

## OCR letter recognition using Deep Learning

```
import numpy as np
import pandas as pd
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import *
import matplotlib.pyplot as plt

/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/
__init__.py:98: UserWarning: unable to load
libtensorflow_io_plugins.so: unable to open file:
libtensorflow_io_plugins.so, from paths:
['/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/
libtensorflow_io_plugins.so']
caused by:
['/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/
libtensorflow_io_plugins.so: undefined symbol:
_ZN3tsl6StatusC1EN10tensorflow5error4CodeESt17basic_string_viewIcSt11c
har_traitsIcEENS_14SourceLocationE']
warnings.warn(f"unable to load libtensorflow_io_plugins.so: {e}")
/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/__ini
t__.py:104: UserWarning: file system plugins are not loaded: unable to
open file: libtensorflow_io.so, from paths:
['/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/
libtensorflow_io.so']
caused by:
['/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/
libtensorflow_io.so: undefined symbol:
_ZTVN10tensorflow13GcsFileSystemE']
warnings.warn(f"file system plugins are not loaded: {e}")

# Load the OCR letter recognition dataset
url =
'https://archive.ics.uci.edu/ml/machine-learning-databases/letter-
recognition/letter-recognition.data'
dataset = pd.read_csv(url, header=None)
```

### OR

Load the OCR letter recognition dataset, Link

```
url = 'letter-recognition.data'
```

```
dataset = pd.read_csv(url, header=None)
```

```
# Split the dataset into features and labels
X = dataset.iloc[:, 1:].values #selecting all rows and selecting all
```

```

columns from index 1
y = dataset.iloc[:, 0].values    #selecting all rows and selecting
column with index 0

print(y[0])

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# Encode the labels into numeric value
label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)

print(y[0])

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#splitting dataset into training and testing
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=1)

X_train = X_train / 15.0
X_test = X_test / 15.0

#we are using sequential model where layers are stacked one after
another,
#output of previous layer is given to as input to next layer

model = Sequential()
#1st layer is dense layer which consists on 128 neurons, since it is
1st layer we need to define input_shape of our training data
model.add(Dense(128, activation='relu', input_shape=(16,)))
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(26, activation='softmax')) #softmax is used to
predict multiclass category outcome

#now we will compile the model

#sparse_categorical_crossentropy (scc) produces a category index of
the most likely matching category.
model.compile(loss='sparse_categorical_crossentropy',
optimizer='adam', metrics=['accuracy'])

#The batch size is a number of samples processed before the model is
updated.
#verbose is the choice that how you want to see the output of your
Nural Network while it's training.
#If you set verbose = 0, It will show nothing
history = model.fit(X_train, y_train, validation_data=(X_test,
y_test), epochs=50, batch_size=12, verbose=1)

```

Epoch 1/50  
1334/1334 [=====] - 4s 3ms/step - loss:  
2.6237 - accuracy: 0.2200 - val\_loss: 1.7889 - val\_accuracy: 0.5200  
Epoch 2/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.8675 - accuracy: 0.4152 - val\_loss: 1.4179 - val\_accuracy: 0.5953  
Epoch 3/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.6275 - accuracy: 0.4778 - val\_loss: 1.2190 - val\_accuracy: 0.6525  
Epoch 4/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.4847 - accuracy: 0.5254 - val\_loss: 1.1180 - val\_accuracy: 0.6752  
Epoch 5/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.4018 - accuracy: 0.5551 - val\_loss: 1.0480 - val\_accuracy: 0.6917  
Epoch 6/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.3509 - accuracy: 0.5724 - val\_loss: 0.9991 - val\_accuracy: 0.7220  
Epoch 7/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.2906 - accuracy: 0.5952 - val\_loss: 0.9567 - val\_accuracy: 0.7117  
Epoch 8/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.2478 - accuracy: 0.6033 - val\_loss: 0.9193 - val\_accuracy: 0.7305  
Epoch 9/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.2148 - accuracy: 0.6179 - val\_loss: 0.8796 - val\_accuracy: 0.7368  
Epoch 10/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.1853 - accuracy: 0.6227 - val\_loss: 0.8424 - val\_accuracy: 0.7588  
Epoch 11/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.1550 - accuracy: 0.6326 - val\_loss: 0.8344 - val\_accuracy: 0.7552  
Epoch 12/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.1416 - accuracy: 0.6398 - val\_loss: 0.7991 - val\_accuracy: 0.7625  
Epoch 13/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.1110 - accuracy: 0.6500 - val\_loss: 0.7890 - val\_accuracy: 0.7582  
Epoch 14/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.0993 - accuracy: 0.6546 - val\_loss: 0.7669 - val\_accuracy: 0.7790  
Epoch 15/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.0911 - accuracy: 0.6551 - val\_loss: 0.7460 - val\_accuracy: 0.7800  
Epoch 16/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.0815 - accuracy: 0.6576 - val\_loss: 0.7507 - val\_accuracy: 0.7692  
Epoch 17/50  
1334/1334 [=====] - 3s 2ms/step - loss:

1.0675 - accuracy: 0.6633 - val\_loss: 0.7371 - val\_accuracy: 0.7835  
Epoch 18/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.0426 - accuracy: 0.6670 - val\_loss: 0.7095 - val\_accuracy: 0.7928  
Epoch 19/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.0241 - accuracy: 0.6747 - val\_loss: 0.6862 - val\_accuracy: 0.8018  
Epoch 20/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.0250 - accuracy: 0.6739 - val\_loss: 0.6884 - val\_accuracy: 0.8030  
Epoch 21/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.0161 - accuracy: 0.6771 - val\_loss: 0.6768 - val\_accuracy: 0.7940  
Epoch 22/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
0.9871 - accuracy: 0.6864 - val\_loss: 0.6749 - val\_accuracy: 0.7933  
Epoch 23/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
1.0140 - accuracy: 0.6823 - val\_loss: 0.6662 - val\_accuracy: 0.8067  
Epoch 24/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
0.9924 - accuracy: 0.6890 - val\_loss: 0.6563 - val\_accuracy: 0.8025  
Epoch 25/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
0.9856 - accuracy: 0.6877 - val\_loss: 0.6504 - val\_accuracy: 0.8123  
Epoch 26/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
0.9879 - accuracy: 0.6846 - val\_loss: 0.6529 - val\_accuracy: 0.8115  
Epoch 27/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
0.9805 - accuracy: 0.6832 - val\_loss: 0.6500 - val\_accuracy: 0.8165  
Epoch 28/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
0.9765 - accuracy: 0.6931 - val\_loss: 0.6297 - val\_accuracy: 0.8165  
Epoch 29/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
0.9791 - accuracy: 0.6924 - val\_loss: 0.6396 - val\_accuracy: 0.8125  
Epoch 30/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
0.9591 - accuracy: 0.6978 - val\_loss: 0.6327 - val\_accuracy: 0.8117  
Epoch 31/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
0.9679 - accuracy: 0.6915 - val\_loss: 0.6185 - val\_accuracy: 0.8205  
Epoch 32/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
0.9586 - accuracy: 0.6957 - val\_loss: 0.6110 - val\_accuracy: 0.8253  
Epoch 33/50  
1334/1334 [=====] - 3s 2ms/step - loss:  
0.9602 - accuracy: 0.6945 - val\_loss: 0.6108 - val\_accuracy: 0.8230  
Epoch 34/50

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1334/1334 [=====] - 3s 2ms/step - loss:
0.9362 - accuracy: 0.6998 - val_loss: 0.6139 - val_accuracy: 0.8255
Epoch 35/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.9339 - accuracy: 0.6994 - val_loss: 0.5955 - val_accuracy: 0.8282
Epoch 36/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.9429 - accuracy: 0.7021 - val_loss: 0.5999 - val_accuracy: 0.8265
Epoch 37/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.9315 - accuracy: 0.7054 - val_loss: 0.5874 - val_accuracy: 0.8278
Epoch 38/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.9401 - accuracy: 0.7034 - val_loss: 0.5890 - val_accuracy: 0.8278
Epoch 39/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.9241 - accuracy: 0.7041 - val_loss: 0.5909 - val_accuracy: 0.8265
Epoch 40/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.9168 - accuracy: 0.7109 - val_loss: 0.5894 - val_accuracy: 0.8305
Epoch 41/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.9074 - accuracy: 0.7098 - val_loss: 0.5930 - val_accuracy: 0.8200
Epoch 42/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.9054 - accuracy: 0.7084 - val_loss: 0.5810 - val_accuracy: 0.8255
Epoch 43/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.9192 - accuracy: 0.7062 - val_loss: 0.5760 - val_accuracy: 0.8303
Epoch 44/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.8950 - accuracy: 0.7171 - val_loss: 0.5801 - val_accuracy: 0.8257
Epoch 45/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.9087 - accuracy: 0.7116 - val_loss: 0.5602 - val_accuracy: 0.8313
Epoch 46/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.9110 - accuracy: 0.7074 - val_loss: 0.5716 - val_accuracy: 0.8303
Epoch 47/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.9053 - accuracy: 0.7141 - val_loss: 0.5759 - val_accuracy: 0.8313
Epoch 48/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.9121 - accuracy: 0.7105 - val_loss: 0.5714 - val_accuracy: 0.8332
Epoch 49/50
1334/1334 [=====] - 3s 2ms/step - loss:
0.8995 - accuracy: 0.7120 - val_loss: 0.5664 - val_accuracy: 0.8360
Epoch 50/50
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1334/1334 [=====] - 3s 2ms/step - loss: 0.8945 - accuracy: 0.7156 - val_loss: 0.5663 - val_accuracy: 0.8322
```

```
loss, accuracy = model.evaluate(X_test, y_test)
print("Test accuracy:", accuracy)
print("Test loss:", loss)
```

```
125/125 [=====] - 0s 2ms/step - loss: 0.5663
- accuracy: 0.8322
Test accuracy: 0.8322499990463257
Test loss: 0.5662633776664734
```

```
model.save('ocr_model.h5')
# Save the trained model
```

```
from tensorflow.keras.models import load_model
model = load_model('ocr_model.h5')
# Load the trained model
```

```
sample_records = X_test[:1000]
# Select a few records for classification
```

```
# Perform classification
predictions = model.predict(sample_records)
```

```
32/32 [=====] - 0s 1ms/step
```

```
predicted_labels = np.argmax(predictions, axis=1)
predicted_letters = label_encoder.inverse_transform(predicted_labels)
actual_letters = label_encoder.inverse_transform(y_test)
```

```
# Calculate accuracy
accuracy = np.sum(predicted_labels == y[:1000]) /
len(predicted_labels)
```

```
# Print the predicted labels and corresponding actual labels
print("Predicted Labels\tActual Labels")
for i in range(len(predicted_letters)):
    print(f"{predicted_letters[i]}\t\t\t{actual_letters[i]}")
```

```
Predicted LabelsActual Labels
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D	D
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V	V
B	B
H	H
N	N
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X	R
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