[0][0]']

 dense_3 (Dense)             (None, 3)                    99        ['dense_2[0][0]']

 dense_4 (Dense)             (None, 3)                    12        ['dense_3[0][0]']

 sampling (Sampling)         (None, 3)                    0         ['dense_3[0][0]',
                                                                     'dense_4[0][0]']

==================================================================================================
Total params: 1250063 (4.77 MB)
Trainable params: 1250063 (4.77 MB)
Non-trainable params: 0 (0.00 Byte)
__________________________________________________________________________________________________
None
```

```
print(face_decoder.summary())
```

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 3)]               0

 dense_5 (Dense)             (None, 32)                128

 dense_6 (Dense)             (None, 128)               4224

 dense_7 (Dense)             (None, 512)               66048

 dense_8 (Dense)             (None, 2304)              1181952

=================================================================
Total params: 1252352 (4.78 MB)
Trainable params: 1252352 (4.78 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
```

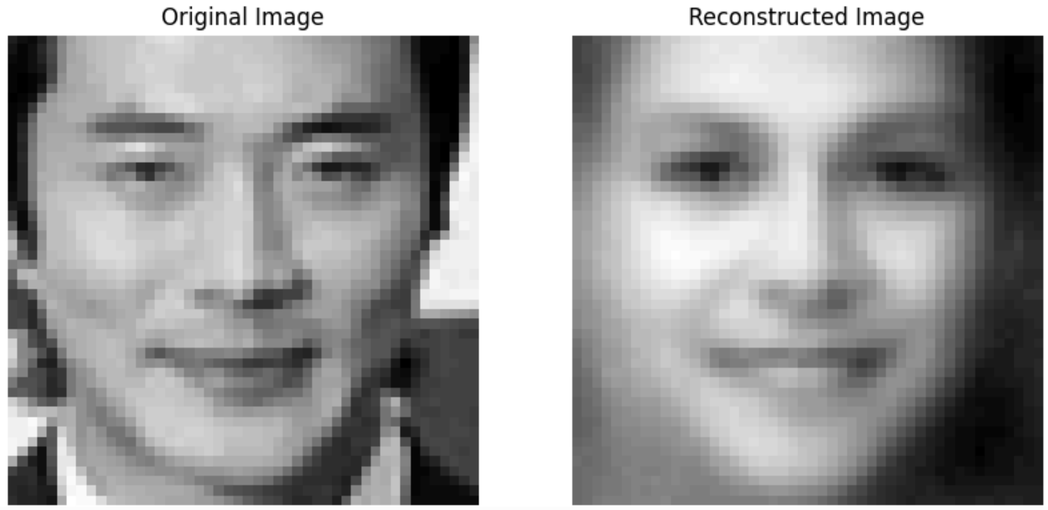
```
history = face_model.fit(
    pixel_data,
    pixel_data,
    validation_split=0.2,
    batch_size=32,
    epochs=100,
    callbacks=[
        tf.keras.callbacks.EarlyStopping(
            monitor='val_loss',
            patience=10,
            restore_best_weights=True
        )
```

```
    ]
)
```

```
Epoch 1/100
593/593 [==============================] - 8s 12ms/step - loss: 0.0256 - val_loss: 0.0216
Epoch 2/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0216 - val_loss: 0.0213
Epoch 3/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0214 - val_loss: 0.0212
Epoch 4/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0212 - val_loss: 0.0212
Epoch 5/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0212 - val_loss: 0.0210
Epoch 6/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0211 - val_loss: 0.0213
Epoch 7/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0210 - val_loss: 0.0209
Epoch 8/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0209 - val_loss: 0.0209
Epoch 9/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0209 - val_loss: 0.0210
Epoch 10/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0208 - val_loss: 0.0206
Epoch 11/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0206 - val_loss: 0.0206
Epoch 12/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0206 - val_loss: 0.0208
Epoch 13/100
593/593 [==============================] - 6s 9ms/step - loss: 0.0206 - val_loss: 0.0207
Epoch 14/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0206 - val_loss: 0.0205
Epoch 15/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0207 - val_loss: 0.0210
Epoch 16/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0207 - val_loss: 0.0204
Epoch 17/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0208 - val_loss: 0.0208
Epoch 18/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0206 - val_loss: 0.0206
Epoch 19/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0205 - val_loss: 0.0207
Epoch 20/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0207 - val_loss: 0.0205
Epoch 21/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0207 - val_loss: 0.0206
Epoch 22/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0207 - val_loss: 0.0209
Epoch 23/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0207 - val_loss: 0.0207
Epoch 24/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0206 - val_loss: 0.0210
Epoch 25/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0205 - val_loss: 0.0205
Epoch 26/100
593/593 [==============================] - 5s 9ms/step - loss: 0.0205 - val_loss: 0.0205
```

```
i = 6

sample = np.array(pixel_data)[i].copy()
sample = sample.reshape(48, 48, 1)

reconstruction = face_model.predict(pixel_data)[i].copy()
reconstruction = reconstruction.reshape(48, 48, 1)

plt.figure(figsize=(10, 5))

plt.subplot(1, 2, 1)
plt.imshow(sample, cmap='gray')
plt.axis('off')
plt.title("Original Image")

plt.subplot(1, 2, 2)
plt.imshow(reconstruction, cmap='gray')
plt.axis('off')
plt.title("Reconstructed Image")

plt.show()
```

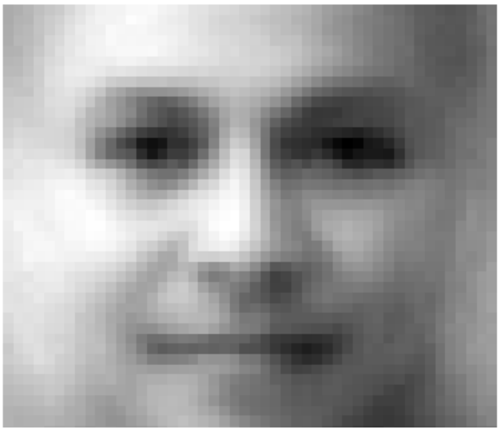
```
741/741 [==============================] - 1s 2ms/step
```



```
# A function to allow us to specify our own latent variable values and plot the constructed image
def generate_face_image(latent1, latent2, latent3):
    latent_vars = np.array([[latent1, latent2, latent3]])
    reconstruction = np.array(face_decoder(latent_vars))
    reconstruction = reconstruction.reshape(48, 48, 1)
    plt.figure()
    plt.imshow(reconstruction, cmap='gray')
    plt.axis('off')
    plt.show()


# Let's get the min and max for each slider on the interactive widget
latent1_min = np.min(face_encoder(pixel_data).numpy()[:, 0])
latent1_max = np.max(face_encoder(pixel_data).numpy()[:, 0])

latent2_min = np.min(face_encoder(pixel_data).numpy()[:, 1])
latent2_max = np.max(face_encoder(pixel_data).numpy()[:, 1])

latent3_min = np.min(face_encoder(pixel_data).numpy()[:, 2])
latent3_max = np.max(face_encoder(pixel_data).numpy()[:, 2])


import tensorflow as tf
print(tf.__version__)
```

```
2.13.1
```

```
# Create the interactive widget
face_image_generator = widgets.interact(
    generate_face_image,
    latent1=(latent1_min, latent1_max),
    latent2=(latent2_min, latent2_max),
    latent3=(latent3_min, latent3_max),
)

# Display the widget
display(face_image_generator)
```



Experiment - 9

Implementing GAN Architecture on MINST dataset

```
from tensorflow.keras.layers import (Dense,
                                     BatchNormalization,
                                     LeakyReLU,
                                     Reshape,
                                     Conv2DTranspose,
                                     Conv2D,
                                     Dropout,
                                     Flatten)
import tensorflow as tf
import matplotlib.pyplot as plt
```

```
# underscore to omit the label arrays
(train_images, train_labels), (_, _) = tf.keras.datasets.mnist.load_data()
```

```
train_images = train_images.reshape(train_images.shape[0], 28, 28, 1).astype('float32')
train_images = (train_images - 127.5) / 127.5 # Normalize the images to [-1, 1]

BUFFER_SIZE = 60000
BATCH_SIZE = 256

# Batch and shuffle the data
train_dataset = tf.data.Dataset.from_tensor_slices(train_images).shuffle(BUFFER_SIZE).batch(BATCH_SIZE)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 [==============================] - 0s 0us/step
```

```
# Set the dimensions of the noise
z_dim = 100
```

```
def generator_model():
    model = tf.keras.Sequential()
    model.add(Dense(7*7*256, use_bias=False, input_shape=(100,)))
    model.add(BatchNormalization())
    model.add(LeakyReLU())

    model.add(Reshape((7, 7, 256)))
    assert model.output_shape == (None, 7, 7, 256) # Note: None is the batch size

    model.add(Conv2DTranspose(128, (5, 5), strides=(1, 1), padding='same', use_bias=False))
    assert model.output_shape == (None, 7, 7, 128)
    model.add(BatchNormalization())
    model.add(LeakyReLU())

    model.add(Conv2DTranspose(64, (5, 5), strides=(2, 2), padding='same', use_bias=False))
    assert model.output_shape == (None, 14, 14, 64)
    model.add(BatchNormalization())
    model.add(LeakyReLU())

    model.add(Conv2DTranspose(1, (5, 5), strides=(2, 2), padding='same', use_bias=False, activation='tanh'))
    assert model.output_shape == (None, 28, 28, 1)

    print(model.summary())

    return model
```

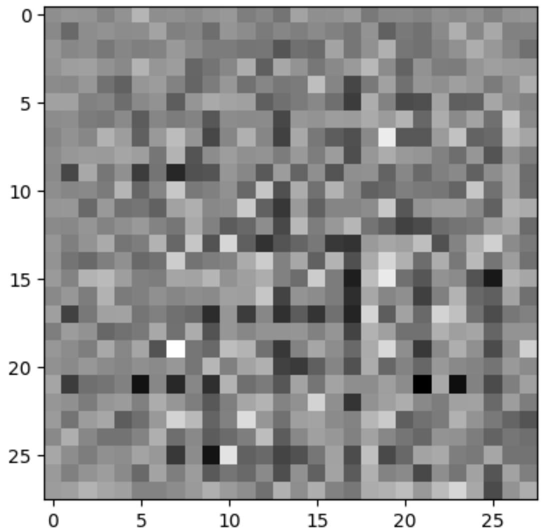
```
generator = generator_model()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense (Dense)               (None, 12544)             1254400   
                                                                 
 batch_normalization (BatchN  (None, 12544)            50176     
 ormalization)                                                   
                                                                 
 leaky_re_lu (LeakyReLU)     (None, 12544)             0         
                                                                 
 reshape (Reshape)           (None, 7, 7, 256)         0         
```

```
 conv2d_transpose (Conv2DTra  (None, 7, 7, 128)        819200
 nspose)

 batch_normalization_1 (Batc  (None, 7, 7, 128)        512
 hNormalization)

 leaky_re_lu_1 (LeakyReLU)   (None, 7, 7, 128)         0

 conv2d_transpose_1 (Conv2DT  (None, 14, 14, 64)       204800
 ranspose)

 batch_normalization_2 (Batc  (None, 14, 14, 64)       256
 hNormalization)

 leaky_re_lu_2 (LeakyReLU)   (None, 14, 14, 64)        0

 conv2d_transpose_2 (Conv2DT  (None, 28, 28, 1)        1600
 ranspose)

=================================================================
Total params: 2,330,944
Trainable params: 2,305,472
Non-trainable params: 25,472
_________________________________________________________________
None
```

```
# Create a random noise and generate a sample
noise = tf.random.normal([1, 100])
generated_image = generator(noise, training=False)
# Visualize the generated sample
plt.imshow(generated_image[0, :, :, 0], cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7fa67e014b50>
```



```
def discriminator_model():
    model = tf.keras.Sequential()

    model.add(Conv2D(64, (5, 5), strides=(2, 2), padding='same', input_shape=[28, 28, 1]))
    model.add(LeakyReLU())
    model.add(Dropout(0.3))

    model.add(Conv2D(128, (5, 5), strides=(2, 2), padding='same'))
    model.add(LeakyReLU())
    model.add(Dropout(0.3))

    model.add(Flatten())
    model.add(Dense(1))

    print(model.summary())

    return model

discriminator = discriminator_model()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_1 (Conv2D)           (None, 14, 14, 64)        1664

 leaky_re_lu_4 (LeakyReLU)   (None, 14, 14, 64)        0
```

```
 dropout (Dropout)           (None, 14, 14, 64)        0

 conv2d_2 (Conv2D)           (None, 7, 7, 128)         204928

 leaky_re_lu_5 (LeakyReLU)   (None, 7, 7, 128)         0

 dropout_1 (Dropout)         (None, 7, 7, 128)         0

 flatten (Flatten)           (None, 6272)              0

 dense_1 (Dense)             (None, 1)                 6273

=================================================================
Total params: 212,865
Trainable params: 212,865
Non-trainable params: 0
_________________________________________________________________
None
```

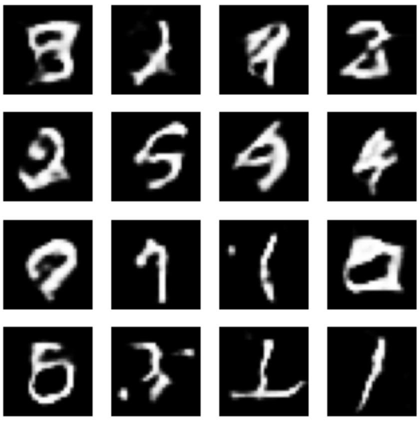
```
# This method returns a helper function to compute cross entropy loss
cross_entropy = tf.keras.losses.BinaryCrossentropy(from_logits=True)

def discriminator_loss(real_output, fake_output):
    real_loss = cross_entropy(tf.ones_like(real_output), real_output)
    fake_loss = cross_entropy(tf.zeros_like(fake_output), fake_output)
    total_loss = real_loss + fake_loss
    return total_loss

def generator_loss(fake_output):
    return cross_entropy(tf.ones_like(fake_output), fake_output)

generator_optimizer = tf.keras.optimizers.Adam(1e-4)
discriminator_optimizer = tf.keras.optimizers.Adam(1e-4)


import os
checkpoint_dir = '/content/drive/MyDrive/AMITY/Deep Learning (codes)/GAN/'
checkpoint_prefix = os.path.join(checkpoint_dir, "ckpt")
checkpoint = tf.train.Checkpoint(generator_optimizer=generator_optimizer,
                                 discriminator_optimizer=discriminator_optimizer,
                                 generator=generator,
                                 discriminator=discriminator)


EPOCHS = 60
# We will reuse this seed overtime (so it's easier)
# to visualize progress in the animated GIF)
num_examples_to_generate = 16
noise_dim = 100
seed = tf.random.normal([num_examples_to_generate, noise_dim])


# tf.function annotation causes the function
# to be "compiled" as part of the training
@tf.function
def train_step(images):

    # 1 - Create a random noise to feed it into the model
    # for the image generation
    noise = tf.random.normal([BATCH_SIZE, noise_dim])

    # 2 - Generate images and calculate loss values
    # GradientTape method records operations for automatic differentiation.
    with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
      generated_images = generator(noise, training=True)

      real_output = discriminator(images, training=True)
      fake_output = discriminator(generated_images, training=True)

      gen_loss = generator_loss(fake_output)
      disc_loss = discriminator_loss(real_output, fake_output)

    # 3 - Calculate gradients using loss values and model variables
    # "gradient" method computes the gradient using
    # operations recorded in context of this tape (gen_tape and disc_tape).

    # It accepts a target (e.g., gen_loss) variable and
    # a source variable (e.g.,generator.trainable_variables)
    # target --> a list or nested structure of Tensors or Variables to be differentiated.
    # source --> a list or nested structure of Tensors or Variables.
    # target will be differentiated against elements in sources.

    # "gradient" method returns a list or nested structure of Tensors
```

```
    # (or IndexedSlices, or None), one for each element in sources.
    # Returned structure is the same as the structure of sources.
    gradients_of_generator = gen_tape.gradient(gen_loss,
                                               generator.trainable_variables)
    gradients_of_discriminator = disc_tape.gradient(disc_loss,
                                                discriminator.trainable_variables)

    # 4 - Process  Gradients and Run the Optimizer
    # "apply_gradients" method processes aggregated gradients.
    # ex: optimizer.apply_gradients(zip(grads, vars))
    """
    Example use of apply_gradients:
    grads = tape.gradient(loss, vars)
    grads = tf.distribute.get_replica_context().all_reduce('sum', grads)
    # Processing aggregated gradients.
    optimizer.apply_gradients(zip(grads, vars), experimental_aggregate_gradients=False)
    """
    generator_optimizer.apply_gradients(zip(gradients_of_generator, generator.trainable_variables))
    discriminator_optimizer.apply_gradients(zip(gradients_of_discriminator, discriminator.trainable_variables))


def generate_and_save_images(model, epoch, test_input):
  # Notice `training` is set to False.
  # This is so all layers run in inference mode (batchnorm).
  # 1 - Generate images
  predictions = model(test_input, training=False)
  # 2 - Plot the generated images
  fig = plt.figure(figsize=(4,4))
  for i in range(predictions.shape[0]):
      plt.subplot(4, 4, i+1)
      plt.imshow(predictions[i, :, :, 0] * 127.5 + 127.5, cmap='gray')
      plt.axis('off')
  # 3 - Save the generated images
  plt.savefig('image_at_epoch_{:04d}.png'.format(epoch))
  plt.show()


import time
from IPython import display # A command shell for interactive computing in Python.

def train(dataset, epochs):
  # A. For each epoch, do the following:
  for epoch in range(epochs):
    start = time.time()
    # 1 - For each batch of the epoch,
    for image_batch in dataset:
      # 1.a - run the custom "train_step" function
      # we just declared above
      train_step(image_batch)

    # 2 - Produce images for the GIF as we go
    display.clear_output(wait=True)
    generate_and_save_images(generator,
                             epoch + 1,
                             seed)

    # 3 - Save the model every 5 epochs as
    # a checkpoint, which we will use later
    if (epoch + 1) % 5 == 0:
      checkpoint.save(file_prefix = checkpoint_prefix)

    # 4 - Print out the completed epoch no. and the time spent
    print ('Time for epoch {} is {} sec'.format(epoch + 1, time.time()-start))

  # B. Generate a final image after the training is completed
  display.clear_output(wait=True)
  generate_and_save_images(generator,
                           epochs,
                           seed)


train(train_dataset, EPOCHS)
```

```
checkpoint.restore(tf.train.latest_checkpoint(checkpoint_dir))
```

<tensorflow.python.checkpoint.checkpoint.CheckpointLoadStatus at 0x7fa5c2d49450>

```
# PIL is a library which may open different image file formats
import PIL
# Display a single image using the epoch number
def display_image(epoch_no):
  return PIL.Image.open('image_at_epoch_{:04d}.png'.format(epoch_no))
display_image(EPOCHS)
```



```
import glob # The glob module is used for Unix style pathname pattern expansion.
import imageio # The library that provides an easy interface to read and write a wide range of image data

anim_file = 'dcgan.gif'

with imageio.get_writer(anim_file, mode='I') as writer:
  filenames = glob.glob('image*.png')
  filenames = sorted(filenames)
  for filename in filenames:
    image = imageio.imread(filename)
    writer.append_data(image)
  # image = imageio.imread(filename)
  # writer.append_data(image)

display.Image(open('dcgan.gif','rb').read())
```