

```
import pandas
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasClassifier
from keras.utils import np_utils
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.preprocessing import LabelEncoder
from sklearn.pipeline import Pipeline
from sklearn import model_selection
from keras.utils.vis_utils import plot_model

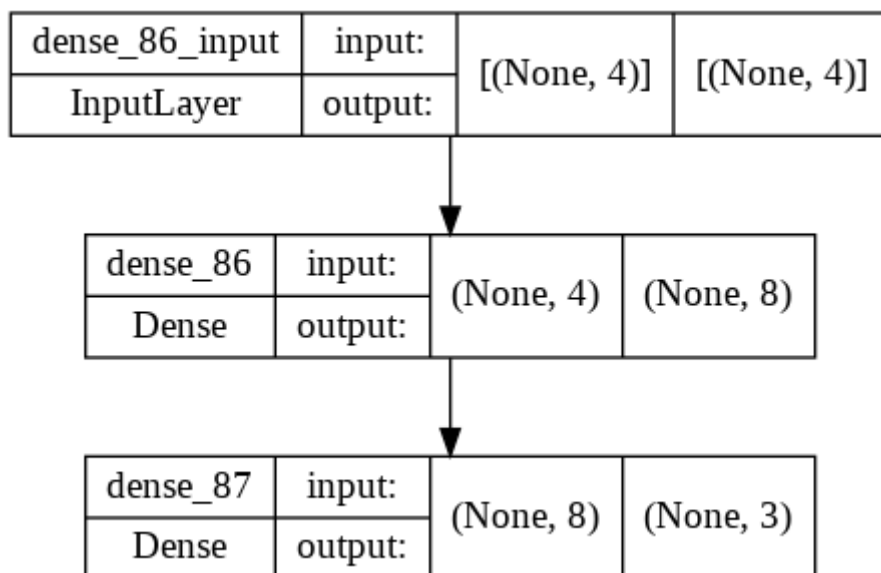
# carregar o dataset, usando skiprows para pular o cabeçalho
dataframe = pandas.read_csv("iris.csv", skiprows=1, header=None)
dataset = dataframe.values
X = dataset[:,0:4].astype(float)
Y = dataset[:,4]

# usando o LabelEncoder para converter as espécies em integers
encoder = LabelEncoder()
encoder.fit(Y)
encoded_Y = encoder.transform(Y)
dummy_y = np_utils.to_categorical(encoded_Y)

# criando o modelo
def baseline_model():
    # create model
    model = Sequential()
    model.add(Dense(8, input_dim=4, activation='relu'))
    model.add(Dense(3, activation='softmax'))
    # Compile model
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

```
return model
```

```
plot_model(baseline_model(), show_shapes=True, show_layer_names=True)
```



```
#treinando 200 épocas e avaliando o modelo com k-Fold
estimator = KerasClassifier(build_fn=baseline_model, epochs=200, batch_size=5, verbose=1)
kfold = KFold(n_splits=10, shuffle=True)
results = cross_val_score(estimator, X, dummy_y, cv=kfold)
print("Acuracia: %.2f%% (%.2f%%)" % (results.mean()*100, results.std()*100))
```

```
Epoch 173/200
27/27 [=====] - 0s 2ms/step - loss: 0.2393 - accuracy: 0.9778
Epoch 174/200
27/27 [=====] - 0s 2ms/step - loss: 0.2383 - accuracy: 0.9852
Epoch 175/200
27/27 [=====] - 0s 2ms/step - loss: 0.2362 - accuracy: 0.9852
Epoch 176/200
27/27 [=====] - 0s 2ms/step - loss: 0.2358 - accuracy: 0.9704
Epoch 177/200
27/27 [=====] - 0s 2ms/step - loss: 0.2357 - accuracy: 0.9852
Epoch 178/200
```

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27/27 [=====] - 0s 2ms/step - loss: 0.2313 - accuracy: 0.9852
Epoch 179/200
27/27 [=====] - 0s 2ms/step - loss: 0.2306 - accuracy: 0.9704
Epoch 180/200
27/27 [=====] - 0s 2ms/step - loss: 0.2286 - accuracy: 0.9852
Epoch 181/200
27/27 [=====] - 0s 2ms/step - loss: 0.2275 - accuracy: 0.9852
Epoch 182/200
27/27 [=====] - 0s 2ms/step - loss: 0.2264 - accuracy: 0.9852
Epoch 183/200
27/27 [=====] - 0s 2ms/step - loss: 0.2236 - accuracy: 0.9852
Epoch 184/200
27/27 [=====] - 0s 2ms/step - loss: 0.2232 - accuracy: 0.9852
Epoch 185/200
27/27 [=====] - 0s 2ms/step - loss: 0.2214 - accuracy: 0.9852
Epoch 186/200
27/27 [=====] - 0s 2ms/step - loss: 0.2207 - accuracy: 0.9704
Epoch 187/200
27/27 [=====] - 0s 2ms/step - loss: 0.2183 - accuracy: 0.9778
Epoch 188/200
27/27 [=====] - 0s 2ms/step - loss: 0.2173 - accuracy: 0.9778
Epoch 189/200
27/27 [=====] - 0s 2ms/step - loss: 0.2165 - accuracy: 0.9852
Epoch 190/200
27/27 [=====] - 0s 2ms/step - loss: 0.2136 - accuracy: 0.9852
Epoch 191/200
27/27 [=====] - 0s 2ms/step - loss: 0.2131 - accuracy: 0.9778
Epoch 192/200
27/27 [=====] - 0s 3ms/step - loss: 0.2111 - accuracy: 0.9852
Epoch 193/200
27/27 [=====] - 0s 2ms/step - loss: 0.2126 - accuracy: 0.9852
Epoch 194/200
27/27 [=====] - 0s 2ms/step - loss: 0.2095 - accuracy: 0.9778
Epoch 195/200
27/27 [=====] - 0s 2ms/step - loss: 0.2074 - accuracy: 0.9852
Epoch 196/200
27/27 [=====] - 0s 2ms/step - loss: 0.2065 - accuracy: 0.9852
Epoch 197/200
27/27 [=====] - 0s 2ms/step - loss: 0.2048 - accuracy: 0.9852
Epoch 198/200
27/27 [=====] - 0s 2ms/step - loss: 0.2041 - accuracy: 0.9778
```

Epoch 199/200

27/27 [=====] - 0s 2ms/step - loss: 0.2034 - accuracy: 0.9778

Epoch 200/200

27/27 [=====] - 0s 2ms/step - loss: 0.2017 - accuracy: 0.9852

3/3 [=====] - 0s 5ms/step - loss: 0.2845 - accuracy: 0.9333

Acuracia: 97.33% (4.42%)

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✓ 2m54s conclusão: 18:53

