DNN Lab

Objectives

- · Understand basic DNN model building process using Keras
- · Analyze model performance and capacity vs generalization tradeoff
- · Modify models to reduce overfitting and improve performance

Exercises

- · Build a DNN model for slump Test Problem
- Start with a model consisting of one hidden layer with 7 neurons
- Analyze results and explore improvements to model in terms of capacity, regularization

Step 1: Import Libraries

```
In [ ]: | %tensorflow_version 2.x
        from numpy.random import seed
        seed(2)
        import tensorflow as tf
        from tensorflow import keras
        from IPython import display
        from matplotlib import cm
        from matplotlib import gridspec
        from matplotlib import pyplot as plt
        import numpy as np
        import pandas as pd
        import os
        import datetime
        from tensorflow.python.data import Dataset
        from sklearn import preprocessing
        from sklearn.preprocessing import StandardScaler, StandardScaler
        from sklearn.model_selection import train_test_split
        print(tf.__version__)
```

2.6.0

Step 2: Import Data

```
In [ ]:
        pd.options.display.max_rows = 10
         pd.options.display.float format = '{:.1f}'.format
         hcv data = pd.read csv("hcvdat0.csv")
         hcv_data = hcv_data.reindex(
             np.random.permutation(hcv data.index))
In [ ]: hcv data.shape[0]
Out[]: 615
In [ ]:
         #removing the redundent index column
         hcv data.drop('Unnamed: 0', axis=1, inplace=True)
         print(hcv_data)
                                       Age Sex ALB
                                                       ALP
                                                                 CHE
                                                                       CHOL
                                                                             CREA
                            Category
                                                                                    GGT
         PROT
                       0=Blood Donor
                                             f 51.5
                                                      81.8
         469
                                        52
                                                                 6.7
                                                                        5.9
                                                                             88.0
                                                                                   16.3
         82.2
         592
                                                                             58.0 201.0
                         3=Cirrhosis
                                        47
                                             m 42.0
                                                       nan
                                                                 6.3
                                                                        5.5
                                                            . . .
         79.0
                                                      58.9
                                                                                   10.8
         265
                       0=Blood Donor
                                        58
                                             m 41.3
                                                                 8.2
                                                                        5.7
                                                                             60.0
         70.1
         84
                       0=Blood Donor
                                        39
                                             m 43.9
                                                      90.1
                                                            . . .
                                                                 9.9
                                                                        4.6
                                                                             98.0
                                                                                   99.3
         66.2
         109
                       0=Blood Donor
                                        42
                                             m 44.1
                                                      46.8
                                                            ... 10.8
                                                                        6.3 95.0
                                                                                   19.7
         73.0
         . .
                                       . . .
                                                                             29.0
         534
             0s=suspect Blood Donor
                                        48
                                             m 24.9 116.9
                                                                 3.4
                                                                        5.2
                                                                                   83.0
         47.8
         584
                           2=Fibrosis
                                        75
                                             f 36.0
                                                       nan
                                                                 6.7
                                                                             57.0 177.0
                                                                        nan
         72.0
         493
                       0=Blood Donor
                                             f 34.7
                                                      90.3
                                        56
                                                            . . .
                                                                 8.1
                                                                        5.5
                                                                             67.0
                                                                                    9.0
         69.4
                       0=Blood Donor
                                             f 27.8
                                                      85.7
         527
                                        63
                                                            . . .
                                                                 6.1
                                                                        4.0
                                                                            63.0
                                                                                   46.0
         56.9
                       0=Blood Donor
                                                      59.3
                                                            ... 11.1
         168
                                        47
                                             m 48.3
                                                                        5.6 88.0
                                                                                   91.5
         73.0
         [615 rows x 13 columns]
In [ ]:
        #The baseline Accuracy measure
         naive_app_min= hcv_data.Category.value_counts().max()/len(hcv_data)
         naive_app_min
Out[]: 0.866666666666667
```

```
In []: #changing Sex column to 0 and 1s
    hcv_data= pd.get_dummies(hcv_data, columns=['Sex'], drop_first=True)
    #changing predictor variable into dummy vars
    hcv_data= pd.get_dummies(hcv_data, columns=['Category'])
    print(hcv_data)
```

	Age ALB	• • •	Category_2=Fibrosis	Category_3=Cirrhosis
469	52 51.5		0	0
592	47 42.0		0	1
265	58 41.3		0	0
84	39 43.9		0	0
109	42 44.1		0	0
			•••	
534	48 24.9		0	0
584	75 36.0		1	0
493	56 34.7		0	0
527	63 27.8		0	0
168	47 48.3		0	0

[615 rows x 17 columns]

```
In [ ]: hcv_data = hcv_data[hcv_data.columns[::-1]]
hcv_data.head()
```

Out[]:

	Category_3=Cirrhosis	Category_2=Fibrosis	Category_1=Hepatitis	Category_0s=suspect Blood Donor	Cate
469	0	0	0	0	
592	1	0	0	0	
265	0	0	0	0	
84	0	0	0	0	
109	0	0	0	0	
4					•

Step 3: Preprocess

```
In []: #removed any NaN values and replaced it with the column mean
for cols in hcv_data.columns[hcv_data.isnull().any()]:
    hcv_data[cols].replace(np.NaN, hcv_data[cols].mean(),inplace=True)
hcv_data[hcv_data.isnull().any(axis=1)]
```

Out[]:

```
Category_3=Cirrhosis Category_2=Fibrosis Category_1=Hepatitis Category_0s=suspect Category_Blood Donor
```

```
In [ ]: #checking to see if any NaN values are present
len(hcv_data[hcv_data.isnull().any(axis=1)])
Out[ ]: 0
```

Train/Validation Split

```
In [ ]: #Creating a training and validation dataset with a 80/20 split
    X_train,X_test, y_train, y_test = train_test_split(hcv_data.iloc[:,5:],hcv_dat
    a.iloc[:,:5], test_size=0.2, random_state=1)
In [ ]: #2.1 showing the head of the training data
    X train.head()
```

Out[]:

	Sex_m	PROT	GGT	CREA	CHOL	CHE	BIL	AST	ALT	ALP	ALB	Age
246	1	72.2	30.2	80.0	6.3	7.5	4.5	21.0	36.9	87.1	46.2	55
344	0	72.8	12.4	64.0	5.1	10.0	3.0	22.0	19.2	62.6	43.4	35
75	1	70.1	17.3	67.0	4.1	6.9	16.7	35.1	47.4	69.4	44.7	38
216	1	67.4	87.8	77.0	6.1	8.9	7.8	23.7	37.0	82.2	82.2	52
444	0	78.2	14.5	69.0	6.8	9.1	5.8	15.9	14.3	45.9	45.4	49

```
In [ ]: #Standardizing training dataset
    scaler = StandardScaler()

    scaledf = scaler.fit_transform(X_train.iloc[:,1:])
    X_train.iloc[:,1:] = pd.DataFrame(scaledf, index=X_train.iloc[:,1:].index, col
    umns=X_train.iloc[:,1:].columns)

#print(X_train)
    #Standardizing validation dataset
    vscaled = scaler.transform(X_test.iloc[:,1:].values)
    X_test.iloc[:,1:] = pd.DataFrame(vscaled, index=X_test.iloc[:,1:].index, colum
    ns=X_test.iloc[:,1:].columns)
    #print(X_test)
```

Step 4: Build Model

https://www.tensorflow.org/api_docs/python/tf/keras/Model (https://www.tensorflow.org/api_docs/python/tf/keras/Model)

https://www.tensorflow.org/api_docs/python/tf/keras/layers/Dense (https://www.tensorflow.org/api_docs/python/tf/keras/layers/Dense)

https://keras.io/optimizers/ (https://keras.io/optimizers/)

Build Model

```
X test.shape
Out[]: (123, 12)
In [ ]:
        12 model = keras.Sequential([
            keras.layers.Dense(24, kernel regularizer=keras.regularizers.l2(0.001), ac
        tivation=tf.nn.relu,
                                input_shape=(X_train.shape[1],)),
            keras.layers.Dropout(0.25),
            keras.layers.Dense(5, kernel regularizer=keras.regularizers.12(0.001), act
        ivation=tf.nn.relu),
            keras.layers.Dropout(0.25),
            #keras.layers.Dense(6, kernel regularizer=keras.regularizers.l2(0.01), act
         ivation=tf.nn.relu),
            #keras.layers.Dropout(0.25),
            #keras.layers.Dense(6, kernel regularizer=keras.regularizers.l2(0.01), act
        ivation=tf.nn.softmax),
            #keras.layers.Dropout(0.50),
            #keras.layers.Dense(4, kernel regularizer=keras.regularizers.l2(0.01), act
         ivation=tf.nn.softmax),
            #keras.layers.Dropout(0.50),
            keras.layers.Dense(5, activation=tf.nn.softmax)
           ])
        12 model.compile(loss=tf.keras.losses.CategoricalCrossentropy(label smoothing=
        0.1),
                         optimizer='sgd',
                         metrics=[tf.keras.metrics.CategoricalAccuracy()])
```

Fit Model

```
In [ ]: logdir = os.path.join("logs", datetime.datetime.now().strftime("%Y%m%d-%H%M%S"
     ))
     tensorboard_callback = tf.keras.callbacks.TensorBoard(logdir, histogram_freq=
     1)
```

In []: 12_model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 24)	312
dropout (Dropout)	(None, 24)	0
dense_1 (Dense)	(None, 5)	125
dropout_1 (Dropout)	(None, 5)	0
dense_2 (Dense)	(None, 5)	30 ======

Total params: 467
Trainable params: 467
Non-trainable params: 0

```
Epoch 1/500
16/16 - 1s - loss: 1.6900 - categorical_accuracy: 0.3415 - val_loss: 1.5711 -
val_categorical_accuracy: 0.5447
Epoch 2/500
16/16 - 0s - loss: 1.5732 - categorical accuracy: 0.5894 - val loss: 1.4726 -
val_categorical_accuracy: 0.7561
Epoch 3/500
16/16 - 0s - loss: 1.4545 - categorical_accuracy: 0.7541 - val_loss: 1.3973 -
val_categorical_accuracy: 0.7967
Epoch 4/500
16/16 - 0s - loss: 1.3586 - categorical accuracy: 0.8089 - val loss: 1.3293 -
val_categorical_accuracy: 0.8130
Epoch 5/500
16/16 - 0s - loss: 1.3176 - categorical accuracy: 0.8232 - val loss: 1.2750 -
val_categorical_accuracy: 0.8293
Epoch 6/500
16/16 - 0s - loss: 1.2329 - categorical accuracy: 0.8557 - val loss: 1.2278 -
val_categorical_accuracy: 0.8374
Epoch 7/500
16/16 - 0s - loss: 1.1750 - categorical accuracy: 0.8699 - val loss: 1.1846 -
val_categorical_accuracy: 0.8374
Epoch 8/500
16/16 - 0s - loss: 1.1246 - categorical accuracy: 0.8740 - val loss: 1.1492 -
val_categorical_accuracy: 0.8374
Epoch 9/500
16/16 - 0s - loss: 1.0659 - categorical accuracy: 0.8740 - val loss: 1.1193 -
val_categorical_accuracy: 0.8374
Epoch 10/500
16/16 - 0s - loss: 1.0600 - categorical accuracy: 0.8699 - val loss: 1.0959 -
val categorical accuracy: 0.8374
Epoch 11/500
16/16 - 0s - loss: 1.0214 - categorical accuracy: 0.8720 - val loss: 1.0763 -
val categorical accuracy: 0.8374
Epoch 12/500
16/16 - 0s - loss: 0.9862 - categorical accuracy: 0.8760 - val loss: 1.0597 -
val categorical accuracy: 0.8374
Epoch 13/500
16/16 - 0s - loss: 0.9643 - categorical accuracy: 0.8740 - val loss: 1.0466 -
val categorical accuracy: 0.8374
Epoch 14/500
16/16 - 0s - loss: 0.9495 - categorical accuracy: 0.8760 - val loss: 1.0369 -
val categorical accuracy: 0.8374
Epoch 15/500
16/16 - 0s - loss: 0.9220 - categorical_accuracy: 0.8740 - val_loss: 1.0274 -
val categorical accuracy: 0.8374
Epoch 16/500
16/16 - 0s - loss: 0.9040 - categorical_accuracy: 0.8740 - val_loss: 1.0202 -
val categorical accuracy: 0.8374
Epoch 17/500
16/16 - 0s - loss: 0.8794 - categorical_accuracy: 0.8740 - val_loss: 1.0146 -
val categorical accuracy: 0.8374
Epoch 18/500
16/16 - 0s - loss: 0.8674 - categorical_accuracy: 0.8740 - val_loss: 1.0117 -
val categorical accuracy: 0.8374
Epoch 19/500
16/16 - 0s - loss: 0.8514 - categorical_accuracy: 0.8740 - val_loss: 1.0085 -
val categorical accuracy: 0.8374
```

```
Epoch 20/500
16/16 - 0s - loss: 0.8394 - categorical accuracy: 0.8740 - val loss: 1.0064 -
val_categorical_accuracy: 0.8374
Epoch 21/500
16/16 - 0s - loss: 0.8492 - categorical accuracy: 0.8740 - val loss: 1.0033 -
val_categorical_accuracy: 0.8374
Epoch 22/500
16/16 - 0s - loss: 0.8264 - categorical accuracy: 0.8740 - val loss: 1.0021 -
val_categorical_accuracy: 0.8374
Epoch 23/500
16/16 - 0s - loss: 0.8227 - categorical accuracy: 0.8740 - val loss: 1.0001 -
val_categorical_accuracy: 0.8374
Epoch 24/500
16/16 - 0s - loss: 0.8381 - categorical_accuracy: 0.8740 - val_loss: 0.9966 -
val_categorical_accuracy: 0.8374
Epoch 25/500
16/16 - 0s - loss: 0.8243 - categorical accuracy: 0.8740 - val loss: 0.9941 -
val_categorical_accuracy: 0.8374
Epoch 26/500
16/16 - 0s - loss: 0.8208 - categorical_accuracy: 0.8740 - val_loss: 0.9933 -
val_categorical_accuracy: 0.8374
Epoch 27/500
16/16 - 0s - loss: 0.8231 - categorical accuracy: 0.8740 - val loss: 0.9872 -
val_categorical_accuracy: 0.8374
Epoch 28/500
16/16 - 0s - loss: 0.7891 - categorical accuracy: 0.8740 - val loss: 0.9843 -
val_categorical_accuracy: 0.8374
Epoch 29/500
16/16 - 0s - loss: 0.7842 - categorical accuracy: 0.8740 - val loss: 0.9812 -
val_categorical_accuracy: 0.8374
Epoch 30/500
16/16 - 0s - loss: 0.7856 - categorical accuracy: 0.8740 - val loss: 0.9792 -
val categorical accuracy: 0.8374
Epoch 31/500
16/16 - 0s - loss: 0.7879 - categorical accuracy: 0.8740 - val loss: 0.9767 -
val categorical accuracy: 0.8374
Epoch 32/500
16/16 - 0s - loss: 0.7856 - categorical accuracy: 0.8740 - val loss: 0.9742 -
val categorical accuracy: 0.8374
Epoch 33/500
16/16 - 0s - loss: 0.7779 - categorical accuracy: 0.8740 - val loss: 0.9731 -
val categorical accuracy: 0.8374
Epoch 34/500
16/16 - 0s - loss: 0.7866 - categorical accuracy: 0.8740 - val loss: 0.9712 -
val categorical accuracy: 0.8374
Epoch 35/500
16/16 - 0s - loss: 0.7817 - categorical_accuracy: 0.8740 - val_loss: 0.9688 -
val categorical accuracy: 0.8374
Epoch 36/500
16/16 - 0s - loss: 0.7679 - categorical_accuracy: 0.8740 - val_loss: 0.9667 -
val categorical accuracy: 0.8374
Epoch 37/500
16/16 - 0s - loss: 0.7748 - categorical_accuracy: 0.8740 - val_loss: 0.9655 -
val categorical accuracy: 0.8374
Epoch 38/500
16/16 - 0s - loss: 0.7566 - categorical_accuracy: 0.8740 - val_loss: 0.9639 -
val categorical accuracy: 0.8374
```

```
Epoch 39/500
16/16 - 0s - loss: 0.7708 - categorical accuracy: 0.8740 - val loss: 0.9615 -
val_categorical_accuracy: 0.8374
Epoch 40/500
16/16 - 0s - loss: 0.7586 - categorical accuracy: 0.8740 - val loss: 0.9610 -
val_categorical_accuracy: 0.8374
Epoch 41/500
16/16 - 0s - loss: 0.7508 - categorical accuracy: 0.8740 - val loss: 0.9628 -
val_categorical_accuracy: 0.8374
Epoch 42/500
16/16 - 0s - loss: 0.7489 - categorical accuracy: 0.8740 - val loss: 0.9623 -
val_categorical_accuracy: 0.8374
Epoch 43/500
16/16 - 0s - loss: 0.7550 - categorical_accuracy: 0.8740 - val_loss: 0.9593 -
val_categorical_accuracy: 0.8374
Epoch 44/500
16/16 - 0s - loss: 0.7553 - categorical accuracy: 0.8740 - val loss: 0.9587 -
val_categorical_accuracy: 0.8374
Epoch 45/500
16/16 - 0s - loss: 0.7490 - categorical_accuracy: 0.8740 - val_loss: 0.9554 -
val_categorical_accuracy: 0.8374
Epoch 46/500
16/16 - 0s - loss: 0.7394 - categorical accuracy: 0.8740 - val loss: 0.9563 -
val_categorical_accuracy: 0.8374
Epoch 47/500
16/16 - 0s - loss: 0.7482 - categorical accuracy: 0.8740 - val loss: 0.9555 -
val_categorical_accuracy: 0.8374
Epoch 48/500
16/16 - 0s - loss: 0.7473 - categorical accuracy: 0.8740 - val loss: 0.9528 -
val_categorical_accuracy: 0.8374
Epoch 49/500
16/16 - 0s - loss: 0.7496 - categorical accuracy: 0.8740 - val loss: 0.9512 -
val categorical accuracy: 0.8374
Epoch 50/500
16/16 - 0s - loss: 0.7526 - categorical accuracy: 0.8740 - val loss: 0.9468 -
val categorical accuracy: 0.8374
Epoch 51/500
16/16 - 0s - loss: 0.7471 - categorical accuracy: 0.8740 - val loss: 0.9460 -
val categorical accuracy: 0.8374
Epoch 52/500
16/16 - 0s - loss: 0.7387 - categorical accuracy: 0.8760 - val loss: 0.9445 -
val categorical accuracy: 0.8374
Epoch 53/500
16/16 - 0s - loss: 0.7332 - categorical accuracy: 0.8740 - val loss: 0.9448 -
val categorical accuracy: 0.8374
Epoch 54/500
16/16 - 0s - loss: 0.7513 - categorical_accuracy: 0.8740 - val_loss: 0.9431 -
val categorical accuracy: 0.8374
Epoch 55/500
16/16 - 0s - loss: 0.7285 - categorical_accuracy: 0.8760 - val_loss: 0.9443 -
val categorical accuracy: 0.8374
Epoch 56/500
16/16 - 0s - loss: 0.7246 - categorical_accuracy: 0.8740 - val_loss: 0.9448 -
val categorical accuracy: 0.8374
Epoch 57/500
16/16 - 0s - loss: 0.7242 - categorical_accuracy: 0.8740 - val_loss: 0.9449 -
val categorical accuracy: 0.8374
```

```
Epoch 58/500
16/16 - 0s - loss: 0.7390 - categorical accuracy: 0.8760 - val loss: 0.9420 -
val_categorical_accuracy: 0.8374
Epoch 59/500
16/16 - 0s - loss: 0.7397 - categorical accuracy: 0.8760 - val loss: 0.9386 -
val_categorical_accuracy: 0.8374
Epoch 60/500
16/16 - 0s - loss: 0.7482 - categorical accuracy: 0.8740 - val loss: 0.9369 -
val_categorical_accuracy: 0.8374
Epoch 61/500
16/16 - 0s - loss: 0.7335 - categorical accuracy: 0.8740 - val loss: 0.9374 -
val_categorical_accuracy: 0.8374
Epoch 62/500
16/16 - 0s - loss: 0.7400 - categorical_accuracy: 0.8740 - val_loss: 0.9359 -
val_categorical_accuracy: 0.8374
Epoch 63/500
16/16 - 0s - loss: 0.7350 - categorical accuracy: 0.8740 - val loss: 0.9354 -
val_categorical_accuracy: 0.8374
Epoch 64/500
16/16 - 0s - loss: 0.7294 - categorical_accuracy: 0.8760 - val_loss: 0.9331 -
val_categorical_accuracy: 0.8374
Epoch 65/500
16/16 - 0s - loss: 0.7222 - categorical accuracy: 0.8760 - val loss: 0.9303 -
val_categorical_accuracy: 0.8374
Epoch 66/500
16/16 - 0s - loss: 0.7414 - categorical accuracy: 0.8760 - val loss: 0.9299 -
val_categorical_accuracy: 0.8374
Epoch 67/500
16/16 - 0s - loss: 0.7311 - categorical accuracy: 0.8801 - val loss: 0.9271 -
val_categorical_accuracy: 0.8374
Epoch 68/500
16/16 - 0s - loss: 0.7099 - categorical accuracy: 0.8740 - val loss: 0.9278 -
val categorical accuracy: 0.8374
Epoch 69/500
16/16 - 0s - loss: 0.7178 - categorical accuracy: 0.8801 - val loss: 0.9255 -
val categorical accuracy: 0.8374
Epoch 70/500
16/16 - 0s - loss: 0.7097 - categorical_accuracy: 0.8760 - val_loss: 0.9237 -
val categorical accuracy: 0.8374
Epoch 71/500
16/16 - 0s - loss: 0.7236 - categorical accuracy: 0.8801 - val loss: 0.9182 -
val categorical accuracy: 0.8374
Epoch 72/500
16/16 - 0s - loss: 0.7366 - categorical accuracy: 0.8760 - val loss: 0.9125 -
val categorical accuracy: 0.8374
Epoch 73/500
16/16 - 0s - loss: 0.7202 - categorical_accuracy: 0.8841 - val_loss: 0.9093 -
val categorical accuracy: 0.8374
Epoch 74/500
16/16 - 0s - loss: 0.7095 - categorical_accuracy: 0.8760 - val_loss: 0.9089 -
val categorical accuracy: 0.8374
Epoch 75/500
16/16 - 0s - loss: 0.7025 - categorical_accuracy: 0.8801 - val_loss: 0.9103 -
val categorical accuracy: 0.8374
Epoch 76/500
16/16 - 0s - loss: 0.7235 - categorical_accuracy: 0.8760 - val_loss: 0.9083 -
val categorical accuracy: 0.8374
```

```
Epoch 77/500
16/16 - 0s - loss: 0.7089 - categorical accuracy: 0.8780 - val loss: 0.9070 -
val_categorical_accuracy: 0.8374
Epoch 78/500
16/16 - 0s - loss: 0.7175 - categorical accuracy: 0.8801 - val loss: 0.9048 -
val_categorical_accuracy: 0.8374
Epoch 79/500
16/16 - 0s - loss: 0.7131 - categorical accuracy: 0.8821 - val loss: 0.9021 -
val_categorical_accuracy: 0.8374
Epoch 80/500
16/16 - 0s - loss: 0.7076 - categorical accuracy: 0.8801 - val loss: 0.8987 -
val_categorical_accuracy: 0.8374
Epoch 81/500
16/16 - 0s - loss: 0.7099 - categorical_accuracy: 0.8862 - val_loss: 0.8952 -
val_categorical_accuracy: 0.8374
Epoch 82/500
16/16 - 0s - loss: 0.6940 - categorical accuracy: 0.8882 - val loss: 0.8943 -
val_categorical_accuracy: 0.8455
Epoch 83/500
16/16 - 0s - loss: 0.7084 - categorical_accuracy: 0.8862 - val_loss: 0.8915 -
val_categorical_accuracy: 0.8537
Epoch 84/500
16/16 - 0s - loss: 0.7013 - categorical accuracy: 0.8841 - val loss: 0.8899 -
val_categorical_accuracy: 0.8537
Epoch 85/500
16/16 - 0s - loss: 0.7106 - categorical accuracy: 0.8882 - val loss: 0.8853 -
val_categorical_accuracy: 0.8537
Epoch 86/500
16/16 - 0s - loss: 0.6854 - categorical accuracy: 0.8882 - val loss: 0.8847 -
val_categorical_accuracy: 0.8537
Epoch 87/500
16/16 - 0s - loss: 0.6838 - categorical accuracy: 0.8862 - val loss: 0.8837 -
val categorical accuracy: 0.8537
Epoch 88/500
16/16 - 0s - loss: 0.7031 - categorical accuracy: 0.8923 - val loss: 0.8809 -
val categorical accuracy: 0.8537
Epoch 89/500
16/16 - 0s - loss: 0.6862 - categorical accuracy: 0.8902 - val loss: 0.8757 -
val categorical accuracy: 0.8537
Epoch 90/500
16/16 - 0s - loss: 0.6892 - categorical accuracy: 0.8821 - val loss: 0.8744 -
val categorical accuracy: 0.8537
Epoch 91/500
16/16 - 0s - loss: 0.6946 - categorical accuracy: 0.8882 - val loss: 0.8736 -
val categorical accuracy: 0.8537
Epoch 92/500
16/16 - 0s - loss: 0.7057 - categorical_accuracy: 0.8862 - val_loss: 0.8729 -
val categorical accuracy: 0.8537
Epoch 93/500
16/16 - 0s - loss: 0.7054 - categorical_accuracy: 0.8862 - val_loss: 0.8689 -
val categorical accuracy: 0.8537
Epoch 94/500
16/16 - 0s - loss: 0.7039 - categorical_accuracy: 0.8862 - val_loss: 0.8683 -
val categorical accuracy: 0.8537
Epoch 95/500
16/16 - 0s - loss: 0.6918 - categorical_accuracy: 0.8882 - val_loss: 0.8669 -
val categorical accuracy: 0.8537
```

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Epoch 96/500
16/16 - 0s - loss: 0.6858 - categorical accuracy: 0.8943 - val loss: 0.8648 -
val_categorical_accuracy: 0.8537
Epoch 97/500
16/16 - 0s - loss: 0.6891 - categorical accuracy: 0.8943 - val loss: 0.8629 -
val_categorical_accuracy: 0.8537
Epoch 98/500
16/16 - 0s - loss: 0.7001 - categorical accuracy: 0.8862 - val loss: 0.8592 -
val categorical accuracy: 0.8537
Epoch 99/500
16/16 - 0s - loss: 0.6902 - categorical accuracy: 0.8902 - val loss: 0.8599 -
val_categorical_accuracy: 0.8537
Epoch 100/500
16/16 - 0s - loss: 0.6826 - categorical_accuracy: 0.8841 - val_loss: 0.8581 -
val_categorical_accuracy: 0.8537
Epoch 101/500
16/16 - 0s - loss: 0.6816 - categorical accuracy: 0.8923 - val loss: 0.8574 -
val_categorical_accuracy: 0.8618
Epoch 102/500
16/16 - 0s - loss: 0.6805 - categorical accuracy: 0.8963 - val loss: 0.8569 -
val categorical accuracy: 0.8618
Epoch 103/500
16/16 - 0s - loss: 0.6919 - categorical accuracy: 0.8902 - val loss: 0.8540 -
val_categorical_accuracy: 0.8618
Epoch 104/500
16/16 - 0s - loss: 0.6871 - categorical accuracy: 0.8841 - val loss: 0.8505 -
val_categorical_accuracy: 0.8618
Epoch 105/500
16/16 - 0s - loss: 0.6996 - categorical accuracy: 0.8821 - val loss: 0.8484 -
val_categorical_accuracy: 0.8618
Epoch 106/500
16/16 - 0s - loss: 0.6719 - categorical accuracy: 0.8984 - val loss: 0.8463 -
val categorical accuracy: 0.8618
Epoch 107/500
16/16 - 0s - loss: 0.6858 - categorical accuracy: 0.8943 - val loss: 0.8439 -
val categorical accuracy: 0.8618
Epoch 108/500
16/16 - 0s - loss: 0.6770 - categorical accuracy: 0.8963 - val loss: 0.8410 -
val categorical accuracy: 0.8618
Epoch 109/500
16/16 - 0s - loss: 0.6929 - categorical accuracy: 0.8882 - val loss: 0.8342 -
val categorical accuracy: 0.8618
Epoch 110/500
16/16 - 0s - loss: 0.6845 - categorical accuracy: 0.8963 - val loss: 0.8330 -
val categorical accuracy: 0.8618
Epoch 111/500
16/16 - 0s - loss: 0.6749 - categorical_accuracy: 0.8963 - val_loss: 0.8318 -
val categorical accuracy: 0.8618
Epoch 112/500
16/16 - 0s - loss: 0.6935 - categorical_accuracy: 0.8882 - val_loss: 0.8324 -
val categorical accuracy: 0.8618
Epoch 113/500
16/16 - 0s - loss: 0.6741 - categorical_accuracy: 0.8963 - val_loss: 0.8323 -
val categorical accuracy: 0.8618
Epoch 114/500
16/16 - 0s - loss: 0.6893 - categorical_accuracy: 0.8963 - val_loss: 0.8304 -
val categorical accuracy: 0.8618
```

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Epoch 115/500
16/16 - 0s - loss: 0.6826 - categorical accuracy: 0.8923 - val loss: 0.8292 -
val_categorical_accuracy: 0.8618
Epoch 116/500
16/16 - 0s - loss: 0.6677 - categorical accuracy: 0.9004 - val loss: 0.8252 -
val_categorical_accuracy: 0.8618
Epoch 117/500
16/16 - 0s - loss: 0.6722 - categorical accuracy: 0.8923 - val loss: 0.8224 -
val categorical accuracy: 0.8618
Epoch 118/500
16/16 - 0s - loss: 0.6732 - categorical accuracy: 0.8943 - val loss: 0.8095 -
val_categorical_accuracy: 0.8618
Epoch 119/500
16/16 - 0s - loss: 0.6740 - categorical_accuracy: 0.8923 - val_loss: 0.8066 -
val_categorical_accuracy: 0.8618
Epoch 120/500
16/16 - 0s - loss: 0.6709 - categorical accuracy: 0.8963 - val loss: 0.8118 -
val_categorical_accuracy: 0.8618
Epoch 121/500
16/16 - 0s - loss: 0.6675 - categorical accuracy: 0.8984 - val loss: 0.8105 -
val categorical accuracy: 0.8618
Epoch 122/500
16/16 - 0s - loss: 0.6640 - categorical accuracy: 0.8943 - val loss: 0.8105 -
val_categorical_accuracy: 0.8618
Epoch 123/500
16/16 - 0s - loss: 0.6753 - categorical accuracy: 0.8923 - val loss: 0.8038 -
val_categorical_accuracy: 0.8618
Epoch 124/500
16/16 - 0s - loss: 0.6691 - categorical accuracy: 0.8943 - val loss: 0.7984 -
val_categorical_accuracy: 0.8618
Epoch 125/500
16/16 - 0s - loss: 0.6679 - categorical accuracy: 0.8963 - val loss: 0.7879 -
val categorical accuracy: 0.8618
Epoch 126/500
16/16 - 0s - loss: 0.6939 - categorical accuracy: 0.8862 - val loss: 0.7853 -
val categorical accuracy: 0.8618
Epoch 127/500
16/16 - 0s - loss: 0.6658 - categorical accuracy: 0.8984 - val loss: 0.7842 -
val categorical accuracy: 0.8618
Epoch 128/500
16/16 - 0s - loss: 0.6715 - categorical accuracy: 0.8923 - val loss: 0.7820 -
val categorical accuracy: 0.8618
Epoch 129/500
16/16 - 0s - loss: 0.6643 - categorical accuracy: 0.8984 - val loss: 0.7822 -
val categorical accuracy: 0.8618
Epoch 130/500
16/16 - 0s - loss: 0.6686 - categorical_accuracy: 0.9024 - val_loss: 0.7773 -
val categorical accuracy: 0.8618
Epoch 131/500
16/16 - 0s - loss: 0.6734 - categorical_accuracy: 0.8984 - val_loss: 0.7763 -
val categorical accuracy: 0.8618
Epoch 132/500
16/16 - 0s - loss: 0.6790 - categorical_accuracy: 0.8902 - val_loss: 0.7680 -
val categorical accuracy: 0.8618
Epoch 133/500
16/16 - 0s - loss: 0.6695 - categorical_accuracy: 0.8841 - val_loss: 0.7637 -
val categorical accuracy: 0.8618
```

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Epoch 134/500
16/16 - 0s - loss: 0.6487 - categorical_accuracy: 0.9024 - val_loss: 0.7631 -
val_categorical_accuracy: 0.8618
Epoch 135/500
16/16 - 0s - loss: 0.6565 - categorical accuracy: 0.9024 - val loss: 0.7635 -
val_categorical_accuracy: 0.8618
Epoch 136/500
16/16 - 0s - loss: 0.6597 - categorical accuracy: 0.8984 - val loss: 0.7631 -
val categorical accuracy: 0.8618
Epoch 137/500
16/16 - 0s - loss: 0.6836 - categorical accuracy: 0.8923 - val loss: 0.7599 -
val_categorical_accuracy: 0.8618
Epoch 138/500
16/16 - 0s - loss: 0.6720 - categorical_accuracy: 0.8923 - val_loss: 0.7574 -
val_categorical_accuracy: 0.8618
Epoch 139/500
16/16 - 0s - loss: 0.6822 - categorical accuracy: 0.8882 - val loss: 0.7475 -
val_categorical_accuracy: 0.8618
Epoch 140/500
16/16 - 0s - loss: 0.6787 - categorical accuracy: 0.8923 - val loss: 0.7442 -
val categorical accuracy: 0.8618
Epoch 141/500
16/16 - 0s - loss: 0.6638 - categorical accuracy: 0.8963 - val loss: 0.7436 -
val_categorical_accuracy: 0.8618
Epoch 142/500
16/16 - 0s - loss: 0.6695 - categorical accuracy: 0.8902 - val loss: 0.7354 -
val_categorical_accuracy: 0.8618
Epoch 143/500
16/16 - 0s - loss: 0.6668 - categorical accuracy: 0.8902 - val loss: 0.7307 -
val_categorical_accuracy: 0.8618
Epoch 144/500
16/16 - 0s - loss: 0.6781 - categorical accuracy: 0.8862 - val loss: 0.7250 -
val categorical accuracy: 0.8618
Epoch 145/500
16/16 - 0s - loss: 0.6525 - categorical accuracy: 0.8984 - val loss: 0.7219 -
val categorical accuracy: 0.8618
Epoch 146/500
16/16 - 0s - loss: 0.6655 - categorical accuracy: 0.8984 - val loss: 0.7210 -
val categorical accuracy: 0.8618
Epoch 147/500
16/16 - 0s - loss: 0.6652 - categorical accuracy: 0.8923 - val loss: 0.7211 -
val categorical accuracy: 0.8618
Epoch 148/500
16/16 - 0s - loss: 0.6650 - categorical accuracy: 0.8902 - val loss: 0.7189 -
val categorical accuracy: 0.8618
Epoch 149/500
16/16 - 0s - loss: 0.6598 - categorical_accuracy: 0.8943 - val_loss: 0.7159 -
val categorical accuracy: 0.8618
Epoch 150/500
16/16 - 0s - loss: 0.6777 - categorical_accuracy: 0.8902 - val_loss: 0.7152 -
val categorical accuracy: 0.8618
Epoch 151/500
16/16 - 0s - loss: 0.6598 - categorical_accuracy: 0.8984 - val_loss: 0.7069 -
val categorical accuracy: 0.8618
Epoch 152/500
16/16 - 0s - loss: 0.6643 - categorical_accuracy: 0.8963 - val_loss: 0.7061 -
val categorical accuracy: 0.8618
```

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Epoch 153/500
16/16 - 0s - loss: 0.6507 - categorical_accuracy: 0.8923 - val_loss: 0.7058 -
val_categorical_accuracy: 0.8618
Epoch 154/500
16/16 - 0s - loss: 0.6715 - categorical accuracy: 0.8902 - val loss: 0.7004 -
val_categorical_accuracy: 0.8618
Epoch 155/500
16/16 - 0s - loss: 0.6489 - categorical accuracy: 0.9024 - val loss: 0.6948 -
val categorical accuracy: 0.8618
Epoch 156/500
16/16 - 0s - loss: 0.6658 - categorical accuracy: 0.9024 - val loss: 0.6937 -
val_categorical_accuracy: 0.8618
Epoch 157/500
16/16 - 0s - loss: 0.6630 - categorical_accuracy: 0.8943 - val_loss: 0.6930 -
val_categorical_accuracy: 0.8618
Epoch 158/500
16/16 - 0s - loss: 0.6535 - categorical accuracy: 0.8963 - val loss: 0.6871 -
val_categorical_accuracy: 0.8618
Epoch 159/500
16/16 - 0s - loss: 0.6541 - categorical accuracy: 0.9004 - val loss: 0.6866 -
val categorical accuracy: 0.8618
Epoch 160/500
16/16 - 0s - loss: 0.6531 - categorical accuracy: 0.8923 - val loss: 0.6887 -
val_categorical_accuracy: 0.8618
Epoch 161/500
16/16 - 0s - loss: 0.6590 - categorical accuracy: 0.8963 - val loss: 0.6883 -
val_categorical_accuracy: 0.8618
Epoch 162/500
16/16 - 0s - loss: 0.6474 - categorical accuracy: 0.9004 - val loss: 0.6879 -
val_categorical_accuracy: 0.8618
Epoch 163/500
16/16 - 0s - loss: 0.6531 - categorical accuracy: 0.9004 - val loss: 0.6831 -
val categorical accuracy: 0.8618
Epoch 164/500
16/16 - 0s - loss: 0.6522 - categorical accuracy: 0.8984 - val loss: 0.6838 -
val categorical accuracy: 0.8618
Epoch 165/500
16/16 - 0s - loss: 0.6548 - categorical accuracy: 0.8943 - val loss: 0.6823 -
val categorical accuracy: 0.8618
Epoch 166/500
16/16 - 0s - loss: 0.6606 - categorical accuracy: 0.8902 - val loss: 0.6809 -
val categorical accuracy: 0.8618
Epoch 167/500
16/16 - 0s - loss: 0.6469 - categorical accuracy: 0.9024 - val loss: 0.6788 -
val categorical accuracy: 0.8699
Epoch 168/500
16/16 - 0s - loss: 0.6445 - categorical_accuracy: 0.8963 - val_loss: 0.6793 -
val categorical accuracy: 0.8618
Epoch 169/500
16/16 - 0s - loss: 0.6502 - categorical_accuracy: 0.8963 - val_loss: 0.6797 -
val categorical accuracy: 0.8618
Epoch 170/500
16/16 - 0s - loss: 0.6718 - categorical_accuracy: 0.8902 - val_loss: 0.6796 -
val categorical accuracy: 0.8618
Epoch 171/500
16/16 - 0s - loss: 0.6694 - categorical_accuracy: 0.8882 - val_loss: 0.6782 -
val categorical accuracy: 0.8618
```

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Epoch 172/500
16/16 - 0s - loss: 0.6420 - categorical accuracy: 0.8963 - val loss: 0.6768 -
val_categorical_accuracy: 0.8699
Epoch 173/500
16/16 - 0s - loss: 0.6409 - categorical accuracy: 0.9024 - val loss: 0.6746 -
val_categorical_accuracy: 0.8699
Epoch 174/500
16/16 - 0s - loss: 0.6491 - categorical accuracy: 0.9024 - val loss: 0.6718 -
val categorical accuracy: 0.8699
Epoch 175/500
16/16 - 0s - loss: 0.6236 - categorical accuracy: 0.9024 - val loss: 0.6698 -
val_categorical_accuracy: 0.8699
Epoch 176/500
16/16 - 0s - loss: 0.6599 - categorical_accuracy: 0.8923 - val_loss: 0.6683 -
val_categorical_accuracy: 0.8618
Epoch 177/500
16/16 - 0s - loss: 0.6451 - categorical accuracy: 0.8984 - val loss: 0.6652 -
val_categorical_accuracy: 0.8699
Epoch 178/500
16/16 - 0s - loss: 0.6454 - categorical accuracy: 0.8963 - val loss: 0.6636 -
val categorical accuracy: 0.8780
Epoch 179/500
16/16 - 0s - loss: 0.6461 - categorical accuracy: 0.8963 - val loss: 0.6629 -
val categorical accuracy: 0.8780
Epoch 180/500
16/16 - 0s - loss: 0.6318 - categorical accuracy: 0.9085 - val loss: 0.6628 -
val_categorical_accuracy: 0.8780
Epoch 181/500
16/16 - 0s - loss: 0.6577 - categorical accuracy: 0.8923 - val loss: 0.6630 -
val_categorical_accuracy: 0.8780
Epoch 182/500
16/16 - 0s - loss: 0.6565 - categorical accuracy: 0.8923 - val loss: 0.6617 -
val categorical accuracy: 0.8780
Epoch 183/500
16/16 - 0s - loss: 0.6600 - categorical accuracy: 0.8862 - val loss: 0.6612 -
val categorical accuracy: 0.8780
Epoch 184/500
16/16 - 0s - loss: 0.6437 - categorical_accuracy: 0.9065 - val_loss: 0.6605 -
val categorical accuracy: 0.8780
Epoch 185/500
16/16 - 0s - loss: 0.6505 - categorical accuracy: 0.9004 - val loss: 0.6603 -
val categorical accuracy: 0.8780
Epoch 186/500
16/16 - 0s - loss: 0.6501 - categorical accuracy: 0.8923 - val loss: 0.6592 -
val categorical accuracy: 0.8780
Epoch 187/500
16/16 - 0s - loss: 0.6353 - categorical_accuracy: 0.9024 - val_loss: 0.6588 -
val categorical accuracy: 0.8780
Epoch 188/500
16/16 - 0s - loss: 0.6568 - categorical_accuracy: 0.8943 - val_loss: 0.6584 -
val categorical accuracy: 0.8780
Epoch 189/500
16/16 - 0s - loss: 0.6634 - categorical_accuracy: 0.8963 - val_loss: 0.6586 -
val categorical accuracy: 0.8780
Epoch 190/500
16/16 - 0s - loss: 0.6243 - categorical_accuracy: 0.8984 - val_loss: 0.6578 -
val categorical accuracy: 0.8780
```

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Epoch 191/500
16/16 - 0s - loss: 0.6396 - categorical accuracy: 0.9004 - val loss: 0.6571 -
val_categorical_accuracy: 0.8780
Epoch 192/500
16/16 - 0s - loss: 0.6536 - categorical accuracy: 0.8963 - val loss: 0.6568 -
val_categorical_accuracy: 0.8780
Epoch 193/500
16/16 - 0s - loss: 0.6592 - categorical accuracy: 0.8882 - val loss: 0.6562 -
val categorical accuracy: 0.8780
Epoch 194/500
16/16 - 0s - loss: 0.6420 - categorical accuracy: 0.9045 - val loss: 0.6559 -
val_categorical_accuracy: 0.8780
Epoch 195/500
16/16 - 0s - loss: 0.6559 - categorical_accuracy: 0.8943 - val_loss: 0.6553 -
val_categorical_accuracy: 0.8780
Epoch 196/500
16/16 - 0s - loss: 0.6502 - categorical accuracy: 0.8923 - val loss: 0.6552 -
val_categorical_accuracy: 0.8780
Epoch 197/500
16/16 - 0s - loss: 0.6658 - categorical accuracy: 0.8923 - val loss: 0.6553 -
val categorical accuracy: 0.8780
Epoch 198/500
16/16 - 0s - loss: 0.6552 - categorical accuracy: 0.8984 - val loss: 0.6548 -
val_categorical_accuracy: 0.8780
Epoch 199/500
16/16 - 0s - loss: 0.6294 - categorical accuracy: 0.9024 - val loss: 0.6541 -
val_categorical_accuracy: 0.8780
Epoch 200/500
16/16 - 0s - loss: 0.6421 - categorical accuracy: 0.8943 - val loss: 0.6537 -
val_categorical_accuracy: 0.8780
Epoch 201/500
16/16 - 0s - loss: 0.6414 - categorical accuracy: 0.9024 - val loss: 0.6535 -
val categorical accuracy: 0.8780
Epoch 202/500
16/16 - 0s - loss: 0.6513 - categorical accuracy: 0.8963 - val loss: 0.6535 -
val categorical accuracy: 0.8780
Epoch 203/500
16/16 - 0s - loss: 0.6642 - categorical accuracy: 0.8882 - val loss: 0.6533 -
val categorical accuracy: 0.8780
Epoch 204/500
16/16 - 0s - loss: 0.6276 - categorical accuracy: 0.9024 - val loss: 0.6529 -
val categorical accuracy: 0.8780
Epoch 205/500
16/16 - 0s - loss: 0.6474 - categorical accuracy: 0.9004 - val loss: 0.6525 -
val categorical accuracy: 0.8780
Epoch 206/500
16/16 - 0s - loss: 0.6466 - categorical_accuracy: 0.8963 - val_loss: 0.6520 -
val categorical accuracy: 0.8780
Epoch 207/500
16/16 - 0s - loss: 0.6313 - categorical_accuracy: 0.9085 - val_loss: 0.6518 -
val categorical accuracy: 0.8780
Epoch 208/500
16/16 - 0s - loss: 0.6485 - categorical_accuracy: 0.8923 - val_loss: 0.6514 -
val categorical accuracy: 0.8780
Epoch 209/500
16/16 - 0s - loss: 0.6681 - categorical_accuracy: 0.8923 - val_loss: 0.6513 -
val categorical accuracy: 0.8780
```

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Epoch 210/500
16/16 - 0s - loss: 0.6408 - categorical accuracy: 0.8984 - val loss: 0.6509 -
val_categorical_accuracy: 0.8780
Epoch 211/500
16/16 - 0s - loss: 0.6454 - categorical accuracy: 0.8963 - val loss: 0.6508 -
val_categorical_accuracy: 0.8780
Epoch 212/500
16/16 - 0s - loss: 0.6335 - categorical accuracy: 0.8984 - val loss: 0.6506 -
val categorical accuracy: 0.8780
Epoch 213/500
16/16 - 0s - loss: 0.6202 - categorical accuracy: 0.8984 - val loss: 0.6501 -
val_categorical_accuracy: 0.8780
Epoch 214/500
16/16 - 0s - loss: 0.6464 - categorical_accuracy: 0.8882 - val_loss: 0.6499 -
val_categorical_accuracy: 0.8780
Epoch 215/500
16/16 - 0s - loss: 0.6515 - categorical accuracy: 0.8963 - val loss: 0.6500 -
val_categorical_accuracy: 0.8780
Epoch 216/500
16/16 - 0s - loss: 0.6292 - categorical accuracy: 0.8963 - val loss: 0.6495 -
val categorical accuracy: 0.8780
Epoch 217/500
16/16 - 0s - loss: 0.6458 - categorical accuracy: 0.8984 - val loss: 0.6492 -
val_categorical_accuracy: 0.8780
Epoch 218/500
16/16 - 0s - loss: 0.6127 - categorical accuracy: 0.9065 - val loss: 0.6487 -
val_categorical_accuracy: 0.8780
Epoch 219/500
16/16 - 0s - loss: 0.6458 - categorical accuracy: 0.8984 - val loss: 0.6486 -
val_categorical_accuracy: 0.8780
Epoch 220/500
16/16 - 0s - loss: 0.6401 - categorical accuracy: 0.8943 - val loss: 0.6483 -
val categorical accuracy: 0.8780
Epoch 221/500
16/16 - 0s - loss: 0.6174 - categorical accuracy: 0.9065 - val loss: 0.6479 -
val categorical accuracy: 0.8780
Epoch 222/500
16/16 - 0s - loss: 0.6389 - categorical accuracy: 0.9065 - val loss: 0.6477 -
val categorical accuracy: 0.8780
Epoch 223/500
16/16 - 0s - loss: 0.6216 - categorical accuracy: 0.9065 - val loss: 0.6478 -
val categorical accuracy: 0.8780
Epoch 224/500
16/16 - 0s - loss: 0.6419 - categorical accuracy: 0.8943 - val loss: 0.6473 -
val categorical accuracy: 0.8862
Epoch 225/500
16/16 - 0s - loss: 0.6280 - categorical_accuracy: 0.8984 - val_loss: 0.6468 -
val categorical accuracy: 0.8780
Epoch 226/500
16/16 - 0s - loss: 0.6350 - categorical_accuracy: 0.8943 - val_loss: 0.6464 -
val categorical accuracy: 0.8862
Epoch 227/500
16/16 - 0s - loss: 0.6271 - categorical_accuracy: 0.9045 - val_loss: 0.6462 -
val categorical accuracy: 0.8862
Epoch 228/500
16/16 - 0s - loss: 0.6283 - categorical_accuracy: 0.9024 - val_loss: 0.6459 -
val categorical accuracy: 0.8862
```

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Epoch 229/500
16/16 - 0s - loss: 0.6276 - categorical_accuracy: 0.9004 - val_loss: 0.6453 -
val_categorical_accuracy: 0.8862
Epoch 230/500
16/16 - 0s - loss: 0.6229 - categorical accuracy: 0.9045 - val loss: 0.6449 -
val_categorical_accuracy: 0.8862
Epoch 231/500
16/16 - 0s - loss: 0.6149 - categorical accuracy: 0.9065 - val loss: 0.6447 -
val_categorical_accuracy: 0.8862
Epoch 232/500
16/16 - 0s - loss: 0.6408 - categorical accuracy: 0.9004 - val loss: 0.6447 -
val_categorical_accuracy: 0.8862
Epoch 233/500
16/16 - 0s - loss: 0.6296 - categorical_accuracy: 0.9146 - val_loss: 0.6444 -
val_categorical_accuracy: 0.8862
Epoch 234/500
16/16 - 0s - loss: 0.6298 - categorical accuracy: 0.9045 - val loss: 0.6443 -
val_categorical_accuracy: 0.8862
Epoch 235/500
16/16 - 0s - loss: 0.6435 - categorical accuracy: 0.9004 - val loss: 0.6447 -
val categorical accuracy: 0.8862
Epoch 236/500
16/16 - 0s - loss: 0.6287 - categorical accuracy: 0.9126 - val loss: 0.6446 -
val_categorical_accuracy: 0.8862
Epoch 237/500
16/16 - 0s - loss: 0.6407 - categorical accuracy: 0.8984 - val loss: 0.6442 -
val_categorical_accuracy: 0.8862
Epoch 238/500
16/16 - 0s - loss: 0.6200 - categorical accuracy: 0.9065 - val loss: 0.6437 -
val_categorical_accuracy: 0.8862
Epoch 239/500
16/16 - 0s - loss: 0.6182 - categorical accuracy: 0.9085 - val loss: 0.6432 -
val categorical accuracy: 0.8862
Epoch 240/500
16/16 - 0s - loss: 0.6219 - categorical accuracy: 0.9045 - val loss: 0.6432 -
val categorical accuracy: 0.8862
Epoch 241/500
16/16 - 0s - loss: 0.6381 - categorical accuracy: 0.9045 - val loss: 0.6431 -
val categorical accuracy: 0.8862
Epoch 242/500
16/16 - 0s - loss: 0.6324 - categorical accuracy: 0.9045 - val loss: 0.6430 -
val categorical accuracy: 0.8862
Epoch 243/500
16/16 - 0s - loss: 0.6325 - categorical accuracy: 0.8943 - val loss: 0.6431 -
val categorical accuracy: 0.8862
Epoch 244/500
16/16 - 0s - loss: 0.6283 - categorical_accuracy: 0.8984 - val_loss: 0.6429 -
val categorical accuracy: 0.8862
Epoch 245/500
16/16 - 0s - loss: 0.6339 - categorical_accuracy: 0.9045 - val_loss: 0.6428 -
val categorical accuracy: 0.8862
Epoch 246/500
16/16 - 0s - loss: 0.6486 - categorical_accuracy: 0.9024 - val_loss: 0.6423 -
val categorical accuracy: 0.8862
Epoch 247/500
16/16 - 0s - loss: 0.6361 - categorical_accuracy: 0.8984 - val_loss: 0.6424 -
val categorical accuracy: 0.8862
```

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Epoch 248/500
16/16 - 0s - loss: 0.6166 - categorical accuracy: 0.9065 - val loss: 0.6422 -
val_categorical_accuracy: 0.8862
Epoch 249/500
16/16 - 0s - loss: 0.6225 - categorical accuracy: 0.9004 - val loss: 0.6424 -
val_categorical_accuracy: 0.8862
Epoch 250/500
16/16 - 0s - loss: 0.6264 - categorical accuracy: 0.9085 - val loss: 0.6418 -
val categorical accuracy: 0.8862
Epoch 251/500
16/16 - 0s - loss: 0.6308 - categorical accuracy: 0.9065 - val loss: 0.6414 -
val_categorical_accuracy: 0.8862
Epoch 252/500
16/16 - 0s - loss: 0.6450 - categorical_accuracy: 0.9004 - val_loss: 0.6411 -
val_categorical_accuracy: 0.8862
Epoch 253/500
16/16 - 0s - loss: 0.6267 - categorical accuracy: 0.9004 - val loss: 0.6410 -
val_categorical_accuracy: 0.8862
Epoch 254/500
16/16 - 0s - loss: 0.6105 - categorical accuracy: 0.9085 - val loss: 0.6408 -
val categorical accuracy: 0.8862
Epoch 255/500
16/16 - 0s - loss: 0.6234 - categorical accuracy: 0.9045 - val loss: 0.6405 -
val_categorical_accuracy: 0.8862
Epoch 256/500
16/16 - 0s - loss: 0.6261 - categorical accuracy: 0.9045 - val loss: 0.6406 -
val_categorical_accuracy: 0.8862
Epoch 257/500
16/16 - 0s - loss: 0.6236 - categorical accuracy: 0.9106 - val loss: 0.6406 -
val_categorical_accuracy: 0.8862
Epoch 258/500
16/16 - 0s - loss: 0.6228 - categorical accuracy: 0.9146 - val loss: 0.6404 -
val categorical accuracy: 0.8862
Epoch 259/500
16/16 - 0s - loss: 0.6241 - categorical accuracy: 0.9106 - val loss: 0.6402 -
val categorical accuracy: 0.8862
Epoch 260/500
16/16 - 0s - loss: 0.6333 - categorical accuracy: 0.9065 - val loss: 0.6400 -
val categorical accuracy: 0.8862
Epoch 261/500
16/16 - 0s - loss: 0.6354 - categorical accuracy: 0.8963 - val loss: 0.6399 -
val categorical accuracy: 0.8862
Epoch 262/500
16/16 - 0s - loss: 0.6348 - categorical accuracy: 0.8963 - val loss: 0.6396 -
val categorical accuracy: 0.8862
Epoch 263/500
16/16 - 0s - loss: 0.6388 - categorical_accuracy: 0.9024 - val_loss: 0.6395 -
val categorical accuracy: 0.8862
Epoch 264/500
16/16 - 0s - loss: 0.6162 - categorical_accuracy: 0.9085 - val_loss: 0.6393 -
val categorical accuracy: 0.8862
Epoch 265/500
16/16 - 0s - loss: 0.6267 - categorical_accuracy: 0.9065 - val_loss: 0.6392 -
val categorical accuracy: 0.8862
Epoch 266/500
16/16 - 0s - loss: 0.6020 - categorical_accuracy: 0.9167 - val_loss: 0.6391 -
val categorical accuracy: 0.8862
```

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Epoch 267/500
16/16 - 0s - loss: 0.6257 - categorical_accuracy: 0.9085 - val_loss: 0.6390 -
val_categorical_accuracy: 0.8862
Epoch 268/500
16/16 - 0s - loss: 0.6163 - categorical accuracy: 0.9065 - val loss: 0.6387 -
val_categorical_accuracy: 0.8862
Epoch 269/500
16/16 - 0s - loss: 0.6356 - categorical accuracy: 0.8943 - val loss: 0.6388 -
val categorical accuracy: 0.8862
Epoch 270/500
16/16 - 0s - loss: 0.6150 - categorical accuracy: 0.9065 - val loss: 0.6385 -
val_categorical_accuracy: 0.8862
Epoch 271/500
16/16 - 0s - loss: 0.6299 - categorical_accuracy: 0.9024 - val_loss: 0.6383 -
val_categorical_accuracy: 0.8862
Epoch 272/500
16/16 - 0s - loss: 0.6079 - categorical accuracy: 0.9045 - val loss: 0.6382 -
val_categorical_accuracy: 0.8862
Epoch 273/500
16/16 - 0s - loss: 0.6277 - categorical accuracy: 0.9065 - val loss: 0.6378 -
val categorical accuracy: 0.8862
Epoch 274/500
16/16 - 0s - loss: 0.6131 - categorical accuracy: 0.9106 - val loss: 0.6375 -
val_categorical_accuracy: 0.8862
Epoch 275/500
16/16 - 0s - loss: 0.6135 - categorical accuracy: 0.9106 - val loss: 0.6369 -
val_categorical_accuracy: 0.8862
Epoch 276/500
16/16 - 0s - loss: 0.6235 - categorical accuracy: 0.9126 - val loss: 0.6369 -
val_categorical_accuracy: 0.8862
Epoch 277/500
16/16 - 0s - loss: 0.6279 - categorical accuracy: 0.9045 - val loss: 0.6366 -
val categorical accuracy: 0.8862
Epoch 278/500
16/16 - 0s - loss: 0.6260 - categorical accuracy: 0.9065 - val loss: 0.6363 -
val categorical accuracy: 0.8862
Epoch 279/500
16/16 - 0s - loss: 0.6150 - categorical accuracy: 0.9126 - val loss: 0.6364 -
val categorical accuracy: 0.8862
Epoch 280/500
16/16 - 0s - loss: 0.6117 - categorical accuracy: 0.9167 - val loss: 0.6361 -
val categorical accuracy: 0.8862
Epoch 281/500
16/16 - 0s - loss: 0.6202 - categorical accuracy: 0.9167 - val loss: 0.6361 -
val categorical accuracy: 0.8862
Epoch 282/500
16/16 - 0s - loss: 0.6086 - categorical_accuracy: 0.9085 - val_loss: 0.6358 -
val categorical accuracy: 0.8862
Epoch 283/500
16/16 - 0s - loss: 0.6120 - categorical_accuracy: 0.9065 - val_loss: 0.6360 -
val categorical accuracy: 0.8862
Epoch 284/500
16/16 - 0s - loss: 0.6292 - categorical_accuracy: 0.9065 - val_loss: 0.6357 -
val categorical accuracy: 0.8862
Epoch 285/500
16/16 - 0s - loss: 0.6140 - categorical_accuracy: 0.9126 - val_loss: 0.6360 -
val categorical accuracy: 0.8862
```

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Epoch 286/500
16/16 - 0s - loss: 0.5995 - categorical_accuracy: 0.9228 - val_loss: 0.6356 -
val_categorical_accuracy: 0.8862
Epoch 287/500
16/16 - 0s - loss: 0.6211 - categorical accuracy: 0.9045 - val loss: 0.6355 -
val_categorical_accuracy: 0.8862
Epoch 288/500
16/16 - 0s - loss: 0.6121 - categorical accuracy: 0.9187 - val loss: 0.6354 -
val categorical accuracy: 0.8862
Epoch 289/500
16/16 - 0s - loss: 0.6428 - categorical accuracy: 0.8963 - val loss: 0.6355 -
val_categorical_accuracy: 0.8862
Epoch 290/500
16/16 - 0s - loss: 0.6133 - categorical_accuracy: 0.9146 - val_loss: 0.6352 -
val_categorical_accuracy: 0.8862
Epoch 291/500
16/16 - 0s - loss: 0.6057 - categorical accuracy: 0.9187 - val loss: 0.6351 -
val_categorical_accuracy: 0.8862
Epoch 292/500
16/16 - 0s - loss: 0.6211 - categorical accuracy: 0.9126 - val loss: 0.6352 -
val categorical accuracy: 0.8862
Epoch 293/500
16/16 - 0s - loss: 0.6093 - categorical accuracy: 0.9065 - val loss: 0.6349 -
val_categorical_accuracy: 0.8862
Epoch 294/500
16/16 - 0s - loss: 0.6033 - categorical accuracy: 0.9228 - val loss: 0.6346 -
val_categorical_accuracy: 0.8862
Epoch 295/500
16/16 - 0s - loss: 0.6289 - categorical accuracy: 0.9004 - val loss: 0.6342 -
val_categorical_accuracy: 0.8862
Epoch 296/500
16/16 - 0s - loss: 0.5982 - categorical accuracy: 0.9085 - val loss: 0.6343 -
val categorical accuracy: 0.8862
Epoch 297/500
16/16 - 0s - loss: 0.6234 - categorical accuracy: 0.9085 - val loss: 0.6343 -
val categorical accuracy: 0.8862
Epoch 298/500
16/16 - 0s - loss: 0.6274 - categorical accuracy: 0.9085 - val loss: 0.6341 -
val categorical accuracy: 0.8862
Epoch 299/500
16/16 - 0s - loss: 0.6119 - categorical accuracy: 0.9085 - val loss: 0.6339 -
val categorical accuracy: 0.8862
Epoch 300/500
16/16 - 0s - loss: 0.6207 - categorical accuracy: 0.9065 - val loss: 0.6336 -
val categorical accuracy: 0.8862
Epoch 301/500
16/16 - 0s - loss: 0.6084 - categorical_accuracy: 0.9065 - val_loss: 0.6335 -
val categorical accuracy: 0.8862
Epoch 302/500
16/16 - 0s - loss: 0.6195 - categorical_accuracy: 0.9106 - val_loss: 0.6335 -
val categorical accuracy: 0.8862
Epoch 303/500
16/16 - 0s - loss: 0.6054 - categorical_accuracy: 0.9167 - val_loss: 0.6335 -
val categorical accuracy: 0.8862
Epoch 304/500
16/16 - 0s - loss: 0.6224 - categorical_accuracy: 0.9106 - val_loss: 0.6335 -
val categorical accuracy: 0.8862
```

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Epoch 305/500
16/16 - 0s - loss: 0.6181 - categorical accuracy: 0.9024 - val loss: 0.6333 -
val_categorical_accuracy: 0.8862
Epoch 306/500
16/16 - 0s - loss: 0.6033 - categorical accuracy: 0.9085 - val loss: 0.6331 -
val_categorical_accuracy: 0.8862
Epoch 307/500
16/16 - 0s - loss: 0.6096 - categorical accuracy: 0.9146 - val loss: 0.6329 -
val categorical accuracy: 0.8862
Epoch 308/500
16/16 - 0s - loss: 0.6232 - categorical accuracy: 0.9146 - val loss: 0.6327 -
val_categorical_accuracy: 0.8862
Epoch 309/500
16/16 - 0s - loss: 0.6053 - categorical_accuracy: 0.9167 - val_loss: 0.6327 -
val_categorical_accuracy: 0.8862
Epoch 310/500
16/16 - 0s - loss: 0.6088 - categorical accuracy: 0.9085 - val loss: 0.6326 -
val_categorical_accuracy: 0.8862
Epoch 311/500
16/16 - 0s - loss: 0.6143 - categorical accuracy: 0.9065 - val loss: 0.6325 -
val categorical accuracy: 0.8862
Epoch 312/500
16/16 - 0s - loss: 0.6210 - categorical accuracy: 0.9167 - val loss: 0.6326 -
val_categorical_accuracy: 0.8862
Epoch 313/500
16/16 - 0s - loss: 0.6182 - categorical accuracy: 0.9167 - val loss: 0.6322 -
val_categorical_accuracy: 0.8862
Epoch 314/500
16/16 - 0s - loss: 0.6084 - categorical accuracy: 0.9207 - val loss: 0.6318 -
val_categorical_accuracy: 0.8862
Epoch 315/500
16/16 - 0s - loss: 0.6130 - categorical accuracy: 0.9167 - val loss: 0.6317 -
val categorical accuracy: 0.8862
Epoch 316/500
16/16 - 0s - loss: 0.6087 - categorical accuracy: 0.9207 - val loss: 0.6314 -
val categorical accuracy: 0.8862
Epoch 317/500
16/16 - 0s - loss: 0.6305 - categorical accuracy: 0.9045 - val loss: 0.6312 -
val categorical accuracy: 0.8862
Epoch 318/500
16/16 - 0s - loss: 0.6065 - categorical accuracy: 0.9085 - val loss: 0.6308 -
val categorical accuracy: 0.8862
Epoch 319/500
16/16 - 0s - loss: 0.5965 - categorical accuracy: 0.9167 - val loss: 0.6306 -
val categorical accuracy: 0.8862
Epoch 320/500
16/16 - 0s - loss: 0.6158 - categorical_accuracy: 0.9126 - val_loss: 0.6304 -
val categorical accuracy: 0.8862
Epoch 321/500
16/16 - 0s - loss: 0.6271 - categorical_accuracy: 0.9045 - val_loss: 0.6300 -
val categorical accuracy: 0.8862
Epoch 322/500
16/16 - 0s - loss: 0.6135 - categorical_accuracy: 0.9146 - val_loss: 0.6301 -
val categorical accuracy: 0.8862
Epoch 323/500
16/16 - 0s - loss: 0.6166 - categorical_accuracy: 0.9126 - val_loss: 0.6298 -
val categorical accuracy: 0.8862
```

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Epoch 324/500
16/16 - 0s - loss: 0.6258 - categorical accuracy: 0.9085 - val loss: 0.6297 -
val categorical accuracy: 0.8862
Epoch 325/500
16/16 - 0s - loss: 0.6173 - categorical accuracy: 0.9065 - val loss: 0.6294 -
val_categorical_accuracy: 0.8862
Epoch 326/500
16/16 - 0s - loss: 0.6294 - categorical accuracy: 0.9045 - val loss: 0.6293 -
val categorical accuracy: 0.8862
Epoch 327/500
16/16 - 0s - loss: 0.6004 - categorical accuracy: 0.9228 - val loss: 0.6293 -
val_categorical_accuracy: 0.8862
Epoch 328/500
16/16 - 0s - loss: 0.6106 - categorical_accuracy: 0.9146 - val_loss: 0.6291 -
val_categorical_accuracy: 0.8862
Epoch 329/500
16/16 - 0s - loss: 0.6083 - categorical accuracy: 0.9085 - val loss: 0.6292 -
val_categorical_accuracy: 0.8862
Epoch 330/500
16/16 - 0s - loss: 0.6039 - categorical accuracy: 0.9248 - val loss: 0.6291 -
val categorical accuracy: 0.8862
Epoch 331/500
16/16 - 0s - loss: 0.6158 - categorical accuracy: 0.9106 - val loss: 0.6291 -
val_categorical_accuracy: 0.8862
Epoch 332/500
16/16 - 0s - loss: 0.5868 - categorical accuracy: 0.9248 - val loss: 0.6287 -
val_categorical_accuracy: 0.8862
Epoch 333/500
16/16 - 0s - loss: 0.6099 - categorical accuracy: 0.9187 - val loss: 0.6286 -
val_categorical_accuracy: 0.8862
Epoch 334/500
16/16 - 0s - loss: 0.6181 - categorical accuracy: 0.9045 - val loss: 0.6284 -
val categorical accuracy: 0.8862
Epoch 335/500
16/16 - 0s - loss: 0.5988 - categorical accuracy: 0.9167 - val loss: 0.6284 -
val categorical accuracy: 0.8862
Epoch 336/500
16/16 - 0s - loss: 0.5817 - categorical_accuracy: 0.9228 - val_loss: 0.6284 -
val categorical accuracy: 0.8862
Epoch 337/500
16/16 - 0s - loss: 0.6138 - categorical accuracy: 0.9106 - val loss: 0.6282 -
val categorical accuracy: 0.8862
Epoch 338/500
16/16 - 0s - loss: 0.6207 - categorical accuracy: 0.9126 - val loss: 0.6279 -
val categorical accuracy: 0.8862
Epoch 339/500
16/16 - 0s - loss: 0.5960 - categorical_accuracy: 0.9146 - val_loss: 0.6279 -
val categorical accuracy: 0.8862
Epoch 340/500
16/16 - 0s - loss: 0.6159 - categorical_accuracy: 0.9146 - val_loss: 0.6280 -
val categorical accuracy: 0.8862
Epoch 341/500
16/16 - 0s - loss: 0.6231 - categorical_accuracy: 0.9146 - val_loss: 0.6280 -
val categorical accuracy: 0.8862
Epoch 342/500
16/16 - 0s - loss: 0.6017 - categorical_accuracy: 0.9126 - val_loss: 0.6277 -
val categorical accuracy: 0.8862
```

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Epoch 343/500
16/16 - 0s - loss: 0.5921 - categorical accuracy: 0.9167 - val loss: 0.6277 -
val_categorical_accuracy: 0.8862
Epoch 344/500
16/16 - 0s - loss: 0.6063 - categorical accuracy: 0.9187 - val loss: 0.6275 -
val_categorical_accuracy: 0.8862
Epoch 345/500
16/16 - 0s - loss: 0.6388 - categorical accuracy: 0.8923 - val loss: 0.6274 -
val categorical accuracy: 0.8862
Epoch 346/500
16/16 - 0s - loss: 0.6141 - categorical accuracy: 0.9126 - val loss: 0.6273 -
val_categorical_accuracy: 0.8862
Epoch 347/500
16/16 - 0s - loss: 0.6120 - categorical_accuracy: 0.9126 - val_loss: 0.6271 -
val_categorical_accuracy: 0.8862
Epoch 348/500
16/16 - 0s - loss: 0.6195 - categorical accuracy: 0.9126 - val loss: 0.6270 -
val_categorical_accuracy: 0.8862
Epoch 349/500
16/16 - 0s - loss: 0.6251 - categorical accuracy: 0.9024 - val loss: 0.6271 -
val categorical accuracy: 0.8862
Epoch 350/500
16/16 - 0s - loss: 0.5992 - categorical accuracy: 0.9207 - val loss: 0.6267 -
val_categorical_accuracy: 0.8862
Epoch 351/500
16/16 - 0s - loss: 0.6187 - categorical accuracy: 0.9085 - val loss: 0.6267 -
val_categorical_accuracy: 0.8862
Epoch 352/500
16/16 - 0s - loss: 0.6050 - categorical accuracy: 0.9207 - val loss: 0.6265 -
val_categorical_accuracy: 0.8862
Epoch 353/500
16/16 - 0s - loss: 0.5965 - categorical accuracy: 0.9248 - val loss: 0.6265 -
val categorical accuracy: 0.8862
Epoch 354/500
16/16 - 0s - loss: 0.5989 - categorical accuracy: 0.9207 - val loss: 0.6266 -
val categorical accuracy: 0.8862
Epoch 355/500
16/16 - 0s - loss: 0.5889 - categorical accuracy: 0.9228 - val loss: 0.6264 -
val categorical accuracy: 0.8862
Epoch 356/500
16/16 - 0s - loss: 0.6285 - categorical accuracy: 0.9024 - val loss: 0.6263 -
val categorical accuracy: 0.8862
Epoch 357/500
16/16 - 0s - loss: 0.5998 - categorical accuracy: 0.9228 - val loss: 0.6261 -
val categorical accuracy: 0.8862
Epoch 358/500
16/16 - 0s - loss: 0.6104 - categorical_accuracy: 0.9106 - val_loss: 0.6260 -
val categorical accuracy: 0.8862
Epoch 359/500
16/16 - 0s - loss: 0.5890 - categorical_accuracy: 0.9268 - val_loss: 0.6258 -
val categorical accuracy: 0.8862
Epoch 360/500
16/16 - 0s - loss: 0.6044 - categorical_accuracy: 0.9106 - val_loss: 0.6256 -
val categorical accuracy: 0.8862
Epoch 361/500
16/16 - 0s - loss: 0.6252 - categorical_accuracy: 0.9065 - val_loss: 0.6257 -
val categorical accuracy: 0.8862
```

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Epoch 362/500
16/16 - 0s - loss: 0.6098 - categorical accuracy: 0.9106 - val loss: 0.6258 -
val_categorical_accuracy: 0.8862
Epoch 363/500
16/16 - 0s - loss: 0.6050 - categorical accuracy: 0.9106 - val loss: 0.6259 -
val_categorical_accuracy: 0.8862
Epoch 364/500
16/16 - 0s - loss: 0.5877 - categorical accuracy: 0.9228 - val loss: 0.6258 -
val categorical accuracy: 0.8862
Epoch 365/500
16/16 - 0s - loss: 0.6092 - categorical accuracy: 0.9106 - val loss: 0.6260 -
val_categorical_accuracy: 0.8862
Epoch 366/500
16/16 - 0s - loss: 0.5972 - categorical_accuracy: 0.9228 - val_loss: 0.6257 -
val_categorical_accuracy: 0.8862
Epoch 367/500
16/16 - 0s - loss: 0.5925 - categorical accuracy: 0.9207 - val loss: 0.6255 -
val_categorical_accuracy: 0.8862
Epoch 368/500
16/16 - 0s - loss: 0.6123 - categorical accuracy: 0.9187 - val loss: 0.6254 -
val categorical accuracy: 0.8862
Epoch 369/500
16/16 - 0s - loss: 0.5913 - categorical accuracy: 0.9228 - val loss: 0.6251 -
val_categorical_accuracy: 0.8862
Epoch 370/500
16/16 - 0s - loss: 0.5913 - categorical accuracy: 0.9248 - val loss: 0.6247 -
val_categorical_accuracy: 0.8862
Epoch 371/500
16/16 - 0s - loss: 0.5934 - categorical accuracy: 0.9167 - val loss: 0.6242 -
val_categorical_accuracy: 0.8862
Epoch 372/500
16/16 - 0s - loss: 0.6030 - categorical accuracy: 0.9187 - val loss: 0.6239 -
val categorical accuracy: 0.8862
Epoch 373/500
16/16 - 0s - loss: 0.6028 - categorical accuracy: 0.9289 - val loss: 0.6241 -
val categorical accuracy: 0.8862
Epoch 374/500
16/16 - 0s - loss: 0.6174 - categorical accuracy: 0.9065 - val loss: 0.6238 -
val categorical accuracy: 0.8862
Epoch 375/500
16/16 - 0s - loss: 0.6018 - categorical accuracy: 0.9187 - val loss: 0.6237 -
val categorical accuracy: 0.8862
Epoch 376/500
16/16 - 0s - loss: 0.5962 - categorical accuracy: 0.9146 - val loss: 0.6239 -
val categorical accuracy: 0.8862
Epoch 377/500
16/16 - 0s - loss: 0.5954 - categorical_accuracy: 0.9167 - val_loss: 0.6233 -
val categorical accuracy: 0.8862
Epoch 378/500
16/16 - 0s - loss: 0.6076 - categorical_accuracy: 0.9106 - val_loss: 0.6230 -
val categorical accuracy: 0.8862
Epoch 379/500
16/16 - 0s - loss: 0.6006 - categorical_accuracy: 0.9126 - val_loss: 0.6232 -
val categorical accuracy: 0.8862
Epoch 380/500
16/16 - 0s - loss: 0.6045 - categorical_accuracy: 0.9065 - val_loss: 0.6233 -
val categorical accuracy: 0.8862
```

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Epoch 381/500
16/16 - 0s - loss: 0.5806 - categorical accuracy: 0.9228 - val loss: 0.6230 -
val_categorical_accuracy: 0.8862
Epoch 382/500
16/16 - 0s - loss: 0.6352 - categorical accuracy: 0.9024 - val loss: 0.6233 -
val_categorical_accuracy: 0.8862
Epoch 383/500
16/16 - 0s - loss: 0.5827 - categorical accuracy: 0.9268 - val loss: 0.6233 -
val_categorical_accuracy: 0.8862
Epoch 384/500
16/16 - 0s - loss: 0.5977 - categorical accuracy: 0.9228 - val loss: 0.6231 -
val_categorical_accuracy: 0.8862
Epoch 385/500
16/16 - 0s - loss: 0.6130 - categorical_accuracy: 0.9045 - val_loss: 0.6230 -
val_categorical_accuracy: 0.8862
Epoch 386/500
16/16 - 0s - loss: 0.5822 - categorical accuracy: 0.9248 - val loss: 0.6229 -
val_categorical_accuracy: 0.8862
Epoch 387/500
16/16 - 0s - loss: 0.6001 - categorical accuracy: 0.9126 - val loss: 0.6230 -
val categorical accuracy: 0.8862
Epoch 388/500
16/16 - 0s - loss: 0.6099 - categorical accuracy: 0.9065 - val loss: 0.6230 -
val_categorical_accuracy: 0.8862
Epoch 389/500
16/16 - 0s - loss: 0.5892 - categorical accuracy: 0.9207 - val loss: 0.6227 -
val_categorical_accuracy: 0.8862
Epoch 390/500
16/16 - 0s - loss: 0.6046 - categorical accuracy: 0.9126 - val loss: 0.6227 -
val_categorical_accuracy: 0.8862
Epoch 391/500
16/16 - 0s - loss: 0.6001 - categorical accuracy: 0.9146 - val loss: 0.6227 -
val categorical accuracy: 0.8862
Epoch 392/500
16/16 - 0s - loss: 0.5871 - categorical accuracy: 0.9207 - val loss: 0.6226 -
val categorical accuracy: 0.8862
Epoch 393/500
16/16 - 0s - loss: 0.5944 - categorical accuracy: 0.9106 - val loss: 0.6225 -
val categorical accuracy: 0.8862
Epoch 394/500
16/16 - 0s - loss: 0.5886 - categorical accuracy: 0.9289 - val loss: 0.6222 -
val categorical accuracy: 0.8862
Epoch 395/500
16/16 - 0s - loss: 0.6066 - categorical accuracy: 0.9146 - val loss: 0.6222 -
val categorical accuracy: 0.8862
Epoch 396/500
16/16 - 0s - loss: 0.6061 - categorical_accuracy: 0.9146 - val_loss: 0.6225 -
val categorical accuracy: 0.8862
Epoch 397/500
16/16 - 0s - loss: 0.5853 - categorical_accuracy: 0.9228 - val_loss: 0.6227 -
val categorical accuracy: 0.8862
Epoch 398/500
16/16 - 0s - loss: 0.6008 - categorical_accuracy: 0.9207 - val_loss: 0.6229 -
val categorical accuracy: 0.8862
Epoch 399/500
16/16 - 0s - loss: 0.6154 - categorical_accuracy: 0.9167 - val_loss: 0.6227 -
val categorical accuracy: 0.8862
```

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Epoch 400/500
16/16 - 0s - loss: 0.5979 - categorical accuracy: 0.9126 - val loss: 0.6225 -
val_categorical_accuracy: 0.8862
Epoch 401/500
16/16 - 0s - loss: 0.5970 - categorical accuracy: 0.9126 - val loss: 0.6224 -
val_categorical_accuracy: 0.8862
Epoch 402/500
16/16 - 0s - loss: 0.6034 - categorical accuracy: 0.9146 - val loss: 0.6223 -
val categorical accuracy: 0.8862
Epoch 403/500
16/16 - 0s - loss: 0.6258 - categorical accuracy: 0.9024 - val loss: 0.6222 -
val_categorical_accuracy: 0.8862
Epoch 404/500
16/16 - 0s - loss: 0.5866 - categorical_accuracy: 0.9228 - val_loss: 0.6219 -
val_categorical_accuracy: 0.8862
Epoch 405/500
16/16 - 0s - loss: 0.5859 - categorical accuracy: 0.9146 - val loss: 0.6220 -
val_categorical_accuracy: 0.8862
Epoch 406/500
16/16 - 0s - loss: 0.5783 - categorical accuracy: 0.9268 - val loss: 0.6219 -
val categorical accuracy: 0.8862
Epoch 407/500
16/16 - 0s - loss: 0.5869 - categorical accuracy: 0.9207 - val loss: 0.6216 -
val_categorical_accuracy: 0.8862
Epoch 408/500
16/16 - 0s - loss: 0.5842 - categorical accuracy: 0.9207 - val loss: 0.6214 -
val_categorical_accuracy: 0.8862
Epoch 409/500
16/16 - 0s - loss: 0.6098 - categorical accuracy: 0.9187 - val loss: 0.6214 -
val_categorical_accuracy: 0.8862
Epoch 410/500
16/16 - 0s - loss: 0.6099 - categorical accuracy: 0.9085 - val loss: 0.6214 -
val categorical accuracy: 0.8862
Epoch 411/500
16/16 - 0s - loss: 0.5966 - categorical accuracy: 0.9146 - val loss: 0.6214 -
val categorical accuracy: 0.8862
Epoch 412/500
16/16 - 0s - loss: 0.5918 - categorical accuracy: 0.9248 - val loss: 0.6213 -
val categorical accuracy: 0.8862
Epoch 413/500
16/16 - 0s - loss: 0.6065 - categorical accuracy: 0.9085 - val loss: 0.6212 -
val categorical accuracy: 0.8862
Epoch 414/500
16/16 - 0s - loss: 0.5986 - categorical accuracy: 0.9187 - val loss: 0.6211 -
val categorical accuracy: 0.8862
Epoch 415/500
16/16 - 0s - loss: 0.6075 - categorical_accuracy: 0.9187 - val_loss: 0.6209 -
val categorical accuracy: 0.8862
Epoch 416/500
16/16 - 0s - loss: 0.5914 - categorical_accuracy: 0.9187 - val_loss: 0.6208 -
val categorical accuracy: 0.8862
Epoch 417/500
16/16 - 0s - loss: 0.6088 - categorical_accuracy: 0.9187 - val_loss: 0.6210 -
val categorical accuracy: 0.8862
Epoch 418/500
16/16 - 0s - loss: 0.5819 - categorical_accuracy: 0.9146 - val_loss: 0.6206 -
val categorical accuracy: 0.8862
```

```
Epoch 419/500
16/16 - 0s - loss: 0.5867 - categorical_accuracy: 0.9309 - val_loss: 0.6202 -
val_categorical_accuracy: 0.8862
Epoch 420/500
16/16 - 0s - loss: 0.6183 - categorical accuracy: 0.9045 - val loss: 0.6202 -
val_categorical_accuracy: 0.8862
Epoch 421/500
16/16 - 0s - loss: 0.6030 - categorical accuracy: 0.9167 - val loss: 0.6199 -
val categorical accuracy: 0.8862
Epoch 422/500
16/16 - 0s - loss: 0.5824 - categorical accuracy: 0.9207 - val loss: 0.6198 -
val_categorical_accuracy: 0.8862
Epoch 423/500
16/16 - 0s - loss: 0.6017 - categorical_accuracy: 0.9187 - val_loss: 0.6195 -
val_categorical_accuracy: 0.8862
Epoch 424/500
16/16 - 0s - loss: 0.5881 - categorical accuracy: 0.9268 - val loss: 0.6193 -
val_categorical_accuracy: 0.8862
Epoch 425/500
16/16 - 0s - loss: 0.6084 - categorical accuracy: 0.9167 - val loss: 0.6191 -
val categorical accuracy: 0.8862
Epoch 426/500
16/16 - 0s - loss: 0.6179 - categorical accuracy: 0.9146 - val loss: 0.6191 -
val_categorical_accuracy: 0.8862
Epoch 427/500
16/16 - 0s - loss: 0.5888 - categorical accuracy: 0.9167 - val loss: 0.6190 -
val_categorical_accuracy: 0.8862
Epoch 428/500
16/16 - 0s - loss: 0.6115 - categorical accuracy: 0.9126 - val loss: 0.6191 -
val_categorical_accuracy: 0.8862
Epoch 429/500
16/16 - 0s - loss: 0.5782 - categorical accuracy: 0.9228 - val loss: 0.6189 -
val categorical accuracy: 0.8862
Epoch 430/500
16/16 - 0s - loss: 0.5949 - categorical accuracy: 0.9207 - val loss: 0.6187 -
val categorical accuracy: 0.8862
Epoch 431/500
16/16 - 0s - loss: 0.5829 - categorical accuracy: 0.9329 - val loss: 0.6185 -
val categorical accuracy: 0.8862
Epoch 432/500
16/16 - 0s - loss: 0.6079 - categorical accuracy: 0.9146 - val loss: 0.6185 -
val categorical accuracy: 0.8862
Epoch 433/500
16/16 - 0s - loss: 0.6008 - categorical accuracy: 0.9207 - val loss: 0.6184 -
val categorical accuracy: 0.8862
Epoch 434/500
16/16 - 0s - loss: 0.5758 - categorical_accuracy: 0.9248 - val_loss: 0.6182 -
val categorical accuracy: 0.8862
Epoch 435/500
16/16 - 0s - loss: 0.5939 - categorical_accuracy: 0.9207 - val_loss: 0.6180 -
val categorical accuracy: 0.8862
Epoch 436/500
16/16 - 0s - loss: 0.5730 - categorical_accuracy: 0.9309 - val_loss: 0.6177 -
val categorical accuracy: 0.8862
Epoch 437/500
16/16 - 0s - loss: 0.5926 - categorical_accuracy: 0.9167 - val_loss: 0.6177 -
val categorical accuracy: 0.8862
```

```
Epoch 438/500
16/16 - 0s - loss: 0.5869 - categorical accuracy: 0.9146 - val loss: 0.6178 -
val_categorical_accuracy: 0.8862
Epoch 439/500
16/16 - 0s - loss: 0.5947 - categorical accuracy: 0.9146 - val loss: 0.6177 -
val_categorical_accuracy: 0.8862
Epoch 440/500
16/16 - 0s - loss: 0.6063 - categorical accuracy: 0.9126 - val loss: 0.6177 -
val categorical accuracy: 0.8862
Epoch 441/500
16/16 - 0s - loss: 0.5944 - categorical accuracy: 0.9146 - val loss: 0.6174 -
val_categorical_accuracy: 0.8862
Epoch 442/500
16/16 - 0s - loss: 0.6046 - categorical_accuracy: 0.9207 - val_loss: 0.6172 -
val_categorical_accuracy: 0.8862
Epoch 443/500
16/16 - 0s - loss: 0.6084 - categorical accuracy: 0.9106 - val loss: 0.6172 -
val_categorical_accuracy: 0.8862
Epoch 444/500
16/16 - 0s - loss: 0.6031 - categorical accuracy: 0.9045 - val loss: 0.6171 -
val categorical accuracy: 0.8862
Epoch 445/500
16/16 - 0s - loss: 0.5955 - categorical accuracy: 0.9187 - val loss: 0.6170 -
val categorical accuracy: 0.8943
Epoch 446/500
16/16 - 0s - loss: 0.6194 - categorical accuracy: 0.9106 - val loss: 0.6169 -
val_categorical_accuracy: 0.8862
Epoch 447/500
16/16 - 0s - loss: 0.6019 - categorical accuracy: 0.9187 - val loss: 0.6170 -
val_categorical_accuracy: 0.8862
Epoch 448/500
16/16 - 0s - loss: 0.5936 - categorical accuracy: 0.9268 - val loss: 0.6170 -
val categorical accuracy: 0.8862
Epoch 449/500
16/16 - 0s - loss: 0.6010 - categorical accuracy: 0.9207 - val loss: 0.6169 -
val categorical accuracy: 0.8862
Epoch 450/500
16/16 - 0s - loss: 0.5952 - categorical accuracy: 0.9207 - val loss: 0.6167 -
val categorical accuracy: 0.8862
Epoch 451/500
16/16 - 0s - loss: 0.5818 - categorical accuracy: 0.9207 - val loss: 0.6164 -
val categorical accuracy: 0.8862
Epoch 452/500
16/16 - 0s - loss: 0.5834 - categorical accuracy: 0.9207 - val loss: 0.6160 -
val categorical accuracy: 0.8862
Epoch 453/500
16/16 - 0s - loss: 0.5947 - categorical_accuracy: 0.9248 - val_loss: 0.6159 -
val categorical accuracy: 0.8862
Epoch 454/500
16/16 - 0s - loss: 0.6006 - categorical_accuracy: 0.9167 - val_loss: 0.6161 -
val categorical accuracy: 0.8862
Epoch 455/500
16/16 - 0s - loss: 0.5986 - categorical_accuracy: 0.9187 - val_loss: 0.6161 -
val categorical accuracy: 0.8862
Epoch 456/500
16/16 - 0s - loss: 0.5949 - categorical_accuracy: 0.9187 - val_loss: 0.6159 -
val categorical accuracy: 0.8862
```

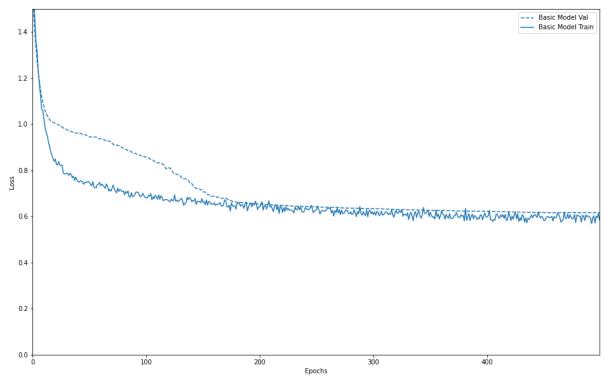
```
Epoch 457/500
16/16 - 0s - loss: 0.5963 - categorical accuracy: 0.9248 - val loss: 0.6161 -
val_categorical_accuracy: 0.8862
Epoch 458/500
16/16 - 0s - loss: 0.6004 - categorical accuracy: 0.9167 - val loss: 0.6161 -
val_categorical_accuracy: 0.8862
Epoch 459/500
16/16 - 0s - loss: 0.5802 - categorical_accuracy: 0.9228 - val_loss: 0.6160 -
val_categorical_accuracy: 0.8862
Epoch 460/500
16/16 - 0s - loss: 0.5992 - categorical accuracy: 0.9126 - val loss: 0.6160 -
val_categorical_accuracy: 0.8862
Epoch 461/500
16/16 - 0s - loss: 0.5937 - categorical_accuracy: 0.9248 - val_loss: 0.6160 -
val_categorical_accuracy: 0.8862
Epoch 462/500
16/16 - 0s - loss: 0.5961 - categorical accuracy: 0.9167 - val loss: 0.6161 -
val_categorical_accuracy: 0.8862
Epoch 463/500
16/16 - 0s - loss: 0.6143 - categorical accuracy: 0.9146 - val loss: 0.6162 -
val categorical accuracy: 0.8862
Epoch 464/500
16/16 - 0s - loss: 0.6092 - categorical accuracy: 0.9085 - val loss: 0.6164 -
val_categorical_accuracy: 0.8862
Epoch 465/500
16/16 - 0s - loss: 0.5962 - categorical accuracy: 0.9167 - val loss: 0.6162 -
val_categorical_accuracy: 0.8862
Epoch 466/500
16/16 - 0s - loss: 0.5758 - categorical accuracy: 0.9248 - val loss: 0.6163 -
val_categorical_accuracy: 0.8862
Epoch 467/500
16/16 - 0s - loss: 0.5823 - categorical accuracy: 0.9146 - val loss: 0.6164 -
val categorical accuracy: 0.8862
Epoch 468/500
16/16 - 0s - loss: 0.5875 - categorical accuracy: 0.9228 - val loss: 0.6162 -
val categorical accuracy: 0.8862
Epoch 469/500
16/16 - 0s - loss: 0.6182 - categorical accuracy: 0.9106 - val loss: 0.6163 -
val categorical accuracy: 0.8862
Epoch 470/500
16/16 - 0s - loss: 0.5915 - categorical accuracy: 0.9309 - val loss: 0.6165 -
val categorical accuracy: 0.8862
Epoch 471/500
16/16 - 0s - loss: 0.5918 - categorical accuracy: 0.9207 - val loss: 0.6166 -
val categorical accuracy: 0.8862
Epoch 472/500
16/16 - 0s - loss: 0.6119 - categorical_accuracy: 0.9167 - val_loss: 0.6168 -
val categorical accuracy: 0.8862
Epoch 473/500
16/16 - 0s - loss: 0.5913 - categorical_accuracy: 0.9248 - val_loss: 0.6167 -
val categorical accuracy: 0.8862
Epoch 474/500
16/16 - 0s - loss: 0.6069 - categorical_accuracy: 0.9187 - val_loss: 0.6169 -
val categorical accuracy: 0.8862
Epoch 475/500
16/16 - 0s - loss: 0.5963 - categorical_accuracy: 0.9187 - val_loss: 0.6167 -
val categorical accuracy: 0.8862
```

```
Epoch 476/500
16/16 - 0s - loss: 0.5877 - categorical_accuracy: 0.9207 - val_loss: 0.6169 -
val_categorical_accuracy: 0.8862
Epoch 477/500
16/16 - 0s - loss: 0.5937 - categorical accuracy: 0.9167 - val loss: 0.6167 -
val_categorical_accuracy: 0.8862
Epoch 478/500
16/16 - 0s - loss: 0.6089 - categorical accuracy: 0.9106 - val loss: 0.6166 -
val categorical accuracy: 0.8862
Epoch 479/500
16/16 - 0s - loss: 0.5736 - categorical accuracy: 0.9309 - val loss: 0.6165 -
val_categorical_accuracy: 0.8862
Epoch 480/500
16/16 - 0s - loss: 0.6061 - categorical_accuracy: 0.9167 - val_loss: 0.6161 -
val_categorical_accuracy: 0.8862
Epoch 481/500
16/16 - 0s - loss: 0.6040 - categorical accuracy: 0.9187 - val loss: 0.6161 -
val_categorical_accuracy: 0.8862
Epoch 482/500
16/16 - 0s - loss: 0.6007 - categorical accuracy: 0.9126 - val loss: 0.6161 -
val categorical accuracy: 0.8862
Epoch 483/500
16/16 - 0s - loss: 0.6013 - categorical accuracy: 0.9167 - val loss: 0.6163 -
val_categorical_accuracy: 0.8862
Epoch 484/500
16/16 - 0s - loss: 0.5759 - categorical accuracy: 0.9289 - val loss: 0.6161 -
val_categorical_accuracy: 0.8862
Epoch 485/500
16/16 - 0s - loss: 0.6049 - categorical accuracy: 0.9167 - val loss: 0.6161 -
val_categorical_accuracy: 0.8862
Epoch 486/500
16/16 - 0s - loss: 0.6008 - categorical accuracy: 0.9187 - val loss: 0.6162 -
val categorical accuracy: 0.8862
Epoch 487/500
16/16 - 0s - loss: 0.5824 - categorical accuracy: 0.9187 - val loss: 0.6162 -
val categorical accuracy: 0.8862
Epoch 488/500
16/16 - 0s - loss: 0.6070 - categorical accuracy: 0.9187 - val loss: 0.6163 -
val categorical accuracy: 0.8862
Epoch 489/500
16/16 - 0s - loss: 0.5986 - categorical accuracy: 0.9146 - val loss: 0.6163 -
val categorical accuracy: 0.8862
Epoch 490/500
16/16 - 0s - loss: 0.6024 - categorical accuracy: 0.9167 - val loss: 0.6163 -
val categorical accuracy: 0.8862
Epoch 491/500
16/16 - 0s - loss: 0.5998 - categorical_accuracy: 0.9106 - val_loss: 0.6161 -
val categorical accuracy: 0.8862
Epoch 492/500
16/16 - 0s - loss: 0.5921 - categorical_accuracy: 0.9228 - val_loss: 0.6162 -
val categorical accuracy: 0.8862
Epoch 493/500
16/16 - 0s - loss: 0.5685 - categorical_accuracy: 0.9289 - val_loss: 0.6161 -
val categorical accuracy: 0.8862
Epoch 494/500
16/16 - 0s - loss: 0.5954 - categorical_accuracy: 0.9146 - val_loss: 0.6164 -
val categorical accuracy: 0.8780
```

```
Epoch 495/500
16/16 - 0s - loss: 0.6026 - categorical_accuracy: 0.9207 - val_loss: 0.6164 -
val_categorical_accuracy: 0.8780
Epoch 496/500
16/16 - 0s - loss: 0.5715 - categorical accuracy: 0.9309 - val loss: 0.6162 -
val_categorical_accuracy: 0.8862
Epoch 497/500
16/16 - 0s - loss: 0.6010 - categorical_accuracy: 0.9146 - val_loss: 0.6160 -
val_categorical_accuracy: 0.8862
Epoch 498/500
16/16 - 0s - loss: 0.5941 - categorical_accuracy: 0.9248 - val_loss: 0.6159 -
val_categorical_accuracy: 0.8862
Epoch 499/500
16/16 - 0s - loss: 0.6145 - categorical_accuracy: 0.9187 - val_loss: 0.6159 -
val_categorical_accuracy: 0.8862
Epoch 500/500
16/16 - 0s - loss: 0.5840 - categorical accuracy: 0.9228 - val loss: 0.6160 -
val_categorical_accuracy: 0.8862
```

Step 5: Plot Results

```
In [ ]:
        import matplotlib.pyplot as plt
        def plot_history(histories, key='loss'):
          plt.figure(figsize=(16,10))
          for name, history in histories:
            val = plt.plot(12_history.epoch, 12_history.history['val_'+key],
                            '--', label=name.title()+' Val')
            plt.plot(12 history.epoch, 12 history.history[key], color=val[0].get color
        (),
                      label=name.title()+' Train')
          plt.xlabel('Epochs')
          plt.ylabel(key.replace('_',' ').title())
          plt.legend()
          plt.xlim([0,max(12_history.epoch)])
          plt.ylim([0,1.5])
        plot_history([('Basic Model', 12_history)])
        #Plot Multiple Model Results
        #plot_history([('Plain', m1_history),('L1',model1)])
```



Predictions

In []: valpreds = np.round(12_model.predict_on_batch(X_test),3)
print(valpreds)

```
[[0.021 0.021 0.024 0.016 0.919]
 [0.022 0.023 0.027 0.018 0.911]
 [0.022 0.023 0.028 0.018 0.908]
 [0.024 0.026 0.029 0.02 0.901]
 [0.022 0.023 0.028 0.018 0.908]
 [0.227 0.355 0.261 0.123 0.034]
 [0.053 0.05 0.043 0.032 0.823]
 [0.02 0.02 0.024 0.016 0.921]
 [0.022 0.022 0.027 0.018 0.911]
 [0.029 0.031 0.032 0.022 0.886]
 [0.022 0.023 0.026 0.017 0.912]
 [0.094 0.111 0.097 0.065 0.633]
 [0.025 0.027 0.03 0.02 0.899]
 [0.02 0.02 0.027 0.018 0.915]
 [0.023 0.024 0.025 0.017 0.912]
 [0.021 0.022 0.026 0.017 0.914]
 [0.02 0.02 0.024 0.016 0.92 ]
 [0.018 0.018 0.025 0.016 0.923]
 [0.033 0.034 0.038 0.026 0.87 ]
 [0.021 0.022 0.026 0.017 0.914]
 [0.024 0.025 0.027 0.018 0.907]
 [0.022 0.022 0.026 0.017 0.913]
 [0.02 0.02 0.022 0.015 0.923]
 [0.022 0.023 0.028 0.018 0.909]
 [0.023 0.024 0.026 0.017 0.909]
 [0.143 0.2
             0.144 0.09 0.423]
 [0.021 0.021 0.027 0.018 0.913]
 [0.022 0.023 0.027 0.018 0.911]
 [0.018 0.018 0.022 0.014 0.928]
 [0.02 0.02 0.025 0.016 0.919]
 [0.022 0.023 0.026 0.017 0.911]
 [0.363 0.153 0.097 0.118 0.268]
 [0.023 0.024 0.027 0.018 0.908]
 [0.029 0.032 0.033 0.022 0.884]
 [0.023 0.023 0.026 0.017 0.912]
 [0.03 0.034 0.036 0.024 0.877]
 [0.02 0.02 0.027 0.018 0.915]
 [0.069 0.065 0.056 0.043 0.768]
 [0.025 0.026 0.029 0.02 0.9
 [0.022 0.023 0.028 0.019 0.908]
 [0.157 0.211 0.181 0.108 0.342]
 [0.975 0.004 0.002 0.02 0.
 [0.137 0.108 0.081 0.071 0.604]
 [0.046 0.044 0.045 0.033 0.832]
 [0.016 0.016 0.022 0.014 0.932]
 [0.019 0.019 0.023 0.015 0.924]
 [0.099 0.425 0.385 0.086 0.005]
 [0.03 0.033 0.036 0.024 0.877]
 [0.028 0.03 0.03 0.02 0.891]
 [0.059 0.099 0.098 0.052 0.692]
 [0.026 0.029 0.032 0.022 0.891]
 [0.021 0.022 0.026 0.017 0.914]
 [0.033 0.034 0.036 0.025 0.872]
 [0.02 0.02 0.023 0.016 0.921]
 [0.108 0.296 0.252 0.098 0.246]
 [0.018 0.018 0.024 0.016 0.924]
[0.024 0.025 0.027 0.018 0.907]
```

```
[0.021 0.022 0.029 0.019 0.907]
[0.02 0.02 0.025 0.017 0.918]
[0.024 0.025 0.028 0.018 0.905]
[0.563 0.148 0.076 0.119 0.094]
[0.202 0.368 0.279 0.119 0.031]
[0.021 0.021 0.025 0.016 0.917]
[0.024 0.026 0.036 0.024 0.89 ]
[0.024 0.025 0.026 0.018 0.907]
[0.022 0.023 0.026 0.017 0.912]
[0.059 0.061 0.058 0.043 0.779]
[0.021 0.021 0.027 0.018 0.913]
[0.022 0.023 0.025 0.017 0.913]
[0.75 0.067 0.047 0.115 0.021]
[0.021 0.022 0.025 0.016 0.916]
[0.103 0.087 0.078 0.065 0.667]
[0.367 0.169 0.097 0.116 0.252]
[0.953 0.016 0.004 0.027 0.
[0.113 0.213 0.209 0.101 0.365]
[0.041 0.06 0.079 0.045 0.775]
[0.02 0.02 0.026 0.017 0.918]
[0.11 0.225 0.179 0.088 0.398]
[0.039 0.038 0.038 0.027 0.857]
      0.293 0.271 0.099 0.237]
[0.1
[0.02 0.021 0.03 0.02 0.908]
[0.025 0.027 0.033 0.022 0.893]
[0.06 0.057 0.049 0.037 0.797]
[0.026 0.028 0.029 0.019 0.898]
[0.022 0.023 0.029 0.019 0.906]
[0.028 0.032 0.037 0.024 0.879]
[0.03 0.032 0.031 0.021 0.885]
[0.046 0.051 0.043 0.03 0.83 ]
[0.757 0.073 0.043 0.104 0.023]
[0.116 0.136 0.097 0.065 0.586]
[0.015 0.014 0.022 0.015 0.934]
[0.019 0.019 0.025 0.016 0.922]
[0.02 0.02 0.026 0.017 0.918]
[0.021 0.022 0.026 0.017 0.914]
[0.022 0.022 0.026 0.017 0.914]
[0.022 0.023 0.025 0.017 0.913]
[0.029 0.032 0.031 0.021 0.888]
[0.18 0.366 0.285 0.118 0.051]
[0.021 0.022 0.027 0.018 0.911]
[0.018 0.018 0.024 0.015 0.925]
[0.019 0.019 0.023 0.015 0.924]
[0.023 0.024 0.027 0.018 0.908]
[0.019 0.019 0.023 0.015 0.924]
[0.033 0.038 0.04 0.025 0.865]
[0.023 0.024 0.027 0.018 0.907]
[0.024 0.025 0.028 0.019 0.904]
[0.021 0.021 0.022 0.015 0.921]
[0.048 0.07 0.07 0.04 0.772]
[0.363 0.318 0.208 0.11 0.001]
[0.021 0.022 0.028 0.019 0.911]
[0.03 0.032 0.031 0.021 0.887]
[0.027 0.03 0.036 0.023 0.884]
[0.439 0.189 0.107 0.127 0.138]
[0.02 0.021 0.027 0.018 0.914]
```

```
[0.029 0.032 0.034 0.023 0.883]

[0.036 0.044 0.044 0.028 0.849]

[0.026 0.028 0.029 0.019 0.897]

[0.144 0.212 0.155 0.093 0.395]

[0.023 0.023 0.027 0.018 0.909]

[0.025 0.027 0.029 0.02 0.899]

[0.126 0.099 0.073 0.063 0.639]

[0.027 0.029 0.029 0.02 0.895]

[0.02 0.021 0.027 0.018 0.915]]
```

		Category_2=Fibrosis	
492	0	0	0
122	0	0	0
158	0	0	0
162	0	0	0
1	0	0	0
608	1	0	0
524	0	0	ő Ø
244	0	0	0
523	0	0	0
159	0	0	0
518	0	0	0
67	0	0	0
237	0	0	0
115	0	0	0
514	0	0	0
224	0	0	0
11	0	0	0
329	0	0	0
277	0	0	0
488	0	0	0
336	0	0	0
211	0	0	0
58	0	0	0
286	0	0	0
225	0	0	0
603	1	0	0
132	0	0	0
31	0	0	0
469	0	0	0
334	0	0	0
103	0	0	0
315	0	0	0
484	0	0	0
439	0	0	0
510	0	0	0
37	0	0	0
180	0	0	0
461	0	0	0
474	0	0	0
30	0	0	0
541	0	0	1
591	1	0	0
316	0	0	0
248	0	0	0
405	0	0	0
447	0	0	0
563	0	0	1
140	0	0	0
418	0	0	0
318	0	0	0
239	0	0	0
129	0	0	0
206	0	0	0
235	0	0	0
550 204	0	0	1
294	0	0	0

	otophon_nong_		
331	0	0	0
48	0	0	0
462	0	0	0
143	0	0	0
596	1	0	0
572	0	1	0
455	0	0	0
116	0	0	0
383	0	0	0
458	0	0	0
233	0	0	0
110	0	0	0
445	0	0	0
586	1	0	0
493	0	0	0
534	0	0	0
538	0	0	0
590	1	0	0
123	0	0	0
77	0		
		0	0
208	0	0	0
562	0	0	1
489	0	0	0
555	0	0	1
26	0	0	0
55	0	0	0
495	0	0	0
371	0	0	0
134	0	0	0
349	0	0	0
314	0	0	0
496	0	0	0
606	1		
		0	0
581	0	1	0
231	0	0	0
234	0	0	0
276	0	0	0
193	0	0	0
494	0	0	0
456	0	0	0
379	0	0	0
553	0	0	1
369	0	0	0
471	0	0	0
328	0	0	0
44	0	0	0
268	0	0	0
323	0	0	0
472	0	0	0
181	0	0	0
498	0	0	0
272	0	0	0
593	1	0	0
20	0	0	0
34	0	0	0
51	0	0	0
559	0	0	1

84 0 0 0 320 0 0 0 414 0 0 0 299 0 0 0 170 0 0 0 258 0 0 0 460 0 0 0 401 0 0 0 88 0 0 0	540	0	0	1
414 0 0 0 299 0 0 0 170 0 0 0 258 0 0 0 460 0 0 0 401 0 0 0	84	0	0	0
299 0 0 0 170 0 0 0 258 0 0 0 460 0 0 0 401 0 0 0	320	0	0	0
170 0 0 0 258 0 0 0 460 0 0 0 401 0 0 0	414	0	0	0
258 0 0 0 460 0 0 0 401 0 0 0	299	0	0	0
460 0 0 0 401 0 0 0	170	0	0	0
401 0 0	258	0	0	0
	460	0	0	0
88 0 0 0	401	0	0	0
	88	0	0	0

88	()	0		
	Category_0s=suspect	Blood Donor	Category	_0=Blood	Donor
492		6			1
122		6			1
158		6			1
162		6			1
1		6			1
608		6			0
524		6			1
244		6			1
523		6			1
159		6			1
518 67		6			1
237		6			1 1
115		6			1
514		6			1
224		6			1
11		é			1
329		é			1
277		é			1
488		é			1
336		ē			1
211		6			1
58		6			1
286		6			1
225		6	1		1
603		6	1		0
132		e	1		1
31		6)		1
469		6	1		1
334		6			1
103		6			1
315		6			1
484		6			1
439		6			1
510		6			1
37		6			1
180		6			1
461		6			1
474		6			1
30		6			1
541		6			0
591		6			0
316		0			1
248		6	ı		1

0

405

1

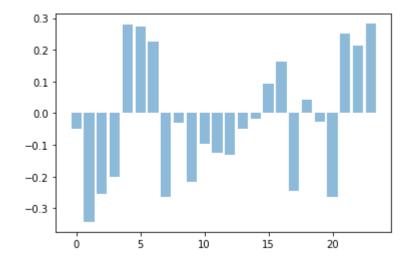
	Stephen_Hong_Hwn_Q1	
447	0	1
563	0	0
140	0	1
418	0	1
318	0	1
239	0	1
129	0	1
206	0	1
235	0	1
550	0	0
294	0	1
331	0	1
48	0	1
462	0	1
143	0	1
596	0	0
572	0	0
455	0	1
116	0	1
383	0	1
458	0	1
233	0	1
110	0	1
445	0	1
586	0	0
493	0	1
534	1	0
538	1	0
590	0	0
123	0	1
77	0	1
208	0	1
562	0	0
489	0	1
555	0	0
26	0	1
55	0	1
495	0	1
371	0	1
134	0	1
349	0	1
314	0	1
496	0	1
606	0	0
581	0	0
231	0	1
234	0	1
276	0	1
193	0	1
494	0	1
456	0	1
379	0	1
553	0	0
369	0	1
471	0	1
328	0	1
44	0	1
	· ·	Τ.

```
268
323
472
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498
272
593
20
34
51
559
540
84
320
414
299
170
258
460
401
88
```

```
In [ ]: # Plot Weights
    nfw = 12_model.get_weights()[0][0]
    y_pos = np.arange(len(nfw))

plt.bar(y_pos, nfw, align='center', alpha=0.5)
```

Out[]: <BarContainer object of 24 artists>



```
In [ ]: print(min(l2_history.history['val_loss']))
```

0.6158662438392639

```
In [ ]: print(max(12_history.history['val_categorical_accuracy']))
```

0.8943089246749878

Baseline Accuracy: The goal of the model is to predict whether the patient belongs in 1 of 5 categories: Blood Donor, Suspected Blood Donor, Hephatitis, Fibrosis, and Cirrhosis. Given the dataset is extremely lopsided towards blood donor our minimum accuracy of the model needs to be 86.6%.

As you can see in the code above the validation categorical accuracy was 89.4%, which is slightly higher than the baseline 86.6%.

When I was running the model I noticed that when I had a more complex model with 3 hidden layers and a lot more neurons the accuracy was slightly lower with 88.4%. The model was a lot more complex and beat the baseline measure. Given the accuracy measure for the simpler method was higher and you should always choose a simpler model if the accuracy are very similar, I overall chose the simpler model.

The othe thing I noticed was when I changed the relu function to softmax the accuracy became noticable worse.