wine

April 11, 2023

```
[]: ## Import Necessary Functions
     import numpy as np
     import matplotlib.pyplot as plt
     #You will use Vine Dataset you can get the detail in the URL below
     #https://archive.ics.uci.edu/ml/datasets/Wine
     from sklearn.datasets import load_wine
     vine = load_wine()
[]: # PRINT FOR YOUR INTUITION SO YOU KNOW THE DIMENSIONS YOU ARE WORKING WITH
     print(vine.data.shape) #.data contains the features
     print(vine.target.shape)
     print(vine.target[0]) #.target contains the target variables
     print(vine.target_names.shape)
     print(vine.feature_names)
    (178, 13)
    (178,)
    (3,)
    ['alcohol', 'malic_acid', 'ash', 'alcalinity_of_ash', 'magnesium',
    'total_phenols', 'flavanoids', 'nonflavanoid_phenols', 'proanthocyanins',
    'color_intensity', 'hue', 'od280/od315_of_diluted_wines', 'proline']
[]: #SPLIT THE DATA INTO TRAINING AND TESTING SET
     #WHEN CALLING THE DATA use vine.data instance as well as vine.target.
     ⇒astype('int')
     #THE SPLIT OF DATA IS UPTO YOU
     from tensorflow.keras.utils import to_categorical
     from sklearn.model_selection import train_test_split
     X, y = load_wine(return_X_y=True)
     y = to_categorical(y)
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X2_train, X2_test, y2_train, y2_test = train_test_split(X,__
      2023-04-10 19:14:14.349554: I tensorflow/core/platform/cpu_feature_guard.cc:193]
    This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
    (oneDNN) to use the following CPU instructions in performance-critical
    operations: SSE3 SSE4.1 SSE4.2 AVX AVX2 FMA
    To enable them in other operations, rebuild TensorFlow with the appropriate
    compiler flags.
[]: X2_train.shape, X2_test.shape
[]: ((124, 13), (54, 13))
[]: y2_train.shape, y2_test.shape
[]: ((124, 3), (54, 3))
[]: print(y2_train)
    [[0. 1. 0.]
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[]: print(X2_train)
    [[1.165e+01 1.670e+00 2.620e+00 ... 1.360e+00 3.210e+00 5.620e+02]
     [1.383e+01 1.570e+00 2.620e+00 ... 1.130e+00 2.570e+00 1.130e+03]
     [1.184e+01 8.900e-01 2.580e+00 ... 7.900e-01 3.080e+00 5.200e+02]
     [1.345e+01 3.700e+00 2.600e+00 ... 8.500e-01 1.560e+00 6.950e+02]
     [1.352e+01 3.170e+00 2.720e+00 ... 8.900e-01 2.060e+00 5.200e+02]
     [1.221e+01 1.190e+00 1.750e+00 ... 1.280e+00 3.070e+00 7.180e+02]]
[]: import tensorflow as tf
    print(tf.__version__)
   2.11.0
[]: input_dim = X2_train.shape[1:]
    output_dim = y.shape[1]
[]: model = tf.keras.Sequential([
        tf.keras.layers.Flatten(input_shape=input_dim),
        #tf.keras.layers.GlobalAveragePooling2D(),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.Dense(128, activation='relu'),
        tf.keras.layers.Dense(256, activation='relu'),
        tf.keras.layers.Dense(output_dim, activation='softmax')
    ])
[]: model.compile(
        loss='categorical_crossentropy',
        optimizer='adam',
        metrics=[
            tf.keras.metrics.BinaryAccuracy(name='accuracy'),
           tf.keras.metrics.Precision(name='precision'),
           tf.keras.metrics.Recall(name='recall')
        ]
    )
[]: testing = model.fit(X2_train, y2_train,__
      →epochs=100,validation_data=(X2_test,y2_test))
   Epoch 1/100
   0.7016 - precision: 1.0000 - recall: 0.1048 - val_loss: 0.9391 - val_accuracy:
   0.6914 - val_precision: 0.5769 - val_recall: 0.2778
   Epoch 2/100
   0.8522 - precision: 0.9859 - recall: 0.5645 - val_loss: 0.7739 - val_accuracy:
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0.7593 - val_precision: 0.6471 - val_recall: 0.6111
Epoch 3/100
0.9462 - precision: 0.9727 - recall: 0.8629 - val_loss: 1.1619 - val_accuracy:
0.6605 - val_precision: 0.4906 - val_recall: 0.4815
Epoch 4/100
0.9839 - precision: 0.9917 - recall: 0.9597 - val_loss: 1.8216 - val_accuracy:
0.6420 - val_precision: 0.4630 - val_recall: 0.4630
Epoch 5/100
0.9785 - precision: 0.9833 - recall: 0.9516 - val_loss: 2.4049 - val_accuracy:
0.6420 - val_precision: 0.4630 - val_recall: 0.4630
Epoch 6/100
0.9919 - precision: 0.9919 - recall: 0.9839 - val_loss: 2.9952 - val_accuracy:
0.6420 - val_precision: 0.4630 - val_recall: 0.4630
Epoch 7/100
0.9919 - precision: 1.0000 - recall: 0.9758 - val_loss: 3.7306 - val_accuracy:
0.6420 - val_precision: 0.4630 - val_recall: 0.4630
Epoch 8/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 4.3490 - val_accuracy:
0.6420 - val_precision: 0.4630 - val_recall: 0.4630
Epoch 9/100
0.9946 - precision: 0.9919 - recall: 0.9919 - val_loss: 4.7162 - val_accuracy:
0.6420 - val_precision: 0.4630 - val_recall: 0.4630
Epoch 10/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 5.0204 - val_accuracy:
0.6420 - val_precision: 0.4630 - val_recall: 0.4630
Epoch 11/100
0.9839 - precision: 0.9758 - recall: 0.9758 - val_loss: 5.2648 - val_accuracy:
0.6420 - val_precision: 0.4630 - val_recall: 0.4630
Epoch 12/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 5.4763 - val_accuracy:
0.6420 - val_precision: 0.4630 - val_recall: 0.4630
Epoch 13/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 5.6019 - val_accuracy:
0.6420 - val_precision: 0.4630 - val_recall: 0.4630
Epoch 14/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 5.6287 - val_accuracy:
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0.6420 - val_precision: 0.4630 - val_recall: 0.4630
Epoch 15/100
0.9892 - precision: 0.9839 - recall: 0.9839 - val_loss: 5.5947 - val_accuracy:
0.6420 - val_precision: 0.4630 - val_recall: 0.4630
Epoch 16/100
0.9866 - precision: 0.9837 - recall: 0.9758 - val_loss: 5.3610 - val_accuracy:
0.6667 - val_precision: 0.5000 - val_recall: 0.5000
Epoch 17/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 5.1325 - val_accuracy:
0.6914 - val_precision: 0.5370 - val_recall: 0.5370
Epoch 18/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 4.9781 - val_accuracy:
0.7037 - val_precision: 0.5556 - val_recall: 0.5556
Epoch 19/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 4.9083 - val_accuracy:
0.7037 - val_precision: 0.5556 - val_recall: 0.5556
Epoch 20/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 4.7990 - val_accuracy:
0.7160 - val_precision: 0.5741 - val_recall: 0.5741
Epoch 21/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 4.6787 - val_accuracy:
0.7160 - val_precision: 0.5741 - val_recall: 0.5741
Epoch 22/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 4.6256 - val_accuracy:
0.7284 - val_precision: 0.5926 - val_recall: 0.5926
Epoch 23/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 4.5292 - val_accuracy:
0.7284 - val_precision: 0.5926 - val_recall: 0.5926
Epoch 24/100
0.9946 - precision: 0.9919 - recall: 0.9919 - val_loss: 4.4385 - val_accuracy:
0.7284 - val_precision: 0.5926 - val_recall: 0.5926
Epoch 25/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 4.3065 - val_accuracy:
0.7284 - val_precision: 0.5926 - val_recall: 0.5926
Epoch 26/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 3.9896 - val_accuracy:
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0.7407 - val_precision: 0.6111 - val_recall: 0.6111
Epoch 27/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 3.7629 - val_accuracy:
0.7531 - val_precision: 0.6296 - val_recall: 0.6296
Epoch 28/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 3.5623 - val_accuracy:
0.7778 - val_precision: 0.6667 - val_recall: 0.6667
Epoch 29/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 3.3852 - val_accuracy:
0.7778 - val_precision: 0.6667 - val_recall: 0.6667
Epoch 30/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 3.2868 - val_accuracy:
0.7901 - val_precision: 0.6852 - val_recall: 0.6852
Epoch 31/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 3.1734 - val_accuracy:
0.7901 - val_precision: 0.6852 - val_recall: 0.6852
Epoch 32/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 3.1340 - val_accuracy:
0.7901 - val_precision: 0.6852 - val_recall: 0.6852
Epoch 33/100
0.9892 - precision: 0.9839 - recall: 0.9839 - val_loss: 2.8653 - val_accuracy:
0.7901 - val_precision: 0.6852 - val_recall: 0.6852
Epoch 34/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 2.6929 - val_accuracy:
0.7901 - val_precision: 0.6852 - val_recall: 0.6852
Epoch 35/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 2.5280 - val_accuracy:
0.8025 - val_precision: 0.7037 - val_recall: 0.7037
Epoch 36/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 2.4109 - val_accuracy:
0.8025 - val_precision: 0.7037 - val_recall: 0.7037
Epoch 37/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 2.3301 - val_accuracy:
0.8025 - val_precision: 0.7037 - val_recall: 0.7037
Epoch 38/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 2.2593 - val_accuracy:
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0.8025 - val_precision: 0.7037 - val_recall: 0.7037
Epoch 39/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 2.2173 - val_accuracy:
0.8025 - val_precision: 0.7037 - val_recall: 0.7037
Epoch 40/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 2.1328 - val_accuracy:
0.8025 - val_precision: 0.7037 - val_recall: 0.7037
Epoch 41/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 2.0564 - val_accuracy:
0.8025 - val_precision: 0.7037 - val_recall: 0.7037
Epoch 42/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 1.9599 - val_accuracy:
0.8025 - val_precision: 0.7037 - val_recall: 0.7037
Epoch 43/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 1.8548 - val_accuracy:
0.8025 - val_precision: 0.7037 - val_recall: 0.7037
Epoch 44/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 1.7456 - val_accuracy:
0.8148 - val_precision: 0.7222 - val_recall: 0.7222
Epoch 45/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 1.6606 - val_accuracy:
0.8272 - val_precision: 0.7407 - val_recall: 0.7407
Epoch 46/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 1.5705 - val_accuracy:
0.8272 - val_precision: 0.7407 - val_recall: 0.7407
Epoch 47/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 1.4884 - val_accuracy:
0.8395 - val_precision: 0.7593 - val_recall: 0.7593
Epoch 48/100
0.9946 - precision: 0.9919 - recall: 0.9919 - val_loss: 1.3642 - val_accuracy:
0.8704 - val_precision: 0.8113 - val_recall: 0.7963
Epoch 49/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 1.2370 - val_accuracy:
0.8704 - val_precision: 0.8113 - val_recall: 0.7963
Epoch 50/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 1.1367 - val_accuracy:
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0.8704 - val_precision: 0.8113 - val_recall: 0.7963
Epoch 51/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 1.0556 - val_accuracy:
0.8704 - val_precision: 0.8113 - val_recall: 0.7963
Epoch 52/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.9957 - val_accuracy:
0.8765 - val_precision: 0.8148 - val_recall: 0.8148
Epoch 53/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.9486 - val_accuracy:
0.8765 - val_precision: 0.8148 - val_recall: 0.8148
Epoch 54/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.9248 - val_accuracy:
0.8765 - val_precision: 0.8148 - val_recall: 0.8148
Epoch 55/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.8919 - val_accuracy:
0.8765 - val_precision: 0.8148 - val_recall: 0.8148
Epoch 56/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.8593 - val_accuracy:
0.8765 - val_precision: 0.8148 - val_recall: 0.8148
Epoch 57/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.8624 - val_accuracy:
0.8765 - val_precision: 0.8148 - val_recall: 0.8148
Epoch 58/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.8618 - val_accuracy:
0.8765 - val_precision: 0.8148 - val_recall: 0.8148
Epoch 59/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.8329 - val_accuracy:
0.8765 - val_precision: 0.8148 - val_recall: 0.8148
Epoch 60/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.7829 - val_accuracy:
0.8889 - val_precision: 0.8333 - val_recall: 0.8333
Epoch 61/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.7325 - val_accuracy:
0.9012 - val_precision: 0.8519 - val_recall: 0.8519
Epoch 62/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.6760 - val_accuracy:
```

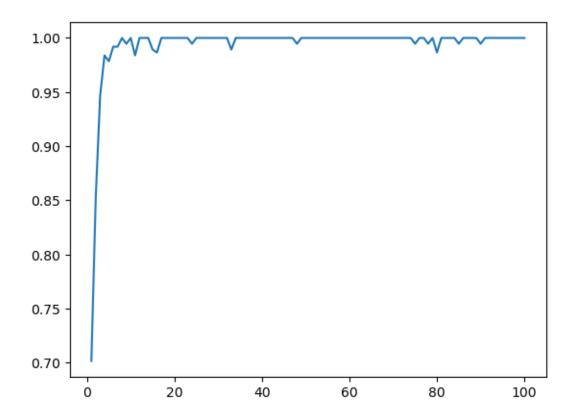
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0.9136 - val_precision: 0.8704 - val_recall: 0.8704
Epoch 63/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.6265 - val_accuracy:
0.9136 - val_precision: 0.8704 - val_recall: 0.8704
Epoch 64/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.5793 - val_accuracy:
0.9259 - val_precision: 0.8889 - val_recall: 0.8889
Epoch 65/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.5323 - val_accuracy:
0.9259 - val_precision: 0.8889 - val_recall: 0.8889
Epoch 66/100
accuracy: 1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.4989 -
val_accuracy: 0.9259 - val_precision: 0.8889 - val_recall: 0.8889
Epoch 67/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.4634 - val_accuracy:
0.9259 - val_precision: 0.8889 - val_recall: 0.8889
Epoch 68/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.4186 - val_accuracy:
0.9259 - val_precision: 0.8889 - val_recall: 0.8889
Epoch 69/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.4092 - val_accuracy:
0.9259 - val_precision: 0.8889 - val_recall: 0.8889
Epoch 70/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.3947 - val_accuracy:
0.9259 - val_precision: 0.8889 - val_recall: 0.8889
Epoch 71/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.3814 - val_accuracy:
0.9259 - val_precision: 0.8889 - val_recall: 0.8889
Epoch 72/100
accuracy: 1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.3701 -
val_accuracy: 0.9383 - val_precision: 0.9074 - val_recall: 0.9074
Epoch 73/100
accuracy: 1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.3588 -
val_accuracy: 0.9506 - val_precision: 0.9259 - val_recall: 0.9259
Epoch 74/100
accuracy: 1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.3444 -
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val_accuracy: 0.9506 - val_precision: 0.9259 - val_recall: 0.9259
Epoch 75/100
0.9946 - precision: 0.9919 - recall: 0.9919 - val_loss: 0.3403 - val_accuracy:
0.9506 - val_precision: 0.9259 - val_recall: 0.9259
Epoch 76/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.3696 - val_accuracy:
0.9383 - val_precision: 0.9074 - val_recall: 0.9074
Epoch 77/100
accuracy: 1.0000 - precision: 1.0000 - recall: 1.0000 - val loss: 0.3780 -
val_accuracy: 0.9383 - val_precision: 0.9074 - val_recall: 0.9074
Epoch 78/100
0.9946 - precision: 0.9919 - recall: 0.9919 - val_loss: 0.3348 - val_accuracy:
0.9383 - val_precision: 0.9074 - val_recall: 0.9074
Epoch 79/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.2077 - val_accuracy:
0.9506 - val_precision: 0.9259 - val_recall: 0.9259
Epoch 80/100
0.9866 - precision: 0.9837 - recall: 0.9758 - val_loss: 0.1549 - val_accuracy:
0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 81/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1622 - val_accuracy:
0.9630 - val_precision: 0.9444 - val_recall: 0.9444
Epoch 82/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1680 - val_accuracy:
0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 83/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1719 - val_accuracy:
0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 84/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1723 - val_accuracy:
0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 85/100
0.9946 - precision: 0.9919 - recall: 0.9919 - val_loss: 0.1607 - val_accuracy:
0.9877 - val_precision: 0.9815 - val_recall: 0.9815
Epoch 86/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1570 - val_accuracy:
```

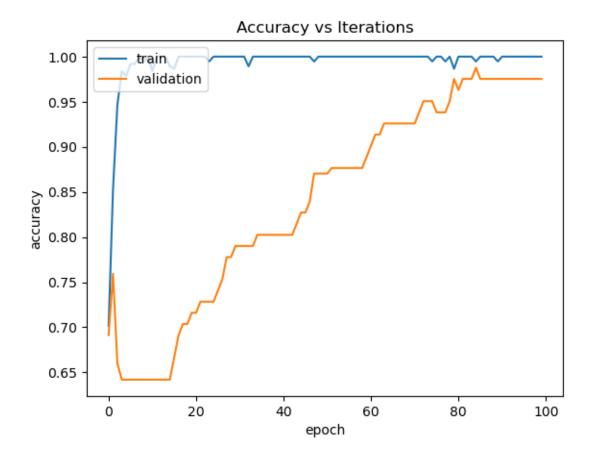
```
0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 87/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1491 - val_accuracy:
0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 88/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1459 - val_accuracy:
0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 89/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1439 - val_accuracy:
0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 90/100
0.9946 - precision: 0.9919 - recall: 0.9919 - val_loss: 0.1408 - val_accuracy:
0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 91/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1380 - val_accuracy:
0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 92/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1364 - val_accuracy:
0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 93/100
accuracy: 1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1354 -
val_accuracy: 0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 94/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1350 - val_accuracy:
0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 95/100
1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1351 - val_accuracy:
0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 96/100
accuracy: 1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1352 -
val_accuracy: 0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 97/100
accuracy: 1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1350 -
val_accuracy: 0.9753 - val_precision: 0.9630 - val_recall: 0.9630
Epoch 98/100
accuracy: 1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1342 -
```

```
val_accuracy: 0.9753 - val_precision: 0.9630 - val_recall: 0.9630
  Epoch 99/100
  accuracy: 1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1329 -
  val_accuracy: 0.9753 - val_precision: 0.9630 - val_recall: 0.9630
  Epoch 100/100
  1.0000 - precision: 1.0000 - recall: 1.0000 - val_loss: 0.1335 - val_accuracy:
  0.9753 - val_precision: 0.9630 - val_recall: 0.9630
[]: print('\nTest accuracy:', testing.history['accuracy'])
  Test accuracy: [0.7016128897666931, 0.852150559425354, 0.9462365508079529,
  0.9838709831237793, 0.9784946441650391, 0.9919354915618896, 0.9919354915618896,
  1.0, 0.9946236610412598, 1.0, 0.9838709831237793, 1.0, 1.0, 1.0,
  0.9892473220825195, 0.9865591526031494, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
  0.9946236610412598, 1.0, 1.0, 0.9946236610412598, 1.0, 0.9865591526031494, 1.0,
  1.0, 1.0, 1.0, 0.9946236610412598, 1.0, 1.0, 1.0, 0.9946236610412598, 1.0,
  []: test_acc = model.evaluate(X2_test, y2_test)
   print('\nTest accuracy:', test_acc)
   plt.plot(
     np.arange(1, 101),
      testing.history['accuracy'], label='Accuracy'
   plt.show
  0.9753 - precision: 0.9630 - recall: 0.9630
  Test accuracy: [0.1335313320159912, 0.9753086566925049, 0.9629629850387573,
  0.9629629850387573]
```

[]: <function matplotlib.pyplot.show(close=None, block=None)>

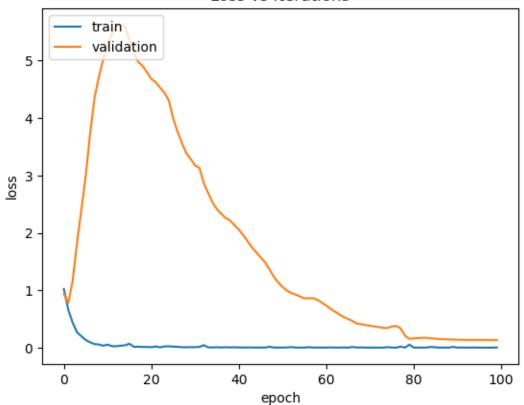


```
[]: plt.plot(testing.history['accuracy'])
   plt.plot(testing.history['val_accuracy'])
   plt.title('Accuracy vs Iterations')
   plt.ylabel('accuracy')
   plt.xlabel('epoch')
   plt.legend(['train', 'validation'], loc='upper left')
   plt.show()
```



```
[]: plt.plot(testing.history['loss'])
   plt.plot(testing.history['val_loss'])
   plt.title('Loss vs Iterations')
   plt.ylabel('loss')
   plt.xlabel('epoch')
   plt.legend(['train', 'validation'], loc='upper left')
   plt.show()
```

Loss vs Iterations



```
[]: model.evaluate(X2_test,y2_test)
```

- []: [0.1335313320159912,
 - 0.9753086566925049,
 - 0.9629629850387573,
 - 0.9629629850387573]

Accuracy: 95.06%