- 1 import tensorflow as tf
- 2 print(tf.__version__)
- [→ 2.4.0

Application of Neural Network to Binary Output Classification

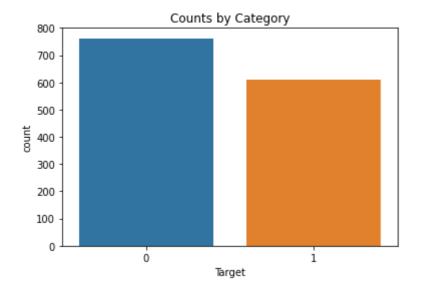
- 1 import seaborn as sns
- 2 import pandas as pd
- 3 import numpy as np
- 4 from tensorflow.keras.layers import Dense, Dropout, Activation
- 5 from tensorflow.keras.models import Model, Sequential
- 6 from tensorflow.keras.optimizers import Adam
- 5 banknote_data = pd.read_csv('https://raw.githubusercontent.com/AbhiRoy96/Banknote-Authentication-UCI-Dataset/master/bank_notes.csv')
- 8 banknote_data.head()

	variance	skewness	curtosis	entropy	Target
0	3.62160	8.6661	-2.8073	-0.44699	0
1	4.54590	8.1674	-2.4586	-1.46210	0
2	3.86600	-2.6383	1.9242	0.10645	0
3	3.45660	9.5228	-4.0112	-3.59440	0
4	0.32924	-4.4552	4.5718	-0.98880	0

1 banknote_data.shape

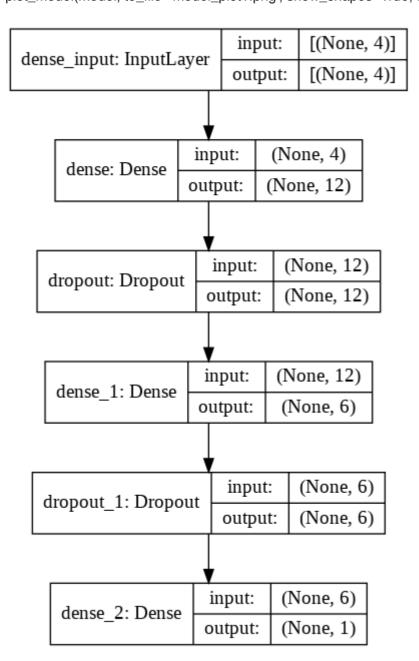
(1372, 5)

- 1 import matplotlib.pyplot as plt
- 2 %matplotlib inline
- 3 ax=plt.axes()
- 4 sns.countplot(x='Target', data=banknote_data, ax=ax)
- 5 ax.set_title('Counts by Category')
- 6 plt.show()



- 1 # Determine X and y
- 2 X = banknote_data.drop(['Target'], axis=1).values
- 3 y = banknote_data[['Target']].values
- 4 print(X.shape)
- 5 print(y.shape)
 - (1372, 4) (1372, 1)
- 1 # Create train and test datasets
- 2 from sklearn.model_selection import train_test_split
- 3 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42)
- 1 # Standardize the variables
- 2 from sklearn.preprocessing import StandardScaler
- 3 sc = StandardScaler()
- 4 X_train = sc.fit_transform(X_train)
- 5 X_test = sc.transform(X_test)
- 1 # Create the Neural Network

- 2 def create_model(learning_rate, dropout_rate):
- 3 model = Sequential()
- 4 model.add(Dense(12, input_dim=X_train.shape[1], activation='relu'))
- 5 model.add(Dropout(dropout_rate))
- 6 model.add(Dense(6, activation='relu'))
- 7 model.add(Dropout(dropout_rate))
- 8 model.add(Dense(1, activation='sigmoid'))
- 9 adam = Adam(Ir=learning_rate)
- 10 model.compile(loss='binary_crossentropy', optimizer=adam, metrics=['accuracy'])
- 11 return model
- 1 # Set the hyperparameters
- 2 dropout_rate = 0.1
- 3 epochs = 20
- 4 batch_size = 4
- 5 learn_rate = 0.001
- 1 model = create_model(learn_rate, dropout_rate)
- 1 # Visualize model structure
- 2 from tensorflow.keras.utils import plot_model
- 3 plot_model(model, to_file='model_plot1.png', show_shapes=True, show_layer_names=True)



1 model_history = model.fit(X_train, y_train, batch_size=batch_size, epochs=epochs, validation_split=0.2, verbose=1)

Epoch 1/20 220/220 [===================================
Epoch 2/20
220/220 [===================================
Epoch 3/20
220/220 [===================================
Epoch 4/20
220/220 [===================================
Epoch 5/20
220/220 [===================================
Epoch 6/20
220/220 [===================================
Epoch 7/20
. 220/220 [===================================
Epoch 8/20
. 220/220 [===================================
Epoch 9/20
. 220/220 [===================================
Epoch 10/20
•

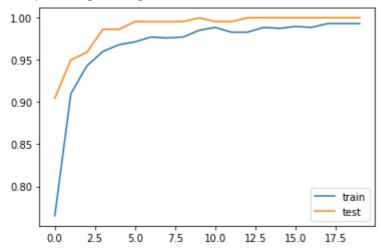
```
220/220 [===
Epoch 11/20
220/220 [===
                 ==] - 0s 2ms/step - loss: 0.0592 - accuracy: 0.9891 - val_loss: 0.0180 - val_accuracy: 0.9955
Epoch 12/20
Epoch 13/20
220/220 [==
                  =] - 0s 2ms/step - loss: 0.0616 - accuracy: 0.9830 - val loss: 0.0124 - val accuracy: 1.0000
Epoch 14/20
Epoch 15/20
220/220 [===========
                 ==] - 0s 2ms/step - loss: 0.0505 - accuracy: 0.9872 - val_loss: 0.0096 - val_accuracy: 1.0000
Epoch 16/20
Epoch 17/20
                 ==] - 0s 2ms/step - loss: 0.0409 - accuracy: 0.9927 - val loss: 0.0093 - val accuracy: 1.0000
220/220 [===
Epoch 18/20
Epoch 19/20
220/220 [===
          Epoch 20/20
```

- 1 # Model Performance
- 2 accuracies = model.evaluate(X_test, y_test, verbose=1)
- 3 print('Test Score;', accuracies[0])
- 4 print('Test Accuracy:', accuracies[1])

Visualize the model performance for the training and test datasets.

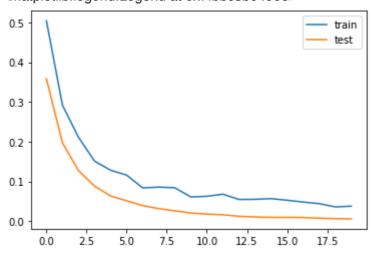
- 1 plt.plot(model_history.history['accuracy'], label = 'accuracy')
- 2 plt.plot(model_history.history['val_accuracy'], label = 'val_accuracy')
- 3 plt.legend(['train', 'test'])

<matplotlib.legend.Legend at 0x7fbbc3b9a278>



- plt.plot(model_history.history['loss'], label = 'loss')
- 2 plt.plot(model_history.history['val_loss'], label = 'val_loss')
- 3 plt.legend(['train','test'])

<matplotlib.legend.Legend at 0x7fbbc3b049e8>



Application of Neural Network to Multiclass Output

There are three changes compared to the simple class output:

- Change the number of nodes in the final dense layer to the number of target labels in the output.
- Change the activation function in the final dense layer from sigmoid to softmax.

- Change the loss function in the compile method of the model from binary_crossentropy to categorical_crossentropy.
- 1 import seaborn as sns
- 2 import pandas as pd
- 3 import numpy as np
- 4 from tensorflow.keras.layers import Dense, Dropout, Activation
- 5 from tensorflow.keras.models import Model, Sequential
- 6 from tensorflow.keras.optimizers import Adam
- 7 iris_data = sns.load_dataset('iris')
- 8 iris_data.head()

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

- 1 X = iris_data.drop(['species'], axis=1)
- 2 y = pd.get_dummies(iris_data.species, prefix='output')
- 3 X.head()

	sepal_length	sepal_width	petal_length	petal_width
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

1 y.head()

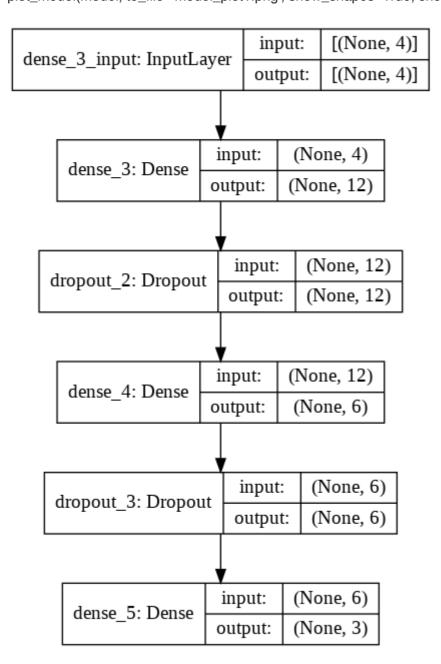
	output_setosa	output_versicolor	output_virginica
0	1	0	0
1	1	0	0
2	1	0	0
3	1	0	0
4	1	0	0

- 1 X = X.values
- y = y.values
- 1 from sklearn.model_selection import train_test_split
- 2 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42)
- 1 from sklearn.preprocessing import StandardScaler
- 2 sc = StandardScaler()
- 3 X_train = sc.fit_transform(X_train)
- 4 X_test = sc.transform(X_test)
- 1 def create_model_multiple_outs(learning_rate, dropout_rate):
- 2 model = Sequential()
- 3 model.add(Dense(12, input_dim=X_train.shape[1], activation='relu'))
- 4 model.add(Dropout(dropout_rate))
- 5 model.add(Dense(6, activation='relu'))
- 6 model.add(Dropout(dropout_rate))
- 7 model.add(Dense(y_train.shape[1], activation='softmax'))
- 8 adam = Adam(Ir=learning_rate)
- 9 model.compile(loss='categorical_crossentropy', optimizer=adam, metrics=['accuracy'])
- 10 return model
- 1 dropout_rate = 0.1
- 2 enoche 50

- 2 6000110 00
- 3 batch_size = 1
- 4 learn_rate = 0.001

Epoch 1/50

- 1 model = create_model_multiple_outs(learn_rate, dropout_rate)
- 2 from tensorflow.keras.utils import plot_model
- 3 plot_model(model, to_file='model_plot1.png', show_shapes=True, show_layer_names=True)



1 model_history = model.fit(X_train, y_train, batch_size=batch_size, epochs=epochs, validation_split=0.2, verbose=1)

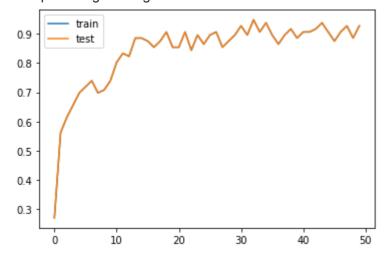
96/96 [====================================	- 1s 3ms/step - loss: 1.0346 - accuracy: 0.2466 - val_loss: 0.8499 - val_accuracy: 0.5833
Epoch 2/50	
	- 0s 2ms/step - loss: 1.0029 - accuracy: 0.5238 - val_loss: 0.7893 - val_accuracy: 0.7500
Epoch 3/50	- 0s 2ms/step - loss: 0.9889 - accuracy: 0.6691 - val_loss: 0.7617 - val_accuracy: 0.8333
90/90 [====================================	- 08 21118/81ep - 1088. 0.9669 - accuracy. 0.6691 - Val_loss. 0.7617 - Val_accuracy. 0.6555
•	- 0s 2ms/step - loss: 0.9122 - accuracy: 0.6031 - val_loss: 0.7213 - val_accuracy: 0.8333
Epoch 5/50	,,,,,,,
	- 0s 2ms/step - loss: 0.8673 - accuracy: 0.7538 - val_loss: 0.6375 - val_accuracy: 0.8333
Epoch 6/50	
	- 0s 2ms/step - loss: 0.7370 - accuracy: 0.7204 - val_loss: 0.5393 - val_accuracy: 0.8333
Epoch 7/50	- 0s 2ms/step - loss: 0.5669 - accuracy: 0.7359 - val_loss: 0.4900 - val_accuracy: 0.8750
Epoch 8/50	- 05 21115/5tep - 1055. 0.5009 - accuracy. 0.7559 - vai_loss. 0.4900 - vai_accuracy. 0.6750
•	- 0s 3ms/step - loss: 0.5290 - accuracy: 0.7288 - val_loss: 0.4462 - val_accuracy: 0.8750
Epoch 9/50	
96/96 [========]	- 0s 1ms/step - loss: 0.5457 - accuracy: 0.6873 - val_loss: 0.4136 - val_accuracy: 0.9167
Epoch 10/50	
	- 0s 2ms/step - loss: 0.4694 - accuracy: 0.7829 - val_loss: 0.3856 - val_accuracy: 0.9583
Epoch 11/50	0. 1 ma/stan lane: 0.4567 acquirequi 0.9017 val. lane: 0.2492 val. acquirequi 0.0167
Epoch 12/50	- 0s 1ms/step - loss: 0.4567 - accuracy: 0.8017 - val_loss: 0.3483 - val_accuracy: 0.9167
·	- 0s 2ms/step - loss: 0.3828 - accuracy: 0.8084 - val_loss: 0.3039 - val_accuracy: 0.9167
Epoch 13/50	
96/96 [=========]	- 0s 2ms/step - loss: 0.3802 - accuracy: 0.8621 - val_loss: 0.2775 - val_accuracy: 0.9167
Epoch 14/50	
•	- 0s 2ms/step - loss: 0.3695 - accuracy: 0.8745 - val_loss: 0.2568 - val_accuracy: 0.9583
Epoch 15/50	0-0
96/96 [====================================	- 0s 2ms/step - loss: 0.3339 - accuracy: 0.8546 - val_loss: 0.2300 - val_accuracy: 0.9583
•	- 0s 2ms/step - loss: 0.3005 - accuracy: 0.8453 - val_loss: 0.2230 - val_accuracy: 0.9583
Epoch 17/50	03 2113/310p 1033. 0.0000 accuracy. 0.0400 vai_lo33. 0.2200 vai_accuracy. 0.0000
•	- 0s 2ms/step - loss: 0.3664 - accuracy: 0.8138 - val_loss: 0.2085 - val_accuracy: 0.9583
Epoch 18/50	
•	- 0s 2ms/step - loss: 0.2964 - accuracy: 0.8898 - val_loss: 0.1988 - val_accuracy: 0.9583
Epoch 19/50	
	- 0s 2ms/step - loss: 0.2170 - accuracy: 0.9475 - val_loss: 0.1817 - val_accuracy: 0.9583
Epoch 20/50	

```
Epoch 21/50
96/96 [=====
                                ==] - 0s 1ms/step - loss: 0.2368 - accuracy: 0.8902 - val_loss: 0.1606 - val_accuracy: 0.9583
Epoch 22/50
96/96 [==============] - 0s 2ms/step - loss: 0.3204 - accuracy: 0.8482 - val_loss: 0.1588 - val_accuracy: 0.9583
Epoch 23/50
                                 =] - 0s 2ms/step - loss: 0.3222 - accuracy: 0.8216 - val_loss: 0.1589 - val_accuracy: 0.9583
96/96 [==
Epoch 24/50
96/96 [==============] - 0s 2ms/step - loss: 0.2102 - accuracy: 0.8818 - val_loss: 0.1647 - val_accuracy: 0.9583
Epoch 25/50
96/96 [=====
                                ==] - 0s 1ms/step - loss: 0.2628 - accuracy: 0.8308 - val_loss: 0.1580 - val_accuracy: 0.9583
Epoch 26/50
96/96 [==============] - 0s 2ms/step - loss: 0.1925 - accuracy: 0.9269 - val_loss: 0.1588 - val_accuracy: 0.9583
Epoch 27/50
                     ========] - 0s 1ms/step - loss: 0.1997 - accuracy: 0.9007 - val_loss: 0.1479 - val_accuracy: 0.9583
96/96 [=====
Epoch 28/50
Epoch 29/50
96/96 [====
                     ==========] - 0s 2ms/step - loss: 0.2318 - accuracy: 0.8953 - val_loss: 0.1337 - val_accuracy: 0.9583
Epoch 30/50
```

- 1 accuracies = model.evaluate(X_test, y_test, verbose=1)
- 2 print('Test Score:', accuracies[0])
- 3 print('Test Accuracy:', accuracies[1])

- import matplotlib.pyplot as plt
- plt.plot(model_history.history['accuracy'], label = 'accuracy')
- 3 plt.plot(model_history.history['accuracy'], label = 'val_accuracy')
- 4 plt.legend(['train', 'test'])

<matplotlib.legend.Legend at 0x7fbbc1fc0fd0>



- 1 import matplotlib.pyplot as plt
- 2 plt.plot(model_history.history['loss'], label = 'loss')
- 3 plt.plot(model_history.history['val_loss'], label = 'val_loss')
- 4 plt.legend(['train', 'test'])

<matplotlib.legend.Legend at 0x7fbbc1f7f4e0>

