

```

import tensorflow as tf
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Conv1D,
MaxPool1D, Flatten, Dense, Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn import datasets, metrics
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

cancerData = datasets.load_breast_cancer()

X = pd.DataFrame(data = cancerData.data,
columns=cancerData.feature_names )
X.head()

```

	mean radius	mean texture	mean perimeter	mean area	mean smoothness \
0	17.99	10.38	122.80	1001.0	0.11840
1	20.57	17.77	132.90	1326.0	0.08474
2	19.69	21.25	130.00	1203.0	0.10960
3	11.42	20.38	77.58	386.1	0.14250
4	20.29	14.34	135.10	1297.0	0.10030

	mean compactness	mean concavity	mean concave points	mean symmetry \
0	0.27760	0.3001	0.14710	0.2419
1	0.07864	0.0869	0.07017	0.1812
2	0.15990	0.1974	0.12790	0.2069
3	0.28390	0.2414	0.10520	0.2597
4	0.13280	0.1980	0.10430	0.1809

	mean fractal dimension	...	worst radius	worst texture	worst perimeter \
0	0.07871	...	25.38	17.33	

184.60				
1	0.05667	...	24.99	23.41
158.80				
2	0.05999	...	23.57	25.53
152.50				
3	0.09744	...	14.91	26.50
98.87				
4	0.05883	...	22.54	16.67
152.20				

	worst area	worst smoothness	worst compactness	worst concavity \
0	2019.0	0.1622	0.6656	0.7119
1	1956.0	0.1238	0.1866	0.2416
2	1709.0	0.1444	0.4245	0.4504
3	567.7	0.2098	0.8663	0.6869
4	1575.0	0.1374	0.2050	0.4000

	worst concave points	worst symmetry	worst fractal dimension
0	0.2654	0.4601	0.11890
1	0.1860	0.2750	0.08902
2	0.2430	0.3613	0.08758
3	0.2575	0.6638	0.17300
4	0.1625	0.2364	0.07678

[5 rows x 30 columns]

y = cancerData.target

X.shape

(569, 30)

X_train,X_test,y_train,y_test=
train_test_split(X,y,test_size=0.2,stratify=y)

X_train.shape

(455, 30)

y_test.shape

(114,)

scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)

X_train = X_train.reshape(455,30,1)

X_test = X_test.reshape(114,30,1)

```

model = Sequential()
model.add(Conv1D(filters=32, kernel_size=2, activation='relu', input_shape=(30, 1)))
model.add(BatchNormalization())
model.add(Dropout(0.2))

model.add(Conv1D(64, 2, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))

model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))

model.add(Dense(1, activation='sigmoid'))

/opt/anaconda3/lib/python3.12/site-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

model.summary()
Model: "sequential"

```

Layer (type) Param #	Output Shape	
conv1d (Conv1D) 96	(None, 29, 32)	
batch_normalization 128 (BatchNormalization)	(None, 29, 32)	
dropout (Dropout) 0	(None, 29, 32)	
conv1d_1 (Conv1D) 4,160	(None, 28, 64)	

256	batch_normalization_1 (BatchNormalization)	(None, 28, 64)
0	dropout_1 (Dropout)	(None, 28, 64)
0	flatten (Flatten)	(None, 1792)
114,752	dense (Dense)	(None, 64)
0	dropout_2 (Dropout)	(None, 64)
65	dense_1 (Dense)	(None, 1)

Total params: 119,457 (466.63 KB)

Trainable params: 119,265 (465.88 KB)

Non-trainable params: 192 (768.00 B)

```
model.compile(optimizer=Adam(learning_rate=0.0005), loss='binary_crossentropy', metrics=['accuracy'])
```

```
history = model.fit(X_train, y_train, epochs=50, verbose=1, validation_data=(X_test, y_test))
```

Epoch 1/50

15/15 ————— 1s 14ms/step - accuracy: 0.6288 - loss: 0.8921 - val_accuracy: 0.9298 - val_loss: 0.5021

Epoch 2/50

15/15 ————— 0s 8ms/step - accuracy: 0.9149 - loss: 0.1983 - val_accuracy: 0.9123 - val_loss: 0.4375

Epoch 3/50

15/15 ————— 0s 8ms/step - accuracy: 0.9492 - loss: 0.1252 - val_accuracy: 0.8772 - val_loss: 0.4025

Epoch 4/50
15/15 _____ 0s 10ms/step - accuracy: 0.9377 - loss: 0.1751 - val_accuracy: 0.8509 - val_loss: 0.3693
Epoch 5/50
15/15 _____ 0s 10ms/step - accuracy: 0.9519 - loss: 0.1343 - val_accuracy: 0.8158 - val_loss: 0.3682
Epoch 6/50
15/15 _____ 0s 8ms/step - accuracy: 0.9453 - loss: 0.1261 - val_accuracy: 0.8333 - val_loss: 0.3411
Epoch 7/50
15/15 _____ 0s 9ms/step - accuracy: 0.9672 - loss: 0.1145 - val_accuracy: 0.8772 - val_loss: 0.3197
Epoch 8/50
15/15 _____ 0s 6ms/step - accuracy: 0.9676 - loss: 0.0966 - val_accuracy: 0.8772 - val_loss: 0.2989
Epoch 9/50
15/15 _____ 0s 6ms/step - accuracy: 0.9798 - loss: 0.0860 - val_accuracy: 0.8509 - val_loss: 0.2911
Epoch 10/50
15/15 _____ 0s 6ms/step - accuracy: 0.9715 - loss: 0.0742 - val_accuracy: 0.8684 - val_loss: 0.2809
Epoch 11/50
15/15 _____ 0s 6ms/step - accuracy: 0.9690 - loss: 0.0883 - val_accuracy: 0.8684 - val_loss: 0.2708
Epoch 12/50
15/15 _____ 0s 7ms/step - accuracy: 0.9769 - loss: 0.0533 - val_accuracy: 0.8860 - val_loss: 0.2556
Epoch 13/50
15/15 _____ 0s 6ms/step - accuracy: 0.9806 - loss: 0.0538 - val_accuracy: 0.8860 - val_loss: 0.2518
Epoch 14/50
15/15 _____ 0s 7ms/step - accuracy: 0.9723 - loss: 0.0588 - val_accuracy: 0.8947 - val_loss: 0.2383
Epoch 15/50
15/15 _____ 0s 6ms/step - accuracy: 0.9812 - loss: 0.0480 - val_accuracy: 0.9035 - val_loss: 0.2174
Epoch 16/50
15/15 _____ 0s 6ms/step - accuracy: 0.9761 - loss: 0.0620 - val_accuracy: 0.9386 - val_loss: 0.1649
Epoch 17/50
15/15 _____ 0s 6ms/step - accuracy: 0.9795 - loss: 0.0678 - val_accuracy: 0.9474 - val_loss: 0.1431
Epoch 18/50
15/15 _____ 0s 6ms/step - accuracy: 0.9728 - loss: 0.0552 - val_accuracy: 0.9474 - val_loss: 0.1464
Epoch 19/50
15/15 _____ 0s 6ms/step - accuracy: 0.9843 - loss: 0.0609 - val_accuracy: 0.9474 - val_loss: 0.1444
Epoch 20/50

15/15 _____ 0s 6ms/step - accuracy: 0.9777 - loss: 0.0612 - val_accuracy: 0.9561 - val_loss: 0.1213
Epoch 21/50
15/15 _____ 0s 5ms/step - accuracy: 0.9877 - loss: 0.0519 - val_accuracy: 0.9561 - val_loss: 0.1270
Epoch 22/50
15/15 _____ 0s 6ms/step - accuracy: 0.9777 - loss: 0.0482 - val_accuracy: 0.9298 - val_loss: 0.1844
Epoch 23/50
15/15 _____ 0s 6ms/step - accuracy: 0.9808 - loss: 0.0467 - val_accuracy: 0.9561 - val_loss: 0.1368
Epoch 24/50
15/15 _____ 0s 6ms/step - accuracy: 0.9621 - loss: 0.0786 - val_accuracy: 0.9649 - val_loss: 0.1196
Epoch 25/50
15/15 _____ 0s 5ms/step - accuracy: 0.9773 - loss: 0.0746 - val_accuracy: 0.9649 - val_loss: 0.1102
Epoch 26/50
15/15 _____ 0s 6ms/step - accuracy: 0.9815 - loss: 0.0367 - val_accuracy: 0.9649 - val_loss: 0.1041
Epoch 27/50
15/15 _____ 0s 7ms/step - accuracy: 0.9809 - loss: 0.0507 - val_accuracy: 0.9649 - val_loss: 0.1077
Epoch 28/50
15/15 _____ 0s 7ms/step - accuracy: 0.9820 - loss: 0.0512 - val_accuracy: 0.9649 - val_loss: 0.1142
Epoch 29/50
15/15 _____ 0s 6ms/step - accuracy: 0.9889 - loss: 0.0453 - val_accuracy: 0.9649 - val_loss: 0.1047
Epoch 30/50
15/15 _____ 0s 6ms/step - accuracy: 0.9788 - loss: 0.0732 - val_accuracy: 0.9561 - val_loss: 0.1068
Epoch 31/50
15/15 _____ 0s 6ms/step - accuracy: 0.9700 - loss: 0.0513 - val_accuracy: 0.9649 - val_loss: 0.1048
Epoch 32/50
15/15 _____ 0s 5ms/step - accuracy: 0.9873 - loss: 0.0349 - val_accuracy: 0.9561 - val_loss: 0.1095
Epoch 33/50
15/15 _____ 0s 6ms/step - accuracy: 0.9830 - loss: 0.0441 - val_accuracy: 0.9561 - val_loss: 0.1183
Epoch 34/50
15/15 _____ 0s 6ms/step - accuracy: 0.9867 - loss: 0.0351 - val_accuracy: 0.9474 - val_loss: 0.1190
Epoch 35/50
15/15 _____ 0s 6ms/step - accuracy: 0.9845 - loss: 0.0308 - val_accuracy: 0.9561 - val_loss: 0.1143
Epoch 36/50
15/15 _____ 0s 7ms/step - accuracy: 0.9629 - loss:

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0.0847 - val_accuracy: 0.9561 - val_loss: 0.1117
Epoch 37/50
15/15 _____ 0s 6ms/step - accuracy: 0.9753 - loss:
0.0723 - val_accuracy: 0.9649 - val_loss: 0.1130
Epoch 38/50
15/15 _____ 0s 6ms/step - accuracy: 0.9797 - loss:
0.0853 - val_accuracy: 0.9649 - val_loss: 0.1149
Epoch 39/50
15/15 _____ 0s 6ms/step - accuracy: 0.9826 - loss:
0.0342 - val_accuracy: 0.9649 - val_loss: 0.1097
Epoch 40/50
15/15 _____ 0s 6ms/step - accuracy: 0.9869 - loss:
0.0309 - val_accuracy: 0.9649 - val_loss: 0.1118
Epoch 41/50
15/15 _____ 0s 5ms/step - accuracy: 0.9860 - loss:
0.0415 - val_accuracy: 0.9561 - val_loss: 0.1141
Epoch 42/50
15/15 _____ 0s 6ms/step - accuracy: 0.9664 - loss:
0.0718 - val_accuracy: 0.9561 - val_loss: 0.1185
Epoch 43/50
15/15 _____ 0s 7ms/step - accuracy: 0.9922 - loss:
0.0227 - val_accuracy: 0.9649 - val_loss: 0.1179
Epoch 44/50
15/15 _____ 0s 7ms/step - accuracy: 0.9830 - loss:
0.0371 - val_accuracy: 0.9649 - val_loss: 0.1271
Epoch 45/50
15/15 _____ 0s 6ms/step - accuracy: 0.9922 - loss:
0.0223 - val_accuracy: 0.9649 - val_loss: 0.1343
Epoch 46/50
15/15 _____ 0s 6ms/step - accuracy: 0.9866 - loss:
0.0319 - val_accuracy: 0.9649 - val_loss: 0.1321
Epoch 47/50
15/15 _____ 0s 6ms/step - accuracy: 0.9879 - loss:
0.0363 - val_accuracy: 0.9561 - val_loss: 0.1345
Epoch 48/50
15/15 _____ 0s 6ms/step - accuracy: 0.9878 - loss:
0.0258 - val_accuracy: 0.9649 - val_loss: 0.1256
Epoch 49/50
15/15 _____ 0s 7ms/step - accuracy: 0.9885 - loss:
0.0285 - val_accuracy: 0.9649 - val_loss: 0.1167
Epoch 50/50
15/15 _____ 0s 7ms/step - accuracy: 0.9803 - loss:
0.0473 - val_accuracy: 0.9649 - val_loss: 0.1007

```

```

def plotLearningCurve(history, epochs):
    epochRange = range(1, epochs+1)
    plt.plot(epochRange, history.history['accuracy'])
    plt.plot(epochRange, history.history['val_accuracy'])
    plt.title('Model Accuracy')
    plt.xlabel('Epoch')

```

```
plt.ylabel('Accuracy')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
```

```
plt.plot(epochRange, history.history['loss'])
plt.plot(epochRange, history.history['val_loss'])
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
```

```
plotLearningCurve(history, 50)
```



