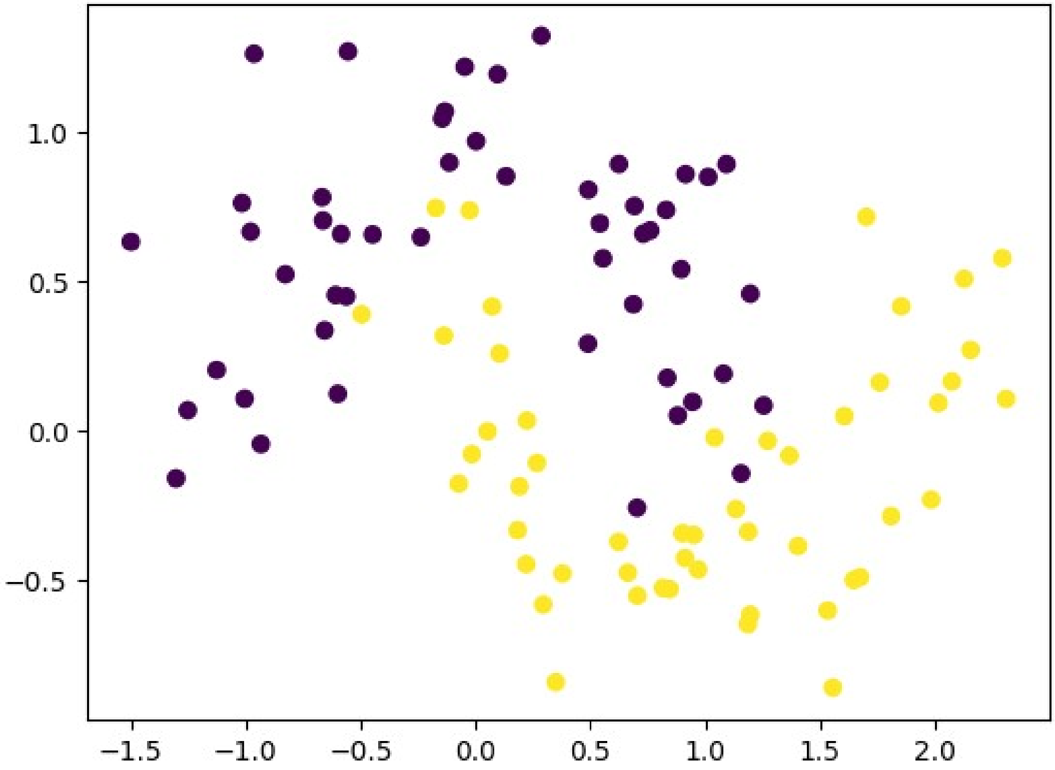
11. Regularization Techniques

```
#!pip install seaborn
#!pip install mlxtend

import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_moons
import seaborn as sns
from mlxtend.plotting import plot_decision_regions

import tensorflow
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
#from tensorflow.keras.layers import Dropout
from tensorflow.keras.optimizers import Adam

X, y = make_moons(100, noise=0.25,random_state=2) # toy dataset with 2
features: 100 samples

import matplotlib.pyplot as plt
plt.scatter(X[:,0], X[:,1], c=y) # to generates different colors with
binary values in data
plt.show()
```

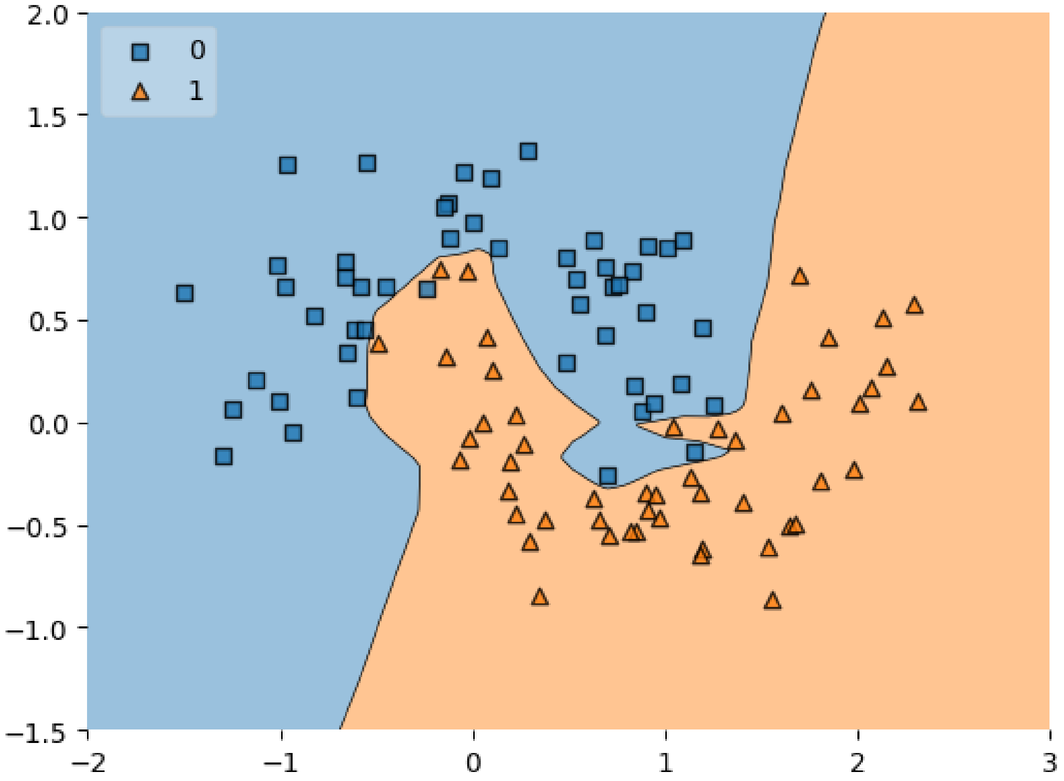


```python
# Generate simple ANN network
model1 = Sequential()

model1.add(Dense(128,input_dim=2, activation="relu"))
model1.add(Dense(128, activation="relu"))
model1.add(Dense(1,activation='sigmoid'))

model1.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense_6 (Dense)             (None, 128)               384       
                                                                 
 dense_7 (Dense)             (None, 128)               16512     
                                                                 
 dense_8 (Dense)             (None, 1)                 129       
                                                                 
=================================================================
Total params: 17,025
Trainable params: 17,025
Non-trainable params: 0
_________________________________________________________________
```

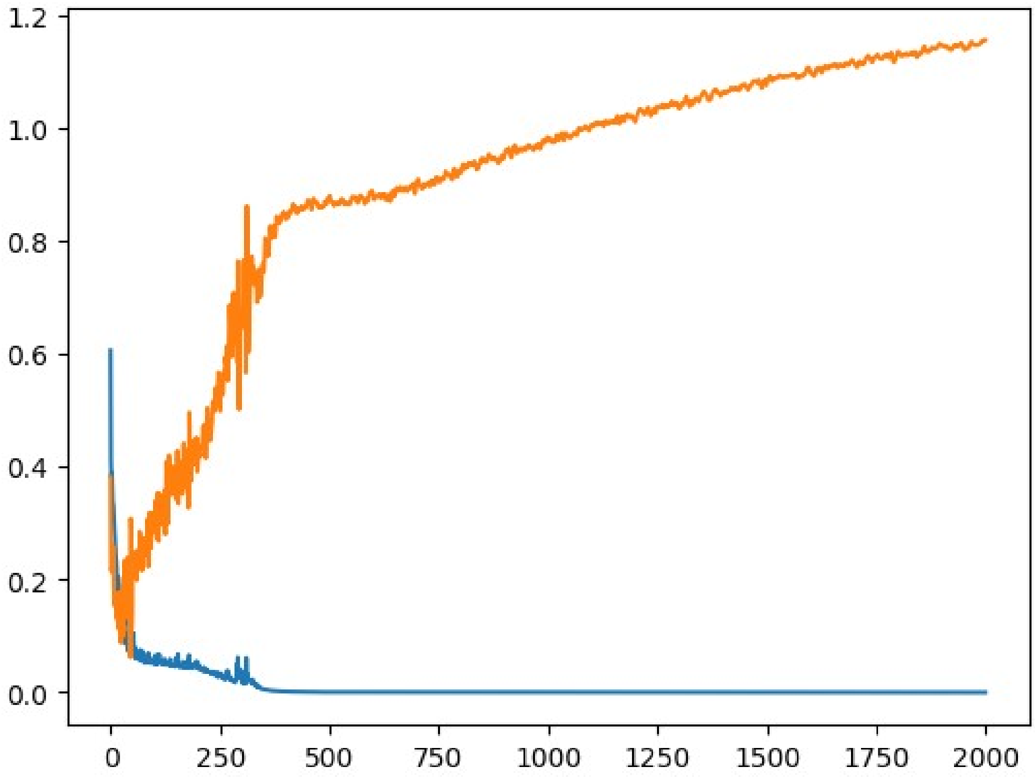
```python
adam = Adam(learning_rate=0.01)
model1.compile(loss='binary_crossentropy', optimizer=adam,
metrics=['accuracy'])

history1 = model1.fit(X, y, epochs=2000, validation_split =
0.2,verbose=0)

plot_decision_regions(X, y.astype('int'), clf=model1, legend=2) # X is
for input data, y=integer labels, clf=model1 trained classifier,
legend=2 location of legend point
plt.xlim(-2,3) # sets the limits of the x-axis
plt.ylim(-1.5,2) # sets the limits of the y-axis
plt.show()
```

```
9600/9600 [==============================] - 13s 1ms/step
```



```
plt.plot(history1.history['loss'])
plt.plot(history1.history['val_loss'])
```

```
[<matplotlib.lines.Line2D at 0x14b4bdaa910>]
```



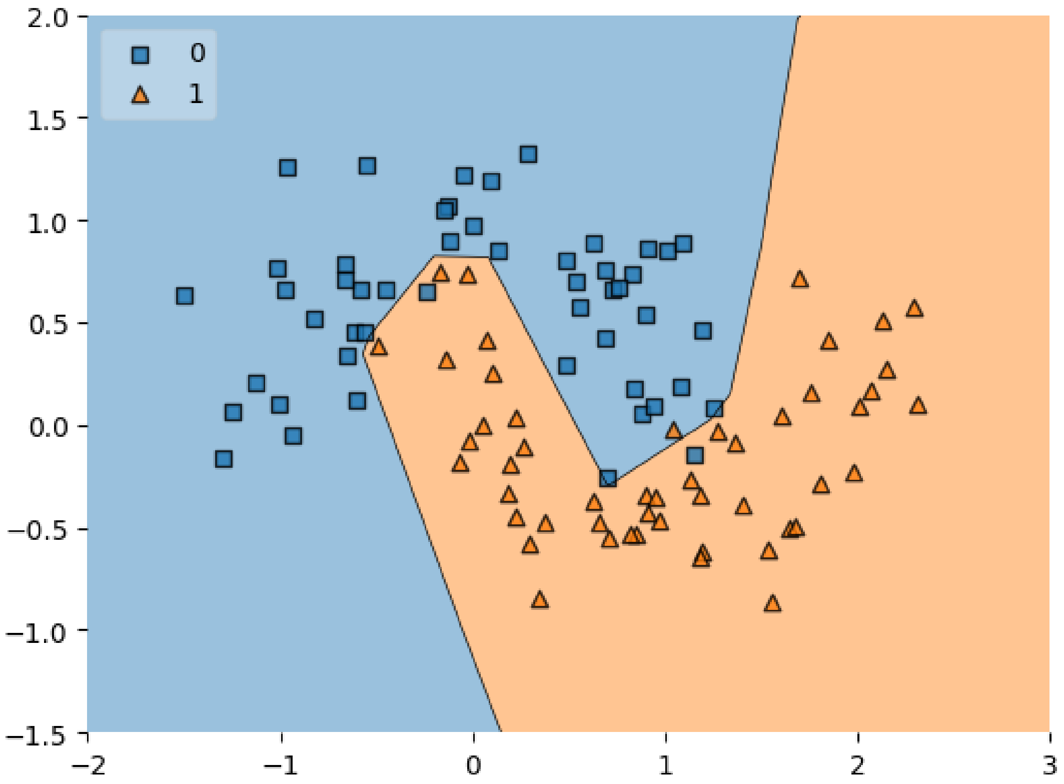
```
model2 = Sequential()

model2.add(Dense(128,input_dim=2,
activation="relu",kernel_regularizer=tensorflow.keras.regularizers.l(0
.001)))
model2.add(Dense(128,
activation="relu",kernel_regularizer=tensorflow.keras.regularizers.l1(
0.001)))
model2.add(Dense(1,activation='sigmoid'))

model2.summary()
```

```
Model: "sequential_3"

_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense_9 (Dense)             (None, 128)               384       
                                                                 
 dense_10 (Dense)            (None, 128)               16512     
                                                                 
 dense_11 (Dense)            (None, 1)                 129       
                                                                 
=================================================================
Total params: 17,025
Trainable params: 17,025
```

```
Non-trainable params: 0
_________________________________________________________________
```

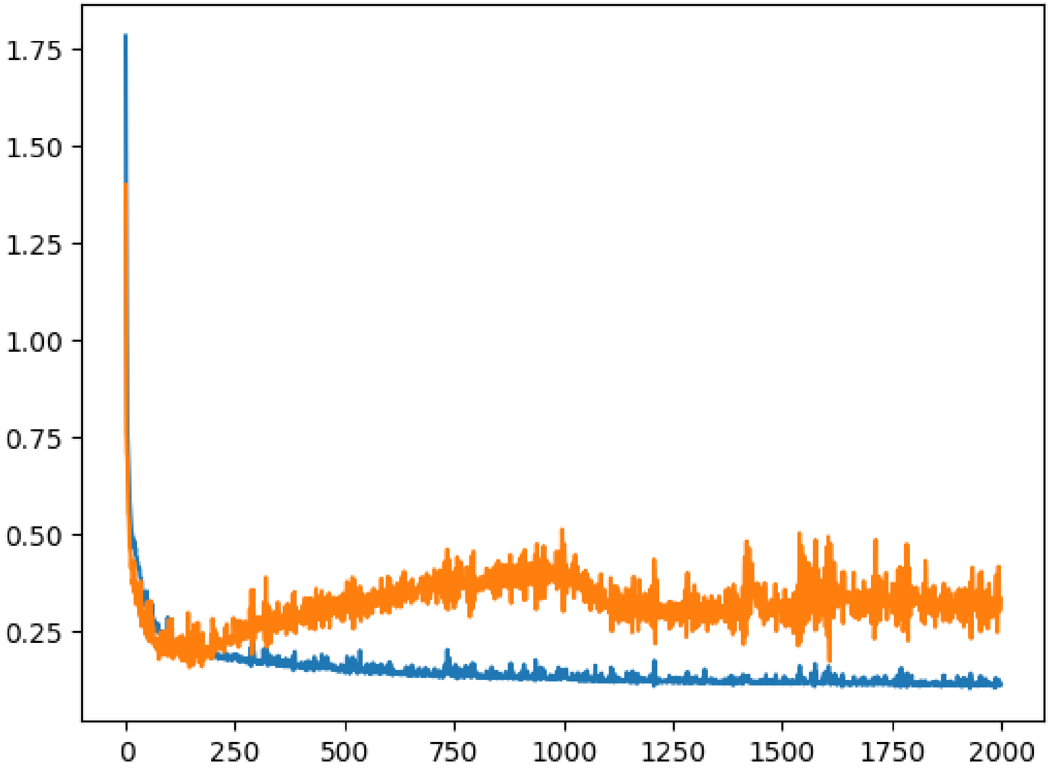
```
adam = Adam(learning_rate=0.01)
model2.compile(loss='binary_crossentropy', optimizer=adam,
metrics=['accuracy'])

history2 = model2.fit(X, y, epochs=2000, validation_split =
0.2,verbose=0)

plot_decision_regions(X, y.astype('int'), clf=model2, legend=2)
plt.xlim(-2,3)
plt.ylim(-1.5,2)
plt.show()
```

```
9600/9600 [==============================] - 13s 1ms/step
```



```
plt.plot(history2.history['loss'])
plt.plot(history2.history['val_loss'])
```

```
[<matplotlib.lines.Line2D at 0x14b4a9158e0>]
```



```
# Calculation of accuarcy of each model

# Calculate the accuracy for model1
acc_model1 = history1.history['accuracy'][-1] * 100

# Calculate the accuracy for model2
acc_model2 = history2.history['accuracy'][-1] * 100

print(f"Accuracy for Model 1: {acc_model1:.2f}%")
print(f"Accuracy for Model 2: {acc_model2:.2f}%")
```

```
Accuracy for Model 1: 100.00%
Accuracy for Model 2: 97.50%
```