Lab 7

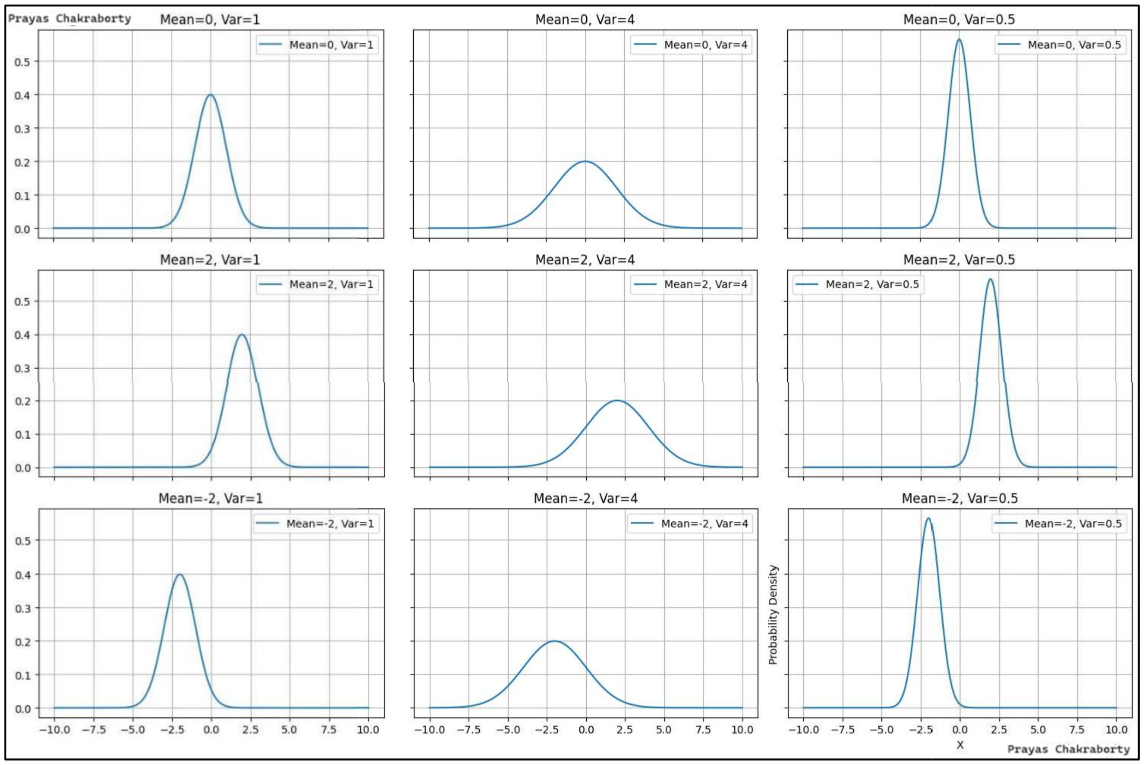
Statistics, Machine Learning, Deep Learning

1. **Write a Python program that computes the value of the Gaussian distribution at a given vector X. Hence, plot the effect of varying mean and variance to the normal distribution.**

   Code:-

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

def gaussian_distribution(x, mean, variance):

    sigma = np.sqrt(variance)
    return (1 / (sigma * np.sqrt(2 * np.pi))) * np.exp(-0.5 * ((x -
mean) ** 2) / variance)

# Define range for x
x = np.linspace(-10, 10, 1000)

# Parameters to vary
means = [0, 2, -2]
variances = [1, 4, 0.5]

# Create subplots
fig, axes = plt.subplots(len(means), len(variances), figsize=(15,
10), sharex=True, sharey=True)

# Plot for varying means
for i, mean in enumerate(means):
    for j, variance in enumerate(variances):
        ax = axes[i, j]
        y = gaussian_distribution(x, mean, variance)
        ax.plot(x, y, label=f'Mean={mean}, Var={variance}')
        ax.set_title(f'Mean={mean}, Var={variance}')
        ax.legend()
        ax.grid(True)

# Set common labels
plt.xlabel('X')
plt.ylabel('Probability Density')
plt.tight_layout()
plt.show()
```

Output:-

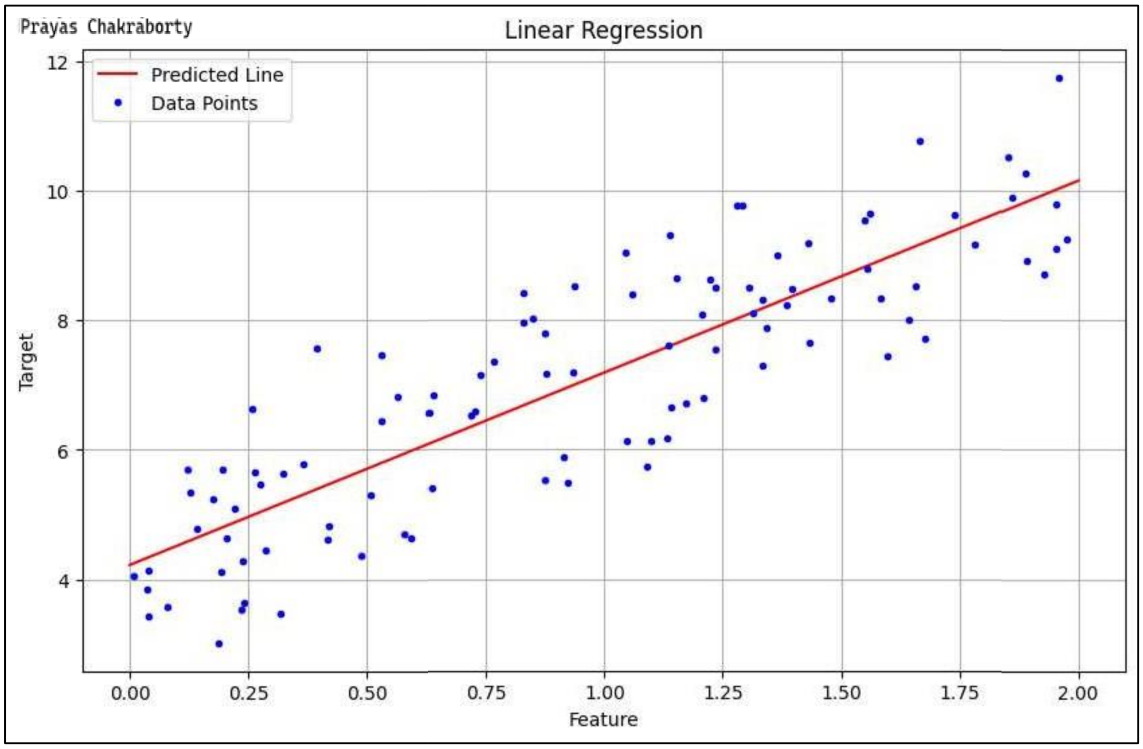


2. **Write a python program to implement linear regression.**
   Code:-

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

# Generate synthetic data
np.random.seed(0)
X = 2 * np.random.rand(100, 1)
y = 4 + 3 * X + np.random.randn(100, 1)  # y = 4 + 3*X + noise

# Add bias term (x0 = 1) to each instance
X_b = np.c_[np.ones((100, 1)), X]  # Add a column of ones to X

# Compute the optimal parameters using the Normal Equation
theta_best = np.linalg.inv(X_b.T.dot(X_b)).dot(X_b.T).dot(y)

# Extract the parameters
intercept, slope = theta_best

# Predict using the fitted model
X_new = np.linspace(0, 2, 100).reshape(100, 1)
X_new_b = np.c_[np.ones((100, 1)), X_new] # Add bias term
y_predict = X_new_b.dot(theta_best)

# Plotting
```

```
plt.figure(figsize=(10,  6))
plt.plot(X_new,  y_predict,  "r-",  label="Predicted  Line")
plt.plot(X,  y,  "b.",  label="Data  Points")
plt.xlabel("Feature")
plt.ylabel("Target")
plt.title("Linear  Regression")
plt.legend()
plt.grid(True)
plt.show()

# Output the parameters
print(f"Intercept: {intercept[0]}")
print(f"Slope: {slope[0]}")
```

Output:-



3. **Write a python program to implement gradient descent.**
   Code:-

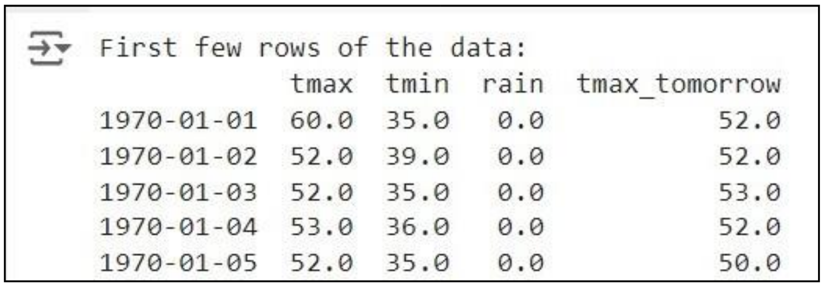
```
# Import necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
import numpy as np
import math

# Load and prepare the data
data_url = "/content/clean_weather.csv"   # Path to your dataset
```

```
data = pd.read_csv(data_url, index_col=0).ffill()  # Forward fill
missing values

# Display the first few rows of the data
print("First few rows of the data:")
print(data.head())

# Plot the relationship between tmax and tmax_tomorrow
plt.figure(figsize=(10, 6))
plt.scatter(data["tmax"], data["tmax_tomorrow"], color='blue',
label='Data Points')
plt.plot([30, 120], [30, 120], color='green', label='Regression
Line')
plt.xlabel('tmax')
plt.ylabel('tmax_tomorrow')
plt.title('Scatter Plot of tmax vs. tmax_tomorrow')
plt.legend()
plt.show()

# Train a linear regression model
lr = LinearRegression()
lr.fit(data[["tmax"]], data["tmax_tomorrow"])

# Display the model parameters
print(f"\nLinear Regression Model Parameters:")
print(f"Weight: {lr.coef_[0]:.2f}")
print(f"Bias: {lr.intercept_:.2f}")

# Loss calculation
loss = lambda w, y: ((w * 80 + 11.99) - y) ** 2
ws = np.arange(-1, 3, 0.1)
losses = loss(ws, 81)

# Plot the loss function
plt.figure(figsize=(10, 6))
plt.scatter(ws, losses, color='blue', label='Loss Values')
plt.plot(1, loss(1, 81), 'ro', label='Loss at Weight=1')
plt.xlabel('Weight')
plt.ylabel('Loss')
plt.title('Loss Function vs. Weight')
plt.legend()
plt.show()

# Gradient calculation
gradient = lambda w, y: ((w * 80 + 11.99) - y) * 2
gradients = gradient(ws, 81)

# Plot the gradient
```

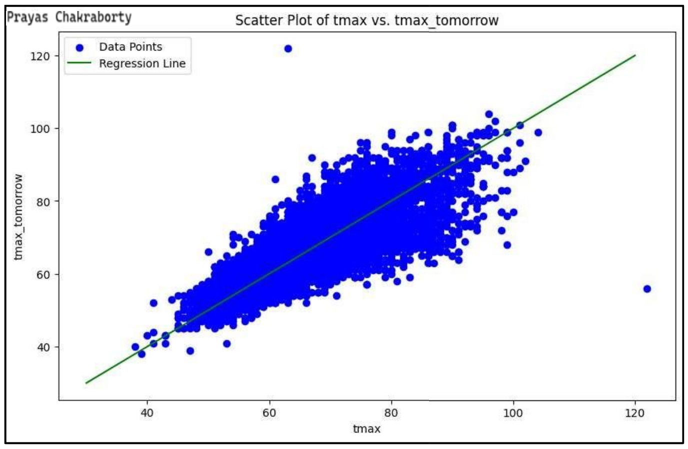
```
plt.figure(figsize=(10, 6))
plt.scatter(ws, gradients, color='blue', label='Gradient Values')
plt.plot(1, gradient(1, 81), 'ro', label='Gradient at Weight=1')
plt.xlabel('Weight')
plt.ylabel('Gradient')
plt.title('Gradient Function vs. Weight')
plt.legend()
plt.show()

# Initialize model parameters
def init_params(predictors):
    k = math.sqrt(1 / predictors)
    np.random.seed(0)
    weights = np.random.rand(predictors, 1) * 2 * k - k
    biases = np.ones((1, 1)) * 2 * k - k
    return [weights, biases]

# Forward pass to make predictions
def forward(params, x):
    weights, biases = params
    return x @ weights + biases

# Mean Squared Error calculation
def mse(actual, predicted):
    return np.mean((actual - predicted) ** 2)

# Backward pass to update parameters
def backward(params, x, lr, grad):
    w_grad = (x.T / x.shape[0]) @ grad
    b_grad = np.mean(grad, axis=0)
    params[0] -= w_grad * lr
    params[1] -= b_grad * lr
    return params

# Gradient Descent
lr = 1e-4
epochs = 50000
params = init_params(train_x.shape[1])

for i in range(epochs):
    predictions = forward(params, train_x)
    grad = mse_grad(train_y, predictions)
    params = backward(params, train_x, lr, grad)

    if i % 10000 == 0:
        predictions = forward(params, valid_x)
        valid_loss = mse(valid_y, predictions)
        print(f"Epoch {i} validation loss: {valid_loss:.2f}")
```

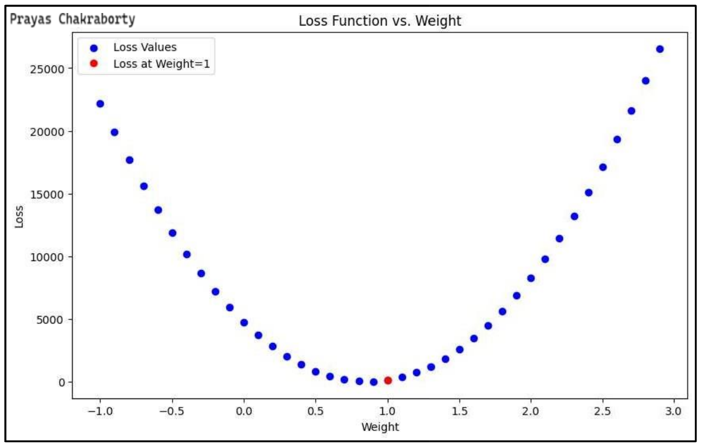
```
# Evaluate the model on the test set
predictions = forward(params, test_x)
test_loss = mse(test_y, predictions)
print(f"\nTest MSE: {test_loss:.2f}")
```

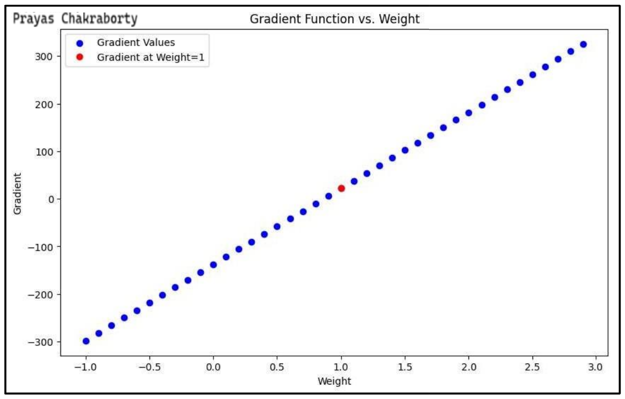
Output:-

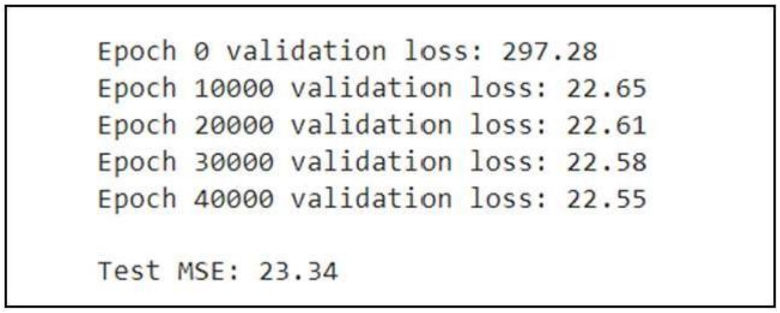


```
First few rows of the data:
            tmax  tmin  rain  tmax_tomorrow
1970-01-01  60.0  35.0   0.0           52.0
1970-01-02  52.0  39.0   0.0           52.0
1970-01-03  52.0  35.0   0.0           53.0
1970-01-04  53.0  36.0   0.0           52.0
1970-01-05  52.0  35.0   0.0           50.0
```





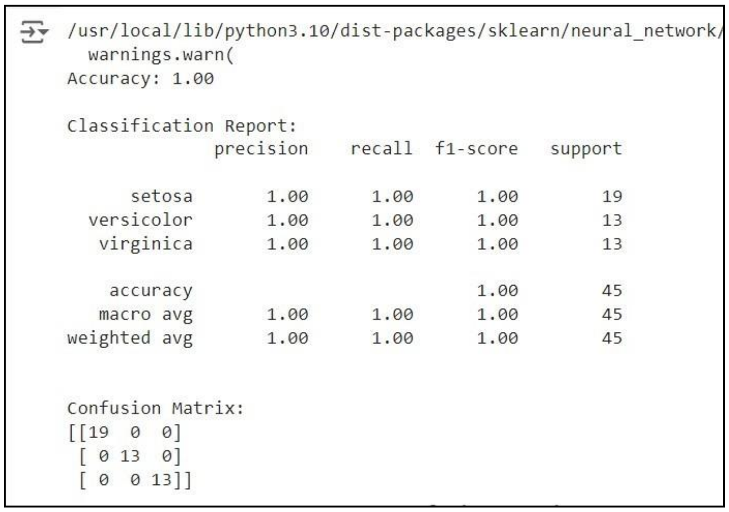




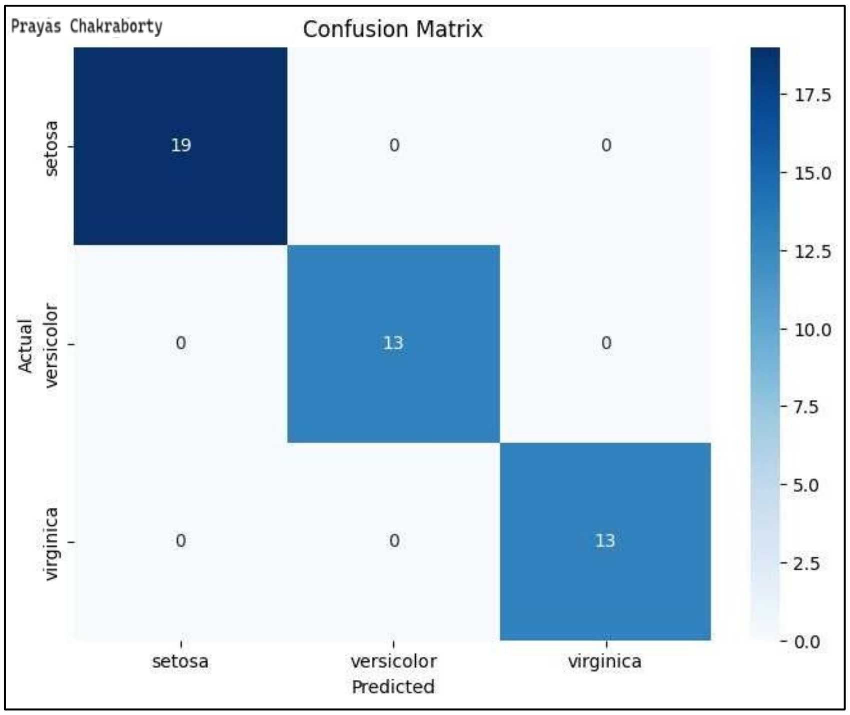
```
Epoch 0 validation loss: 297.28
Epoch 10000 validation loss: 22.65
Epoch 20000 validation loss: 22.61
Epoch 30000 validation loss: 22.58
Epoch 40000 validation loss: 22.55

Test MSE: 23.34
```

4. Write a python program to classify different flower images using MLP.

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
import seaborn as sns

def load_and_preprocess_data():
    # Load the Iris dataset
    iris = load_iris()
    X = iris.data
    y = iris.target
    feature_names = iris.feature_names
    class_names = iris.target_names

    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

    # Standardize features
    scaler = StandardScaler()
    X_train = scaler.fit_transform(X_train)
    X_test = scaler.transform(X_test)

    return X_train, X_test, y_train, y_test, class_names

def build_and_train_model(X_train, y_train):
    # Create an MLP model
    model = MLPClassifier(hidden_layer_sizes=(10, 10), max_iter=500,
random_state=42)

    # Train the model
    model.fit(X_train, y_train)
    return model

def evaluate_model(model, X_test, y_test, class_names):
    # Make predictions
    y_pred = model.predict(X_test)

    # Calculate accuracy
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Accuracy: {accuracy:.2f}")

    # Print classification report
    print("\nClassification Report:")
    print(classification_report(y_test, y_pred,
target_names=class_names))

    # Print confusion matrix
    conf_matrix = confusion_matrix(y_test, y_pred)
    print("\nConfusion  Matrix:")
    print(conf_matrix)

    # Plot confusion matrix
    plt.figure(figsize=(8, 6))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=class_names, yticklabels=class_names)
    plt.title('Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

def main():
    X_train, X_test, y_train, y_test, class_names =
load_and_preprocess_data()
    model = build_and_train_model(X_train, y_train)
    evaluate_model(model, X_test, y_test, class_names)

if __name__ == "__main__":
    main()
```



```
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/
  warnings.warn(
Accuracy: 1.00

Classification Report:
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        19
  versicolor       1.00      1.00      1.00        13
   virginica       1.00      1.00      1.00        13

    accuracy                           1.00        45
   macro avg       1.00      1.00      1.00        45
weighted avg       1.00      1.00      1.00        45


Confusion Matrix:
[[19  0  0]
 [ 0 13  0]
 [ 0  0 13]]
```

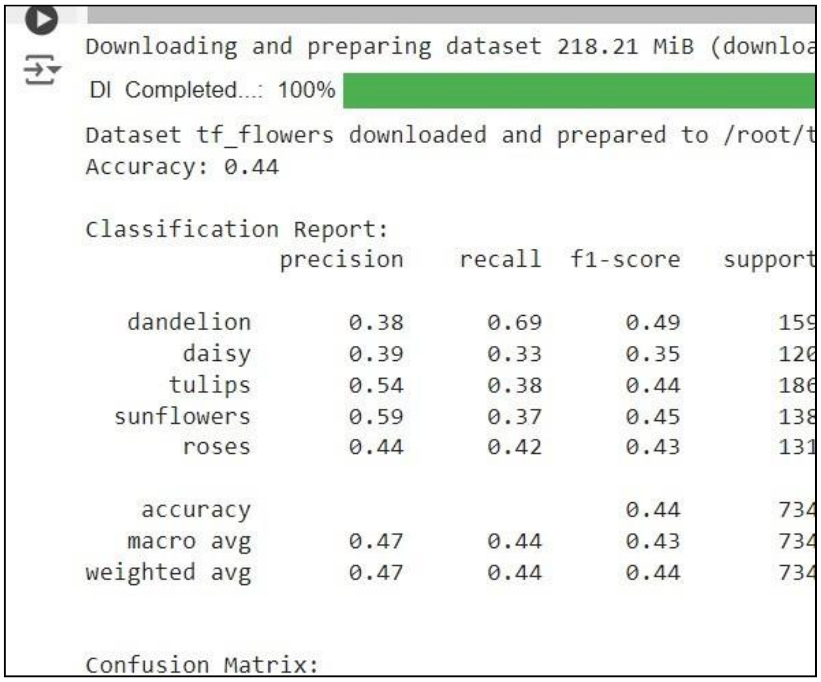


Write a python program to classify different flower images using the SVM classifier.

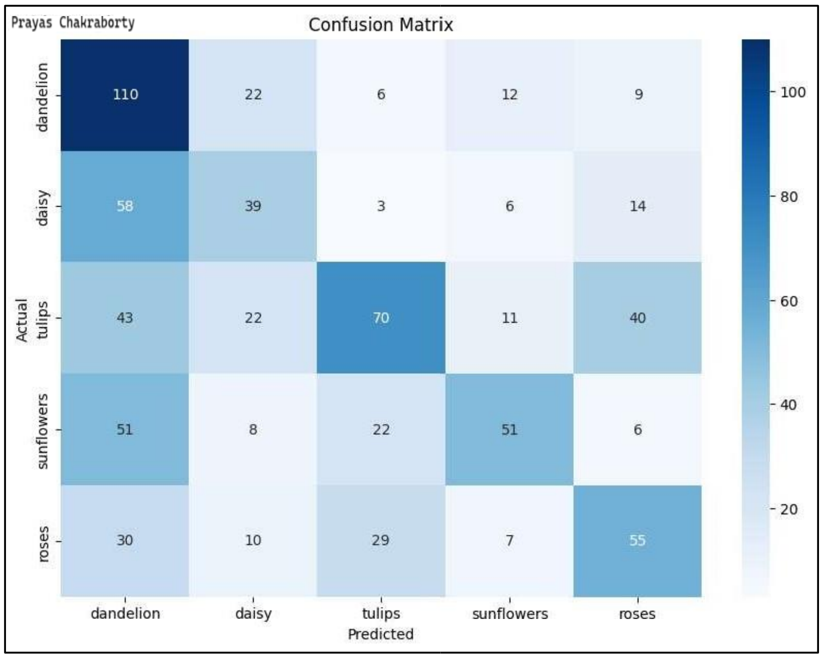
Code:-

```
import numpy as np
import tensorflow as tf
import tensorflow_datasets as tfds
from sklearn import svm
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Load flower dataset
def load_flower_data():
    # Load the Flowers dataset from TensorFlow Datasets
    dataset, info = tfds.load('tf_flowers', with_info=True,
as_supervised=True, split=['train[:80%]', 'train[80%:]'],
shuffle_files=True)

    train_data, test_data = dataset

    # Preprocess and extract features
    def preprocess(image, label):
        image = tf.image.resize(image, [64, 64])  # Resize image to
64x64
        image = tf.cast(image, tf.float32) / 255.0  # Normalize
pixel values
        return image, label

    train_data  = train_data.map(preprocess).batch(32).prefetch(1)
    test_data = test_data.map(preprocess).batch(32).prefetch(1)

    return train_data, test_data, info

# Extract features and labels
def extract_features_labels(data):
    features = []
    labels = []

    for images, batch_labels in data:
        features.extend(images.numpy().reshape(images.shape[0], -1))
 # Flatten images
        labels.extend(batch_labels.numpy())

    return np.array(features), np.array(labels)

def main():
    # Load and preprocess data
    train_data, test_data, info = load_flower_data()

    # Extract features and labels
    X_train, y_train  = extract_features_labels(train_data)
    X_test, y_test = extract_features_labels(test_data)

    # Standardize features
    scaler = StandardScaler()
    X_train  = scaler.fit_transform(X_train)
    X_test = scaler.transform(X_test)

    # Create and train SVM model
    model  = svm.SVC(kernel='linear', C=1.0, random_state=42)
    model.fit(X_train, y_train)
    # Make predictions
    y_pred = model.predict(X_test)

    # Evaluate the model
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Accuracy: {accuracy:.2f}")

    print("\nClassification Report:")
    print(classification_report(y_test, y_pred,
target_names=info.features['label'].names))

    conf_matrix = confusion_matrix(y_test, y_pred)
    print("\nConfusion  Matrix:")
    print(conf_matrix)

    # Plot confusion matrix
    plt.figure(figsize=(10, 7))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=info.features['label'].names,
yticklabels=info.features['label'].names)
    plt.title('Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

if___name__ == "__main__":
    main()
```

Output:-



```
Downloading and preparing dataset 218.21 MiB (downloa
Dl Completed...: 100%
Dataset tf_flowers downloaded and prepared to /root/t
Accuracy: 0.44

Classification Report:
              precision    recall  f1-score   support

   dandelion       0.38      0.69      0.49       159
       daisy       0.39      0.33      0.35       120
      tulips       0.54      0.38      0.44       186
  sunflowers       0.59      0.37      0.45       138
       roses       0.44      0.42      0.43       131

    accuracy                           0.44       734
   macro avg       0.47      0.44      0.43       734
weighted avg       0.47      0.44      0.44       734


Confusion Matrix:
```



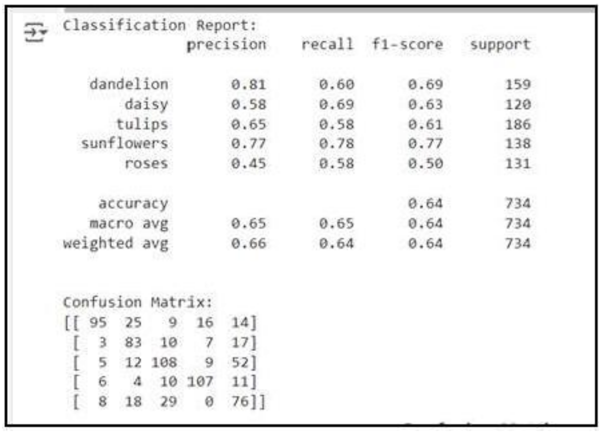
	dandelion	daisy	tulips	sunflowers	roses
dandelion	110	22	6	12	9
daisy	58	39	3	6	14
tulips	43	22	70	11	40
sunflowers	51	8	22	51	6
roses	30	10	29	7	55

4. **Write a python program to classify different flower images using CNN.**
Code:-

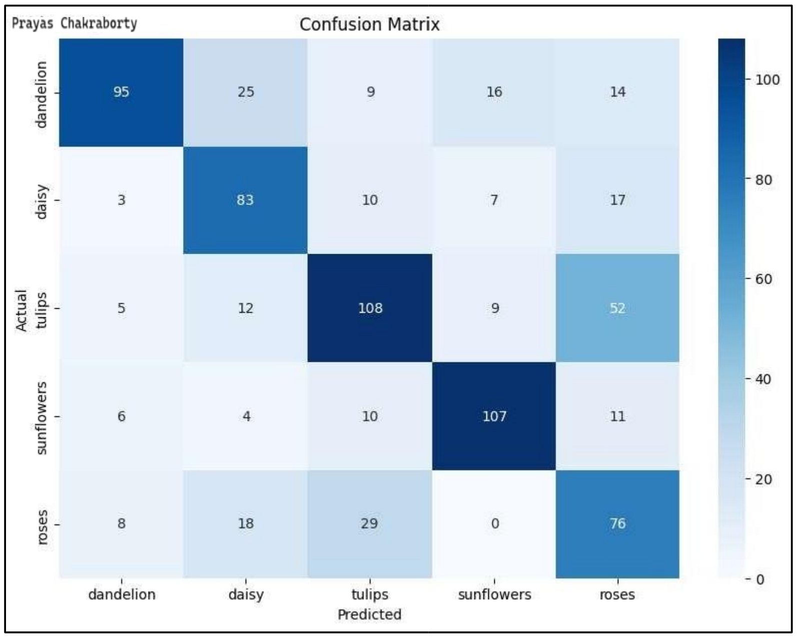
```
import numpy as np
import tensorflow as tf
import tensorflow_datasets as tfds
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten,
Dense
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Load and preprocess flower dataset
def load_flower_data():
    # Load the Flowers dataset
    dataset, info = tfds.load('tf_flowers', with_info=True,
as_supervised=True, split=['train[:80%]', 'train[80%:]'],
shuffle_files=True)
    train_data, test_data = dataset

    # Define preprocessing function
    def preprocess(image, label):
        image = tf.image.resize(image, [128, 128])  # Resize to
128x128
        image = tf.cast(image, tf.float32) / 255.0  # Normalize
pixel values
        return image, label

    # Apply preprocessing
    train_data  =  train_data.map(preprocess).batch(32).prefetch(1)
    test_data  =  test_data.map(preprocess).batch(32).prefetch(1)

    return train_data, test_data, info

# Build CNN model
def build_cnn_model(num_classes):
    model = Sequential([
        Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128,
3)),
        MaxPooling2D((2, 2)),
        Conv2D(64, (3, 3), activation='relu'),
        MaxPooling2D((2, 2)),
        Conv2D(128, (3, 3), activation='relu'),
        MaxPooling2D((2, 2)),
        Flatten(),
        Dense(512, activation='relu'),
        Dense(num_classes, activation='softmax')
    ])

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

    return model

# Evaluate model performance
def evaluate_model(model, test_data, info):
    # Make predictions
    y_true = []
    y_pred = []

    for images, labels in test_data:
        predictions  =  model.predict(images)
        y_true.extend(labels.numpy())
        y_pred.extend(np.argmax(predictions,  axis=1))

    # Convert lists to arrays
    y_true  =  np.array(y_true)
    y_pred  =  np.array(y_pred)

    # Evaluate the model
    accuracy  =  accuracy_score(y_true,  y_pred)
    print(f"Accuracy: {accuracy:.2f}")

    print("\nClassification Report:")
    print(classification_report(y_true, y_pred,
target_names=info.features['label'].names))
```

```
    conf_matrix = confusion_matrix(y_true, y_pred)
    print("\nConfusion Matrix:")
    print(conf_matrix)

    # Plot confusion matrix
    plt.figure(figsize=(10, 7))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=info.features['label'].names,
yticklabels=info.features['label'].names)
    plt.title('Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

def main():
    # Load and preprocess data
    train_data, test_data, info = load_flower_data()

    # Build and train CNN model
    num_classes = len(info.features['label'].names)
    model = build_cnn_model(num_classes)

    # Use EarlyStopping to prevent overfitting
    early_stopping = EarlyStopping(monitor='val_loss', patience=3)

    history = model.fit(train_data,
                        epochs=20,
                        validation_data=test_data,
                        callbacks=[early_stopping])

    # Evaluate model performance
    evaluate_model(model, test_data, info)

if __name__== "__main__":
    main()
```

Output:-



```
Classification Report:
              precision    recall  f1-score   support

   dandelion       0.81      0.60      0.69       159
       daisy       0.58      0.69      0.63       120
      tulips       0.65      0.58      0.61       186
  sunflowers       0.77      0.78      0.77       138
       roses       0.45      0.58      0.50       131

    accuracy                           0.64       734
   macro avg       0.65      0.65      0.64       734
weighted avg       0.66      0.64      0.64       734


Confusion Matrix:
[[ 95  25   9  16  14]
 [  3  83  10   7  17]
 [  5  12 108   9  52]
 [  6   4  10 107  11]
 [  8  18  29   0  76]]
```



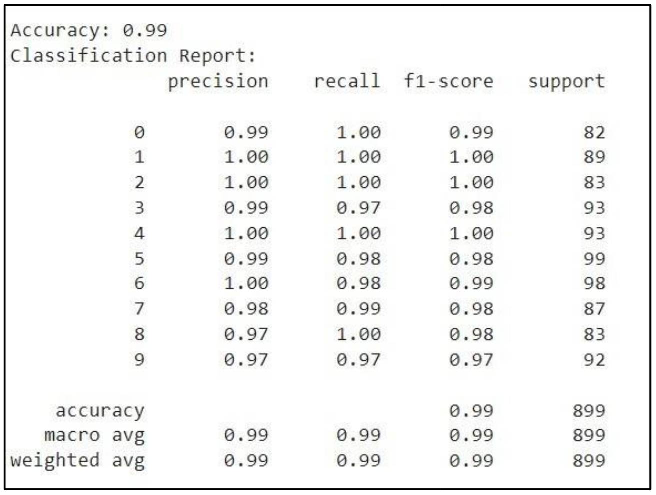
	dandelion	daisy	tulips	sunflowers	roses
dandelion	95	25	9	16	14
daisy	3	83	10	7	17
tulips	5	12	108	9	52
sunflowers	6	4	10	107	11
roses	8	18	29	0	76

5. **Write a python program to classify different handwritten character images using the SVM classifier.**
   Code:-

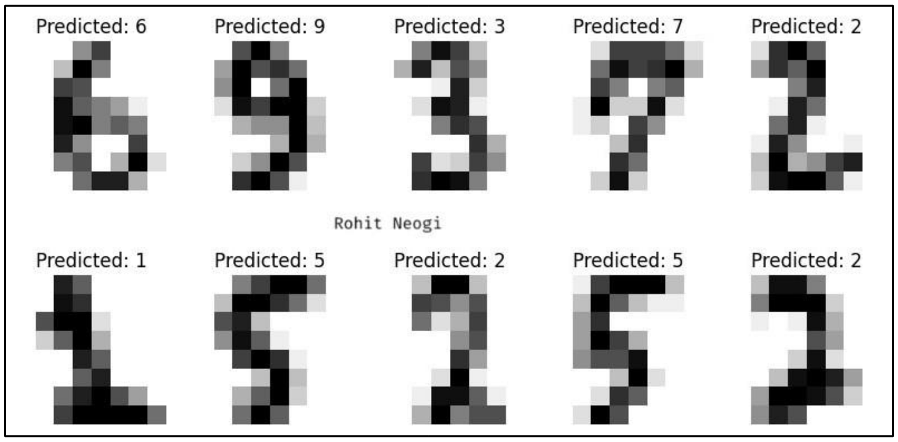
```
import numpy as np
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classificat on_report
import matplotlib.pyplot as plt

# Load the dataset
digits = datasets.load_digits()
X = digits.images
y = digits.target

# Flatten the images
n_samples = len(X)
X = X.reshape((n_samples, -1))

# Split the dataset
X_train, X_test, y_train, y_test = train_test_split(X, ,
test_size=0.5, random_state=42)

# Train the SVM classifier
clf = SVC(gamma=0.001, C=100.)
clf.fit(X_train, y_train)

# Predict and evaluate
y_pred = clf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
```

```
print(f'Accuracy: {accuracy:.2f}')
print('Classification Report:')
print(classification_report(y_test, y_pred))

# Visualize some predictions
plt.figure(figsize=(10, 5))
for i in range(10):
    plt.subplot(2, 5, i  +  1)
    plt.imshow(X_test[i].reshape(8,  8),  cmap=plt.cm.gra _r,
interpolation='nearest')
    plt.title(f'Predicted: {y_pred[i]}')
    plt.axis('off')
plt.show()
```

Output:-



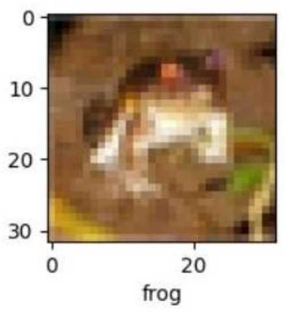
```
Accuracy: 0.99
Classification Report:
              precision    recall  f1-score   support

           0       0.99      1.00      0.99        82
           1       1.00      1.00      1.00        89
           2       1.00      1.00      1.00        83
           3       0.99      0.97      0.98        93
           4       1.00      1.00      1.00        93
           5       0.99      0.98      0.98        99
           6       1.00      0.98      0.99        98
           7       0.98      0.99      0.98        87
           8       0.97      1.00      0.98        83
           9       0.97      0.97      0.97        92

    accuracy                           0.99       899
   macro avg       0.99      0.99      0.99       899
weighted avg       0.99      0.99      0.99       899
```



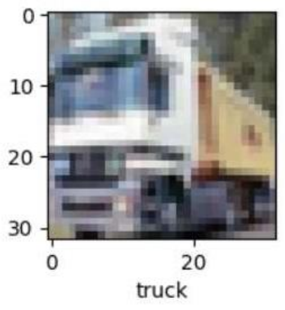
6. **Write a python program to classify different face images using CNN.**
Code:-

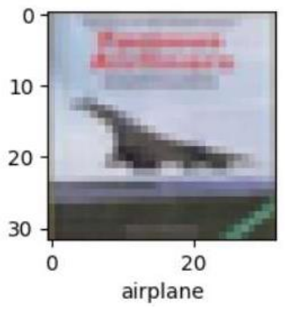
```
import tensorflow as  f
from tensorflow.keras import datasets, layers, models
import matplotlib.pyp ot as plt
import numpy as np
(X_train, y_train), ( _test,y_test) =
datasets.cifar10.load data()
X_train.shape
```

```
X_test.shape

y_train.shape
y_train[:5]

y_train = y_train.res ape(-1,)
y_train[:5]
y_test = y_test.resha e(-1,)
classes =
["airplane","automobi e","bird","cat","deer","dog","frog","hor
se","ship","truck"]

def plot_sample(X, y, index):
    plt.figure(figsiz = (15,2))
    plt.imshow(X[inde ])
    plt.xlabel(classe  [y[index]])

plot_sample(X_train,   _train, 0)
plot_sample(X_train, _train, 1)
plot_sample(X_test, y test,3)

X_train = X_train / 2 5.0
X_test = X_test / 255 0
```
Output:-



Rohit Neogi

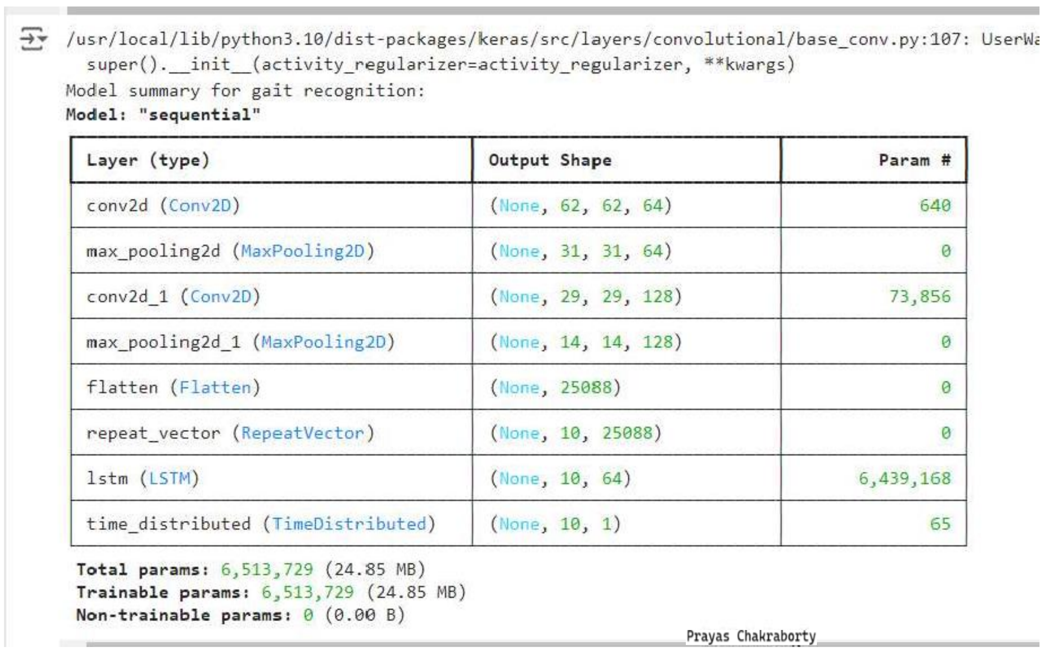




7. **Write a python program to identify a person from the walking style (gait recognition) using convolutional recurrent neural network.**
   Code:-

```
import tensorflow as  f
 from tensorflow.kera  import layers, models
 model = models.Seque tial([
 layers.Conv2D(64,  (3   3), activation='relu', input_shape=(64,
64, 1)),
 layers.MaxPooling2D(  2,  2)),
 layers.Conv2D(128,  ( , 3), activation='relu'),
 layers.MaxPooling2D( 2, 2)),
 layers.Flatten(),
 layers.RepeatVector( 0),
 layers.LSTM(64,  retu n_sequences=True),
 layers.TimeDistribut  d(layers.Dense(1,  activation='sigmoid'))
 ])
 7
model.compile(optimiz r='adam',
loss='binary_crossent opy',metrics=['accuracy'])
 print("Model summary for gait recognition:")
 model.summary()
```

Output:



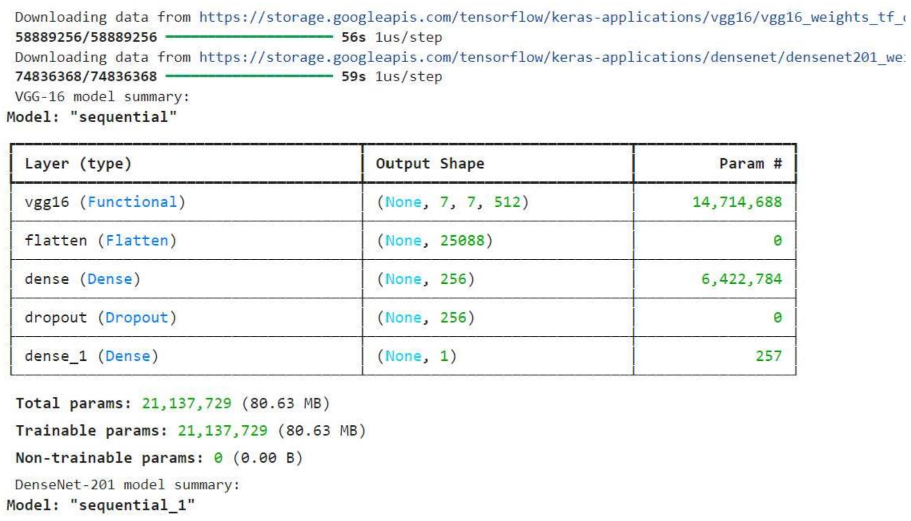
```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWa
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Model summary for gait recognition:
Model: "sequential"
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                         ┃ Output Shape                ┃         Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━┩
│ conv2d (Conv2D)                      │ (None, 62, 62, 64)          │             640 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ max_pooling2d (MaxPooling2D)         │ (None, 31, 31, 64)          │               0 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ conv2d_1 (Conv2D)                    │ (None, 29, 29, 128)         │          73,856 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ max_pooling2d_1 (MaxPooling2D)       │ (None, 14, 14, 128)         │               0 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ flatten (Flatten)                    │ (None, 25088)               │               0 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ repeat_vector (RepeatVector)         │ (None, 10, 25088)           │               0 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ lstm (LSTM)                          │ (None, 10, 64)              │       6,439,168 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ time_distributed (TimeDistributed)   │ (None, 10, 1)               │              65 │
└──────────────────────────────────────┴─────────────────────────────┴─────────────────┘
 Total params: 6,513,729 (24.85 MB)
 Trainable params: 6,513,729 (24.85 MB)
 Non-trainable params: 0 (0.00 B)
```

Prayas Chakraborty

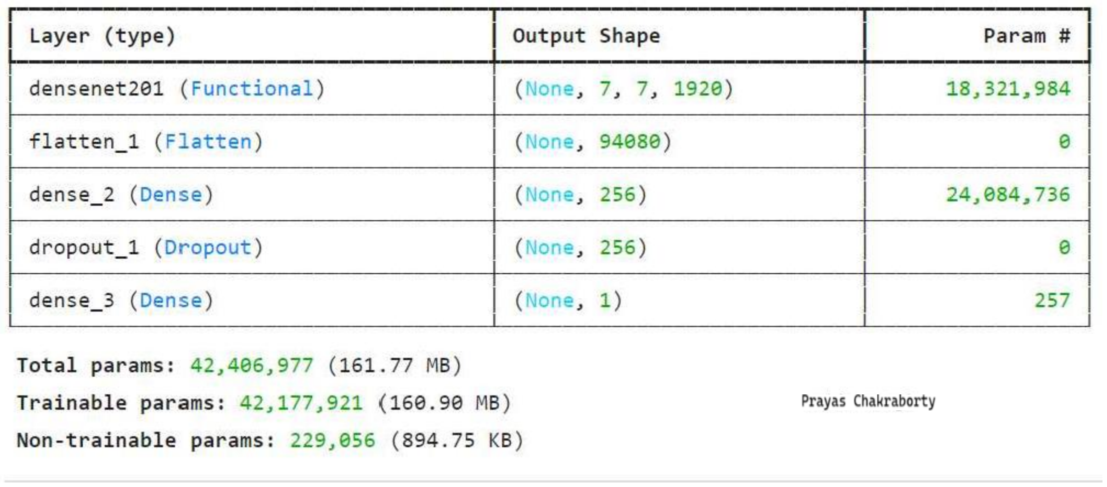
8. **Write a python program to classify breast cancer from histopathological images using VGG-16 and DenseNet-201 CNN architectures.**
Code:-

```
import tensorflow as tf
from tensorflow.keras.applications import VGG1G, DenseNet201
from tensorflow.keras import layers, models
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Load pre-trained VGG1G and DenseNet201 models without the top
layer
vgg1G_model = VGG1G(weights='imagenet', include_top=False,
input_shape=(224, 224, 3))
densenet_model = DenseNet201(weights='imagenet', include_top=False,
input_shape=(224, 224, 3))

# Function to create a model with a base pre-trained model
def create_model(base_model):
    model = models.Sequential([
        base_model,
        layers.Flatten(),
        layers.Dense(25G, activation='relu'),
        layers.Dropout(0.5),
        layers.Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])
    return model

# Create models using VGG1G and DenseNet201 as base models
vgg1G_cancer_model = create_model(vgg1G_model)
densenet_cancer_model = create_model(densenet_model)

# Print the summary of both models
print("VGG-1G model summary:")
vgg1G_cancer_model.summary()

print("DenseNet-201 model summary:")
densenet_cancer_model.summary()
```

Output:



```
 Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_
 58889256/58889256 ━━━━━━━━━━━━━━━━━━━━ 56s 1us/step
 Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/densenet/densenet201_we
 74836368/74836368 ━━━━━━━━━━━━━━━━━━━━ 59s 1us/step
 VGG-16 model summary:
Model: "sequential"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━┓
┃ Layer (type)                    ┃ Output Shape           ┃       Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━┩
│ vgg16 (Functional)              │ (None, 7, 7, 512)      │    14,714,688 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ flatten (Flatten)               │ (None, 25088)          │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dense (Dense)                   │ (None, 256)            │     6,422,784 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dropout (Dropout)               │ (None, 256)            │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_1 (Dense)                 │ (None, 1)              │           257 │
└─────────────────────────────────┴────────────────────────┴───────────────┘

 Total params: 21,137,729 (80.63 MB)
 Trainable params: 21,137,729 (80.63 MB)
 Non-trainable params: 0 (0.00 B)
 DenseNet-201 model summary:
Model: "sequential_1"
```



```
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━┓
┃ Layer (type)                    ┃ Output Shape           ┃       Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━┩
│ densenet201 (Functional)        │ (None, 7, 7, 1920)     │    18,321,984 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ flatten_1 (Flatten)             │ (None, 94080)          │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_2 (Dense)                 │ (None, 256)            │    24,084,736 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dropout_1 (Dropout)             │ (None, 256)            │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_3 (Dense)                 │ (None, 1)              │           257 │
└─────────────────────────────────┴────────────────────────┴───────────────┘

 Total params: 42,406,977 (161.77 MB)
 Trainable params: 42,177,921 (160.90 MB)                      Prayas Chakraborty
 Non-trainable params: 229,056 (894.75 KB)
```