In [1]:
```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import warnings
import seaborn as sns
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Dense
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.model_selection import train_test_split
```

In [2]:
```
## Let'S take a dataset
```

In [3]:
```
from sklearn.datasets import make_circles
x,y = make_circles(n_samples = 10000, random_state=10)
print(x.shape)
```

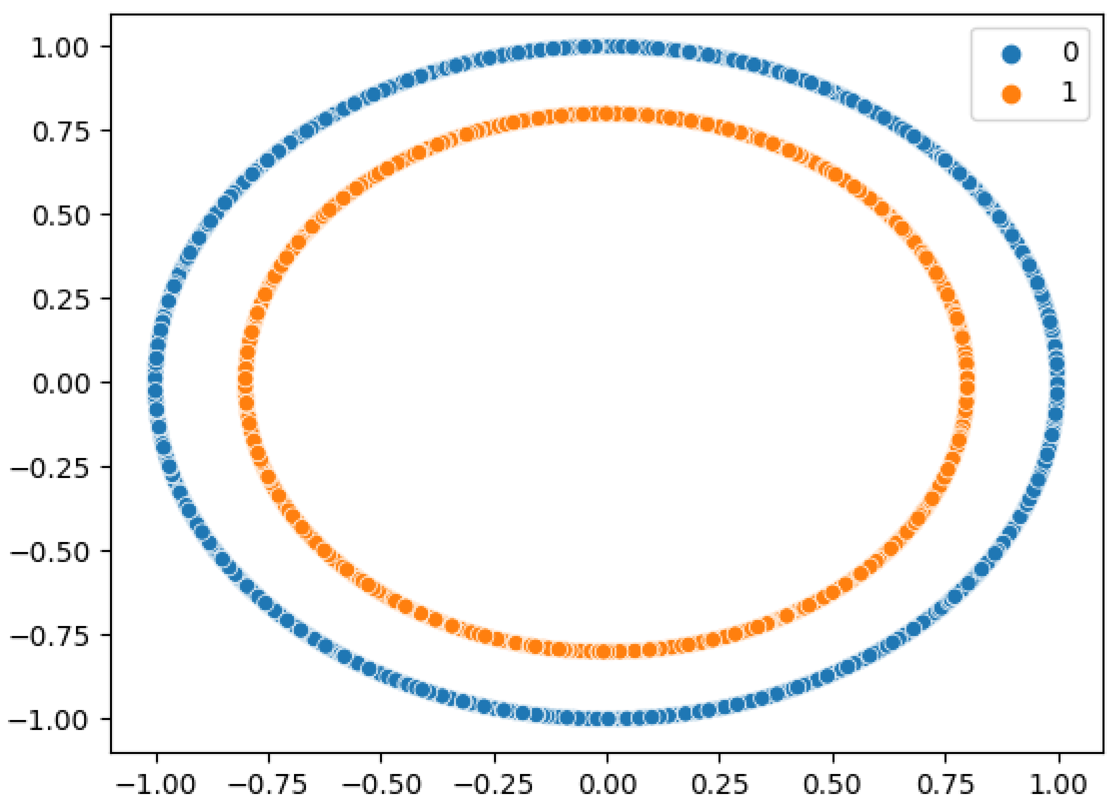
```
(10000, 2)
```

In [4]:
```
y
```

Out[4]:
```
array([0, 1, 0, ..., 0, 1, 0])
```

In [5]:
```
sns.scatterplot(x=x[:,0],y=x[:,1],hue=y)
```

Out[5]:
```
<Axes: >
```

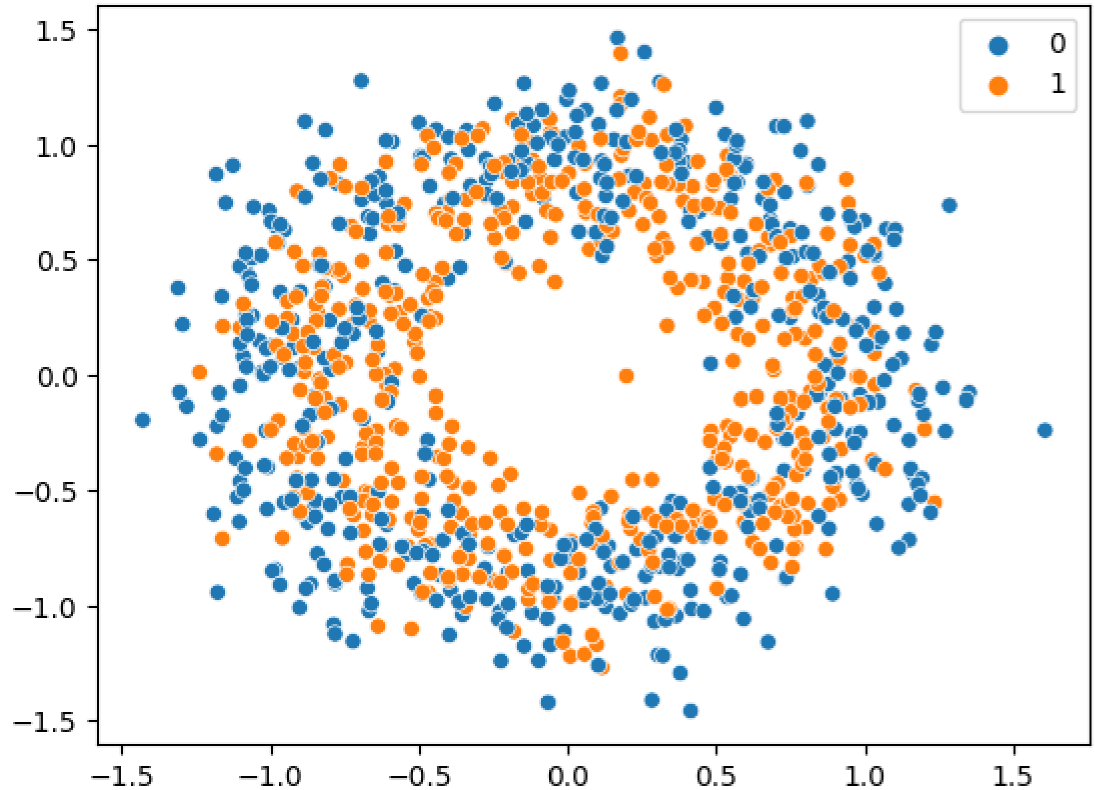


This the clean data , let's add some noise inside this data set

In [6]:
```
x,y = make_circles(n_samples = 1000,noise = 0.2 ,random_state=10)# here i have
print(x.shape)
sns.scatterplot(x=x[:,0],y=x[:,1],hue=y)
```

```
(1000, 2)
```

Out[6]:
```
<Axes: >
```



In [7]:
```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.20, rando
```

In [8]:
```
print(f"The Shape of x_train : {X_train.shape}")
print(f"The Shape of x_test : {X_test.shape}")
print(f"The Shape of y_train : {y_train.shape}")
print(f"The Shape of y_test : {y_test.shape}")
```

```
The Shape of x_train : (800, 2)
The Shape of x_test : (200, 2)
The Shape of y_train : (800,)
The Shape of y_test : (200,)
```

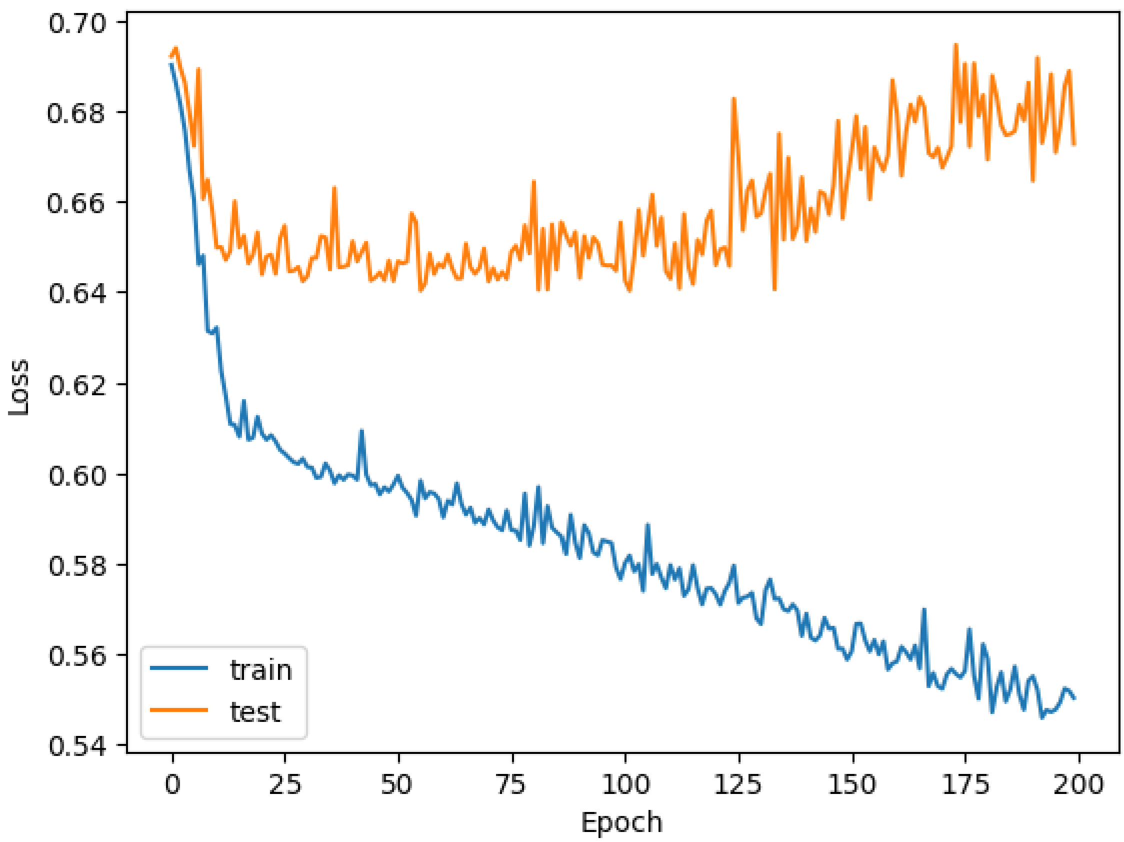
In [9]:
```
model=Sequential()
model.add(Dense(20, input_dim=2, activation='relu'))
model.add(Dense(20, activation='relu'))
model.add(Dense(20, activation='relu'))
model.add(Dense(20, activation='relu'))
model.add(Dense(20, activation='relu'))
model.add(Dense(20, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

In [10]:
```
### Let's Compile the model
model.compile(loss = 'binary_crossentropy', optimizer = 'adam', metrics=["accur

# i am fitting the model
history1 = model.fit(X_train,y_train,validation_data = (X_test,y_test),batch_si
```

```
Epoch 1/200
40/40 [==============================] - 5s 19ms/step - loss: 0.6903 - accu
racy: 0.5088 - val_loss: 0.6922 - val_accuracy: 0.4700
Epoch 2/200
40/40 [==============================] - 0s 9ms/step - loss: 0.6862 - accur
acy: 0.5113 - val_loss: 0.6940 - val_accuracy: 0.4650
Epoch 3/200
40/40 [==============================] - 0s 9ms/step - loss: 0.6814 - accur
acy: 0.5387 - val_loss: 0.6896 - val_accuracy: 0.4850
Epoch 4/200
40/40 [==============================] - 0s 9ms/step - loss: 0.6757 - accur
acy: 0.5663 - val_loss: 0.6863 - val_accuracy: 0.5350
Epoch 5/200
40/40 [==============================] - 0s 10ms/step - loss: 0.6669 - accu
racy: 0.5938 - val_loss: 0.6798 - val_accuracy: 0.5850
Epoch 6/200
40/40 [==============================] - 0s 9ms/step - loss: 0.6604 - accur
acy: 0.6062 - val_loss: 0.6723 - val_accuracy: 0.6050
Epoch 7/200
```

In [11]:
```
plt.plot(history1.history['accuracy'], label='Training Accuracy')
plt.plot(history1.history['val_accuracy'], label='Testing Accuracy')

plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.title('Training and Testing Accuracy Over Epochs')

plt.show()
```

In [12]:
```
plt.plot(history1.history['loss'], label='train')
plt.plot(history1.history['val_loss'], label='test')

plt.xlabel('Epoch')
plt.ylabel('Loss')

plt.legend()
plt.show()
```



Let's Apply more things

weight initialization :

We've added the kernel_initializer parameter to the Dense layers to specify the weight initialization technique. Here, we use the 'he_normal' initializer, which is a common choice for ReLU activations.

BatchNormalization :

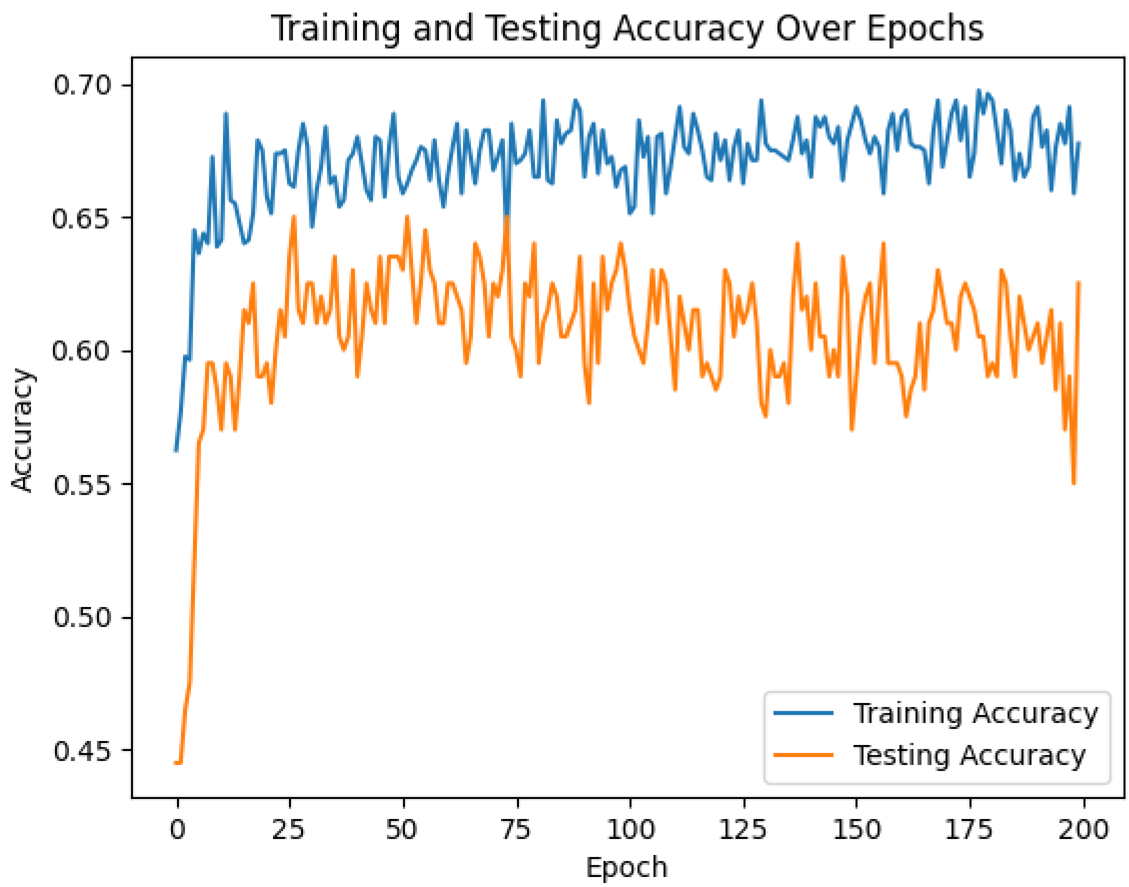
We've added BatchNormalization layers after each Dense layer (except for the output layer). Batch normalization helps stabilize and accelerate training by normalizing the activations.

In [13]:
```
from tensorflow.keras.layers import Dense, BatchNormalization

model1 = Sequential()

# Adding the input layer with weight initialization
model1.add(Dense(20, input_dim=2, activation='relu', kernel_initializer='he_nor

# let's Add BatchNormalization layer after the first hidden layer
model1.add(BatchNormalization())

# let's add the rest of the hidden layers with weight initialization and BatchN
model1.add(Dense(20, activation='relu', kernel_initializer='he_normal'))
model1.add(BatchNormalization())

model1.add(Dense(20, activation='relu', kernel_initializer='he_normal'))
model1.add(BatchNormalization())

model1.add(Dense(20, activation='relu', kernel_initializer='he_normal'))
model.add(BatchNormalization())

model1.add(Dense(20, activation='relu', kernel_initializer='he_normal'))
model1.add(BatchNormalization())

model1.add(Dense(20, activation='relu', kernel_initializer='he_normal'))
model1.add(BatchNormalization())
model1.add(Dense(1, activation='sigmoid'))

model1.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy
```

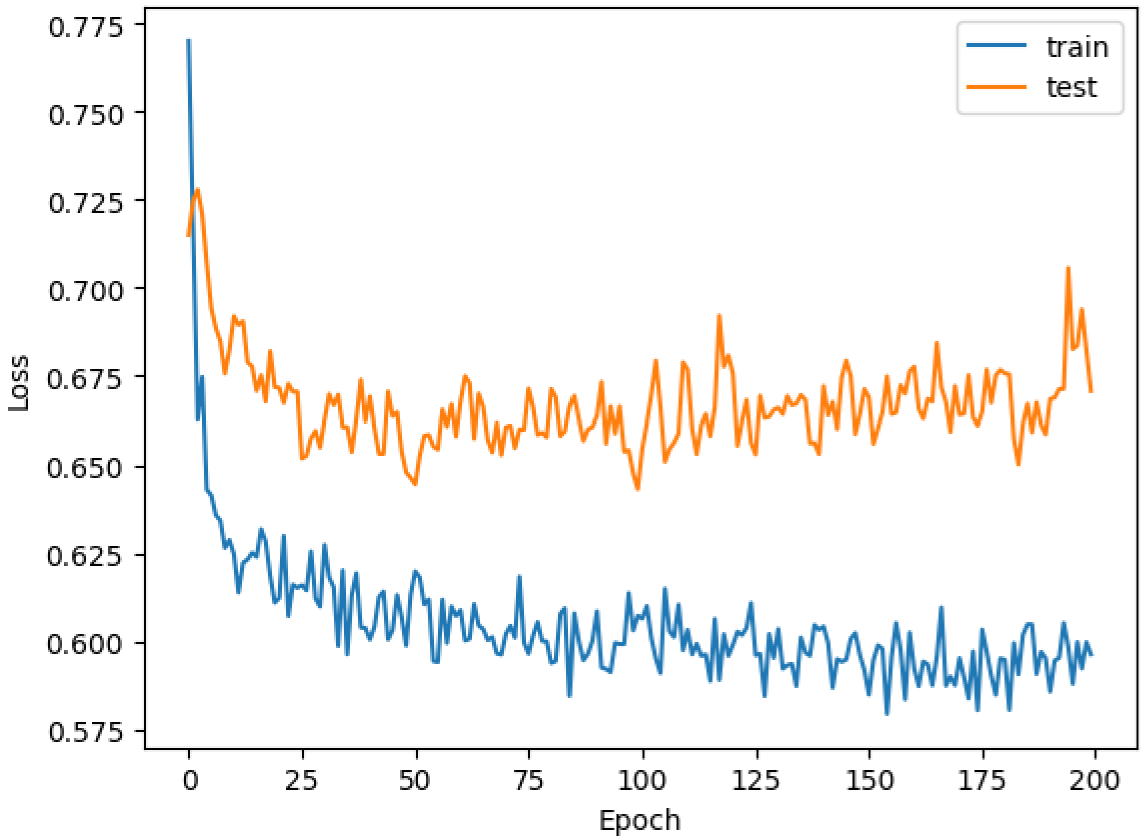
In [14]:
```
# i am fitting the model
epochs = 200
validation_data = (X_test,y_test)
history2 = model1.fit(X_train,y_train,validation_data = validation_data, epochs
```

```
Epoch 1/200
25/25 [==============================] - 6s 16ms/step - loss: 0.7701 - accu
racy: 0.5625 - val_loss: 0.7150 - val_accuracy: 0.4450
Epoch 2/200
25/25 [==============================] - 0s 7ms/step - loss: 0.7158 - accur
acy: 0.5763 - val_loss: 0.7247 - val_accuracy: 0.4450
Epoch 3/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6627 - accur
acy: 0.5975 - val_loss: 0.7279 - val_accuracy: 0.4650
Epoch 4/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6747 - accur
acy: 0.5962 - val_loss: 0.7208 - val_accuracy: 0.4750
Epoch 5/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6430 - accur
acy: 0.6450 - val_loss: 0.7069 - val_accuracy: 0.5200
Epoch 6/200
25/25 [==============================] - 0s 7ms/step - loss: 0.6414 - accur
acy: 0.6363 - val_loss: 0.6942 - val_accuracy: 0.5650
Epoch 7/200
```

In [15]:
```
plt.plot(history2.history['accuracy'], label='Training Accuracy')
plt.plot(history2.history['val_accuracy'], label='Testing Accuracy')

plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.title('Training and Testing Accuracy Over Epochs')

plt.show()
```



In [16]:
```
plt.plot(history2.history['loss'], label='train')
plt.plot(history2.history['val_loss'], label='test')

plt.xlabel('Epoch')
plt.ylabel('Loss')

plt.legend()
plt.show()
```



this graph indicate that for some our model is get same train and test on s some of epochs

Adding the Early Stopping

- **Prevents Overfitting:** Early stopping prevents the model from overfitting the training data by monitoring validation performance and stopping training when it starts to degrade.
- **Saves Training Time:** It saves computational resources and time by stopping training early when further improvements are unlikely.
- **Optimizes Hyperparameters:** Can be used to optimize hyperparameters without training for a fixed number of epochs for each configuration.
- **Avoids Overkill:** Prevents excessive training that may harm model generalization.

In [17]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [18]:
```
from tensorflow.keras.layers import Dense, BatchNormalization
from tensorflow.keras.models import Sequential

# Create model2
model2 = Sequential()

# Adding the input layer with weight initialization
model2.add(Dense(20, input_dim=2, activation='relu', kernel_initializer='he_nor

# Add BatchNormalization layer after the first hidden layer
model2.add(BatchNormalization())

# Add the rest of the hidden layers with weight initialization and BatchNormali
model2.add(Dense(20, activation='relu', kernel_initializer='he_normal'))
model2.add(BatchNormalization())

model2.add(Dense(20, activation='relu', kernel_initializer='he_normal'))
model2.add(BatchNormalization())

model2.add(Dense(20, activation='relu', kernel_initializer='he_normal'))
model2.add(BatchNormalization())

model2.add(Dense(20, activation='relu', kernel_initializer='he_normal'))
model2.add(BatchNormalization())

model2.add(Dense(20, activation='relu', kernel_initializer='he_normal'))
model2.add(BatchNormalization())

model2.add(Dense(1, activation='sigmoid'))

model2.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy
```

In [18]:

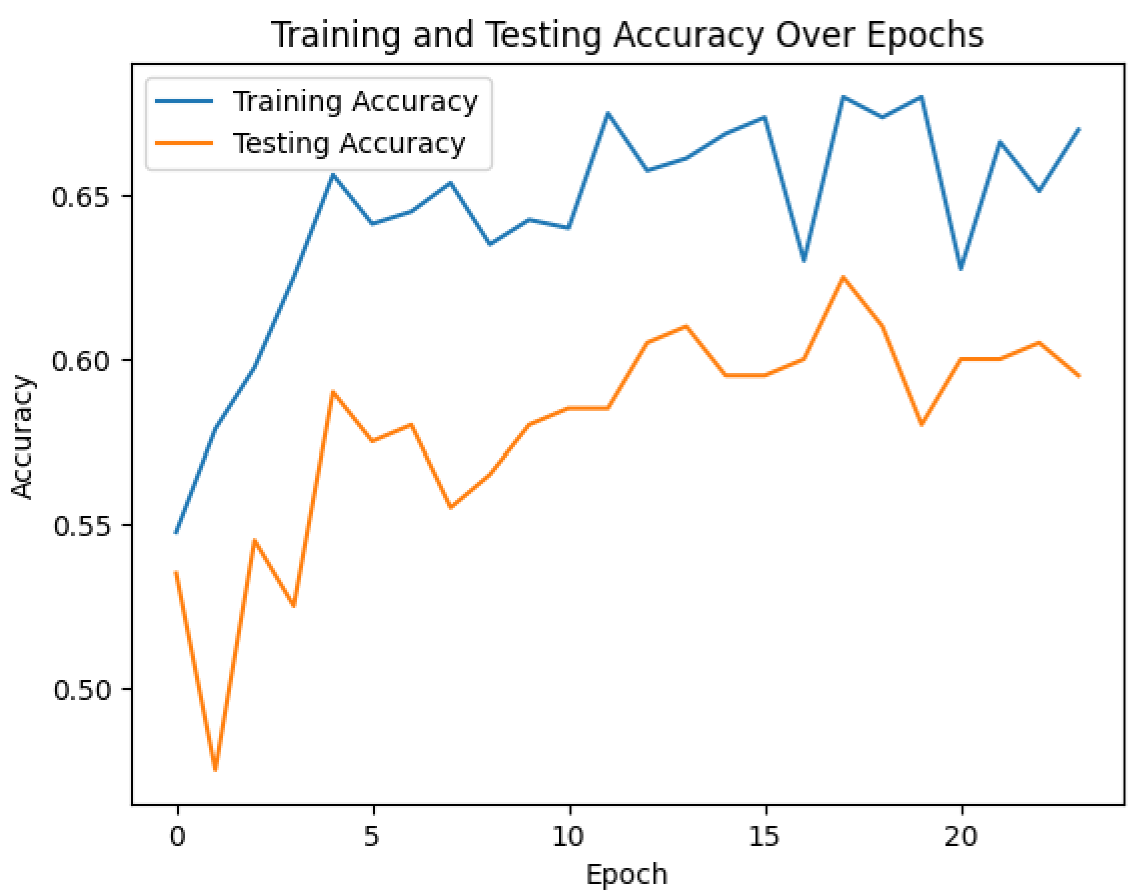
In [19]:
```
from tensorflow.keras.callbacks import EarlyStopping

early_stopping = EarlyStopping(
    monitor='val_loss',
    patience=10,
    restore_best_weights=True
)
```

In [20]:
```
history = model2.fit(X_train, y_train,
                    epochs=200,
                    batch_size=32,
                    validation_data=(X_test,y_test),
                    callbacks=[early_stopping])
```

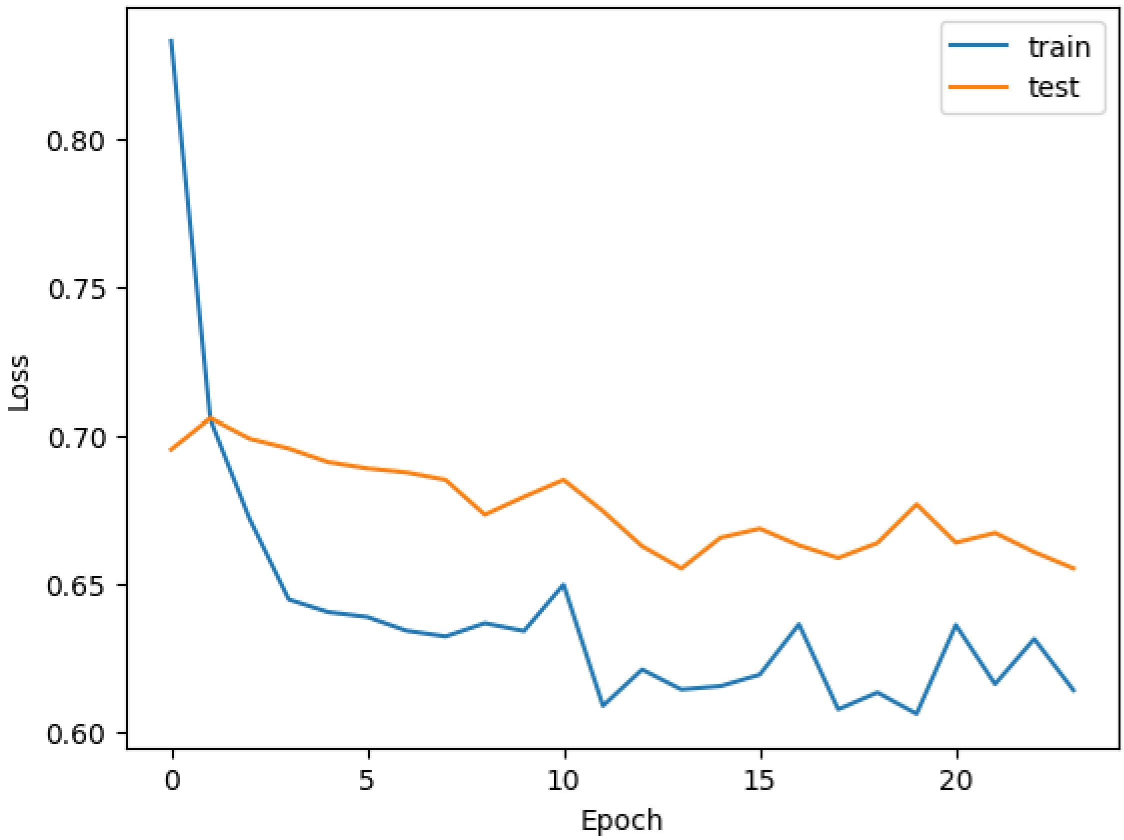
```
Epoch 1/200
25/25 [==============================] - 6s 21ms/step - loss: 0.8331 - accura
cy: 0.5475 - val_loss: 0.6954 - val_accuracy: 0.5350
Epoch 2/200
25/25 [==============================] - 0s 8ms/step - loss: 0.7055 - accurac
y: 0.5788 - val_loss: 0.7059 - val_accuracy: 0.4750
Epoch 3/200
25/25 [==============================] - 0s 9ms/step - loss: 0.6720 - accurac
y: 0.5975 - val_loss: 0.6991 - val_accuracy: 0.5450
Epoch 4/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6448 - accurac
y: 0.6250 - val_loss: 0.6957 - val_accuracy: 0.5250
Epoch 5/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6406 - accurac
y: 0.6562 - val_loss: 0.6912 - val_accuracy: 0.5900
Epoch 6/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6389 - accurac
y: 0.6413 - val_loss: 0.6891 - val_accuracy: 0.5750
Epoch 7/200
25/25 [==============================] - 0s 9ms/step - loss: 0.6343 - accurac
y: 0.6450 - val_loss: 0.6877 - val_accuracy: 0.5800
Epoch 8/200
25/25 [==============================] - 0s 9ms/step - loss: 0.6323 - accurac
y: 0.6538 - val_loss: 0.6852 - val_accuracy: 0.5550
Epoch 9/200
25/25 [==============================] - 0s 9ms/step - loss: 0.6368 - accurac
y: 0.6350 - val_loss: 0.6734 - val_accuracy: 0.5650
Epoch 10/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6342 - accurac
y: 0.6425 - val_loss: 0.6795 - val_accuracy: 0.5800
Epoch 11/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6497 - accurac
y: 0.6400 - val_loss: 0.6852 - val_accuracy: 0.5850
Epoch 12/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6089 - accurac
y: 0.6750 - val_loss: 0.6746 - val_accuracy: 0.5850
Epoch 13/200
25/25 [==============================] - 0s 9ms/step - loss: 0.6212 - accurac
y: 0.6575 - val_loss: 0.6628 - val_accuracy: 0.6050
Epoch 14/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6144 - accurac
y: 0.6612 - val_loss: 0.6553 - val_accuracy: 0.6100
Epoch 15/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6156 - accurac
y: 0.6687 - val_loss: 0.6657 - val_accuracy: 0.5950
Epoch 16/200
25/25 [==============================] - 0s 9ms/step - loss: 0.6194 - accurac
y: 0.6737 - val_loss: 0.6687 - val_accuracy: 0.5950
Epoch 17/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6365 - accurac
y: 0.6300 - val_loss: 0.6631 - val_accuracy: 0.6000
Epoch 18/200
25/25 [==============================] - 0s 9ms/step - loss: 0.6077 - accurac
y: 0.6800 - val_loss: 0.6588 - val_accuracy: 0.6250
Epoch 19/200
25/25 [==============================] - 0s 9ms/step - loss: 0.6134 - accurac
y: 0.6737 - val_loss: 0.6639 - val_accuracy: 0.6100
```

```
Epoch 20/200
25/25 [==============================] - 0s 9ms/step - loss: 0.6062 - accurac
y: 0.6800 - val_loss: 0.6769 - val_accuracy: 0.5800
Epoch 21/200
25/25 [==============================] - 0s 10ms/step - loss: 0.6362 - accura
cy: 0.6275 - val_loss: 0.6640 - val_accuracy: 0.6000
Epoch 22/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6162 - accurac
y: 0.6662 - val_loss: 0.6673 - val_accuracy: 0.6000
Epoch 23/200
25/25 [==============================] - 0s 8ms/step - loss: 0.6315 - accurac
y: 0.6513 - val_loss: 0.6608 - val_accuracy: 0.6050
Epoch 24/200
25/25 [==============================] - 0s 9ms/step - loss: 0.6142 - accurac
y: 0.6700 - val_loss: 0.6553 - val_accuracy: 0.5950
```

In [21]:
```
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Testing Accuracy')

plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.title('Training and Testing Accuracy Over Epochs')

plt.show()
```



In [22]:
```
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')

plt.xlabel('Epoch')
plt.ylabel('Loss')

plt.legend()
plt.show()
```



In [23]:
```
### When i applied the early stopping then our model giving this
```

In [24]:
```
del model
```

Let's Apply all techniques like weight initialization, BatchNormalization, Dropout for regularization and early stopping

In [25]:
```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, BatchNormalization, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.datasets import make_circles
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Generate the dataset
x, y = make_circles(n_samples=10000, noise=0.2, random_state=10)

# Split the dataset into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, randon

# Standardize the input features
scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)

# Create the model
model = Sequential()

# Adding the input layer with weight initialization
model.add(Dense(20, input_dim=2, activation='relu', kernel_initializer='he_norm

# Add BatchNormalization layer after the input layer
model.add(BatchNormalization())

# Add the rest of the hidden layers with weight initialization, BatchNormalizat
model.add(Dense(20, activation='relu', kernel_initializer='he_normal'))
model.add(BatchNormalization())
model.add(Dropout(0.3))  # Dropout for regularization

model.add(Dense(20, activation='relu', kernel_initializer='he_normal'))
model.add(BatchNormalization())
model.add(Dropout(0.3))

model.add(Dense(20, activation='relu', kernel_initializer='he_normal'))
model.add(BatchNormalization())
model.add(Dropout(0.3))

model.add(Dense(1, activation='sigmoid'))

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'

# Early Stopping
early_stopping = EarlyStopping(
    monitor='val_loss',
    patience=10,
    restore_best_weights=True
)

# Train the model
history3 = model.fit(x_train, y_train, validation_data=(x_test, y_test), epochs

# Evaluate the model
_, test_accuracy = model.evaluate(x_test, y_test)
```

```python
print(f"Test Accuracy: {test_accuracy * 100:.2f}%")
```

```
Epoch 1/300
250/250 [==============================] - 6s 7ms/step - loss: 0.7637 - acc
uracy: 0.5664 - val_loss: 0.6144 - val_accuracy: 0.6770
Epoch 2/300
250/250 [==============================] - 1s 6ms/step - loss: 0.6751 - acc
uracy: 0.6014 - val_loss: 0.5862 - val_accuracy: 0.7060
Epoch 3/300
250/250 [==============================] - 1s 6ms/step - loss: 0.6540 - acc
uracy: 0.6206 - val_loss: 0.5842 - val_accuracy: 0.7045
Epoch 4/300
250/250 [==============================] - 1s 6ms/step - loss: 0.6439 - acc
uracy: 0.6386 - val_loss: 0.5834 - val_accuracy: 0.7115
Epoch 5/300
250/250 [==============================] - 1s 6ms/step - loss: 0.6400 - acc
uracy: 0.6378 - val_loss: 0.5799 - val_accuracy: 0.7095
Epoch 6/300
250/250 [==============================] - 2s 8ms/step - loss: 0.6327 - acc
uracy: 0.6490 - val_loss: 0.5778 - val_accuracy: 0.7080
Epoch 7/300
```

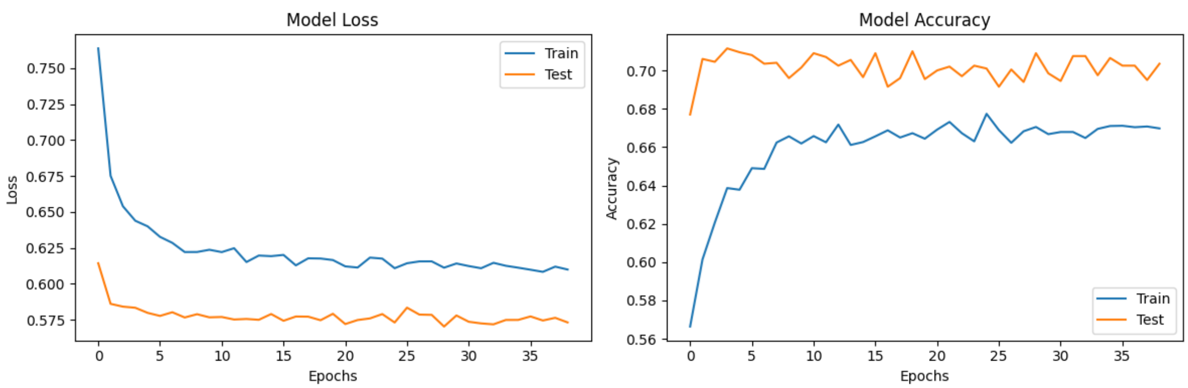
In [26]:

```python
X_test[:10]
```

Out[26]:

```
array([[ 1.02545692, -0.36714766],
       [ 0.37202401, -0.83945157],
       [ 0.12525817,  0.91416509],
       [ 0.43663639, -0.63397758],
       [-0.13566892,  1.13522296],
       [-0.85597747,  0.92028147],
       [ 1.17241886, -0.06765513],
       [-0.36008532,  0.46727528],
       [ 0.60835764, -0.43758121],
       [ 0.28381471, -0.82712367]])
```

In [31]:
```
# Ploting training and testing loss
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history3.history['loss'], label='Train')
plt.plot(history3.history['val_loss'], label='Test')
plt.title('Model Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Ploting training and testing accuracy
plt.subplot(1, 2, 2)
plt.plot(history3.history['accuracy'], label='Train')
plt.plot(history3.history['val_accuracy'], label='Test')
plt.title('Model Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



In [32]:
```
sample_predictions = model.predict(x_test[:10])
sample_predictions_binary = (sample_predictions > 0.5).astype(int)
df = pd.DataFrame({'Actual': y_test[:10], 'Predicted': sample_predictions_binar

print(df)
```

```
1/1 [==============================] - 0s 41ms/step
   Actual  Predicted
0       1          1
1       0          0
2       1          1
3       0          1
4       0          0
5       1          1
6       1          1
7       1          1
8       1          1
9       0          0
```

Thank you for visiting my neural network implementation journey! I hope this notebook provides valuable insights and helps you on your own learning path. Feel free to reach out with any questions or insights. Happy learning!"

In [ ]: