OCR

May 5, 2025

[1]:
```python
#  Step 1: Import Libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt
```

[2]:
```python
#  Step 2: Load Dataset
# Make sure the file is in the current directory or specify the full path
column_names = ['letter', 'x-box', 'y-box', 'width', 'height', 'onpix',␣
↪'x-bar', 'y-bar',
                'x2bar', 'y2bar', 'xybar', 'x2ybr', 'xy2br', 'x-ege', 'xegvy',␣
↪'y-ege', 'yegvx']

df = pd.read_csv('OCR/letter-recognition.data', header=None, names=column_names)
df.head()
```

[2]:
```
  letter  x-box  y-box  width  height  onpix  x-bar  y-bar  x2bar  y2bar  \
0      T      2      8      3       5      1      8     13      0      6
1      I      5     12      3       7      2     10      5      5      4
2      D      4     11      6       8      6     10      6      2      6
3      N      7     11      6       6      3      5      9      4      6
4      G      2      1      3       1      1      8      6      6      6

   xybar  x2ybr  xy2br  x-ege  xegvy  y-ege  yegvx
0      6     10      8      0      8      0      8
1     13      3      9      2      8      4     10
2     10      3      7      3      7      3      9
3      4      4     10      6     10      2      8
4      6      5      9      1      7      5     10
```

[3]:
```python
#  Step 3: Preprocess Data
X = df.drop('letter', axis=1)
y = df['letter']
```

```python
# Encode labels (A-Z => 0-25)
le = LabelEncoder()
y_encoded = le.fit_transform(y)

# One-hot encode targets
y_onehot = to_categorical(y_encoded)

# Normalize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

print("X shape:", X_scaled.shape)
print("y shape (one-hot):", y_onehot.shape)
```

```
X shape: (20000, 16)
y shape (one-hot): (20000, 26)
```

[4]:
```python
#  Step 4: Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_onehot,␣
↪test_size=0.2, random_state=42)
```

[5]:
```python
#  Step 5: Define Deep Neural Network
model = Sequential([
    Dense(128, input_shape=(16,), activation='relu'),
    Dropout(0.3),
    Dense(64, activation='relu'),
    Dropout(0.3),
    Dense(26, activation='softmax')  # 26 output classes (A-Z)
])

model.compile(optimizer='adam', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])
model.summary()
```

```
c:\Users\darsh\AppData\Local\Programs\Python\Python310\lib\site-
packages\keras\src\layers\core\dense.py:87: 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: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 128)	2,176
dropout (Dropout)	(None, 128)	0

```
 dense_1 (Dense)                  (None, 64)                  8,256

 dropout_1 (Dropout)              (None, 64)                      0

 dense_2 (Dense)                  (None, 26)                  1,690
```

Total params: 12,122 (47.35 KB)

Trainable params: 12,122 (47.35 KB)

Non-trainable params: 0 (0.00 B)

[6]:

```python
#  Step 6: Train the Model
history = model.fit(X_train, y_train,
                    validation_split=0.2,
                    epochs=30,
                    batch_size=32)
```

```
Epoch 1/30
400/400              3s 3ms/step -
accuracy: 0.2480 - loss: 2.6086 - val_accuracy: 0.6750 - val_loss: 1.1847
Epoch 2/30
400/400              1s 2ms/step -
accuracy: 0.5767 - loss: 1.3599 - val_accuracy: 0.7337 - val_loss: 0.9168
Epoch 3/30
400/400              1s 2ms/step -
accuracy: 0.6511 - loss: 1.1197 - val_accuracy: 0.7700 - val_loss: 0.7842
Epoch 4/30
400/400              1s 2ms/step -
accuracy: 0.6900 - loss: 0.9760 - val_accuracy: 0.7984 - val_loss: 0.6979
Epoch 5/30
400/400              1s 4ms/step -
accuracy: 0.7199 - loss: 0.8814 - val_accuracy: 0.8109 - val_loss: 0.6425
Epoch 6/30
400/400              2s 3ms/step -
accuracy: 0.7374 - loss: 0.8096 - val_accuracy: 0.8322 - val_loss: 0.5837
Epoch 7/30
400/400              1s 2ms/step -
accuracy: 0.7520 - loss: 0.7848 - val_accuracy: 0.8409 - val_loss: 0.5418
Epoch 8/30
400/400              1s 2ms/step -
accuracy: 0.7639 - loss: 0.7419 - val_accuracy: 0.8522 - val_loss: 0.5126
Epoch 9/30
400/400              1s 3ms/step -
```

```
accuracy: 0.7745 - loss: 0.7116 - val_accuracy: 0.8600 - val_loss: 0.4858
Epoch 10/30
400/400            2s 4ms/step -
accuracy: 0.7889 - loss: 0.6792 - val_accuracy: 0.8662 - val_loss: 0.4546
Epoch 11/30
400/400            2s 4ms/step -
accuracy: 0.7901 - loss: 0.6393 - val_accuracy: 0.8706 - val_loss: 0.4379
Epoch 12/30
400/400            1s 3ms/step -
accuracy: 0.8088 - loss: 0.6244 - val_accuracy: 0.8759 - val_loss: 0.4212
Epoch 13/30
400/400            1s 3ms/step -
accuracy: 0.8099 - loss: 0.6090 - val_accuracy: 0.8719 - val_loss: 0.4154
Epoch 14/30
400/400            1s 3ms/step -
accuracy: 0.8050 - loss: 0.5955 - val_accuracy: 0.8794 - val_loss: 0.3864
Epoch 15/30
400/400            1s 3ms/step -
accuracy: 0.8149 - loss: 0.5757 - val_accuracy: 0.8897 - val_loss: 0.3752
Epoch 16/30
400/400            1s 3ms/step -
accuracy: 0.8145 - loss: 0.5651 - val_accuracy: 0.8894 - val_loss: 0.3715
Epoch 17/30
400/400            1s 3ms/step -
accuracy: 0.8190 - loss: 0.5775 - val_accuracy: 0.8881 - val_loss: 0.3570
Epoch 18/30
400/400            1s 3ms/step -
accuracy: 0.8238 - loss: 0.5497 - val_accuracy: 0.8969 - val_loss: 0.3427
Epoch 19/30
400/400            1s 3ms/step -
accuracy: 0.8349 - loss: 0.5262 - val_accuracy: 0.8969 - val_loss: 0.3313
Epoch 20/30
400/400            1s 3ms/step -
accuracy: 0.8188 - loss: 0.5456 - val_accuracy: 0.9019 - val_loss: 0.3225
Epoch 21/30
400/400            1s 3ms/step -
accuracy: 0.8302 - loss: 0.5173 - val_accuracy: 0.9044 - val_loss: 0.3134
Epoch 22/30
400/400            1s 3ms/step -
accuracy: 0.8366 - loss: 0.5159 - val_accuracy: 0.9034 - val_loss: 0.3057
Epoch 23/30
400/400            2s 4ms/step -
accuracy: 0.8428 - loss: 0.4882 - val_accuracy: 0.9050 - val_loss: 0.3060
Epoch 24/30
400/400            2s 4ms/step -
accuracy: 0.8426 - loss: 0.4945 - val_accuracy: 0.9106 - val_loss: 0.2959
Epoch 25/30
400/400            1s 3ms/step -
```

```
accuracy: 0.8481 - loss: 0.4687 - val_accuracy: 0.9128 - val_loss: 0.2854
Epoch 26/30
400/400              1s 3ms/step -
accuracy: 0.8524 - loss: 0.4517 - val_accuracy: 0.9166 - val_loss: 0.2765
Epoch 27/30
400/400              2s 4ms/step -
accuracy: 0.8516 - loss: 0.4627 - val_accuracy: 0.9150 - val_loss: 0.2748
Epoch 28/30
400/400              1s 3ms/step -
accuracy: 0.8467 - loss: 0.4724 - val_accuracy: 0.9166 - val_loss: 0.2710
Epoch 29/30
400/400              1s 3ms/step -
accuracy: 0.8522 - loss: 0.4526 - val_accuracy: 0.9194 - val_loss: 0.2646
Epoch 30/30
400/400              1s 3ms/step -
accuracy: 0.8600 - loss: 0.4375 - val_accuracy: 0.9191 - val_loss: 0.2612
```

[7]:

```python
#  Step 7: Evaluate the Model
test_loss, test_accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {test_accuracy:.2f}")
```

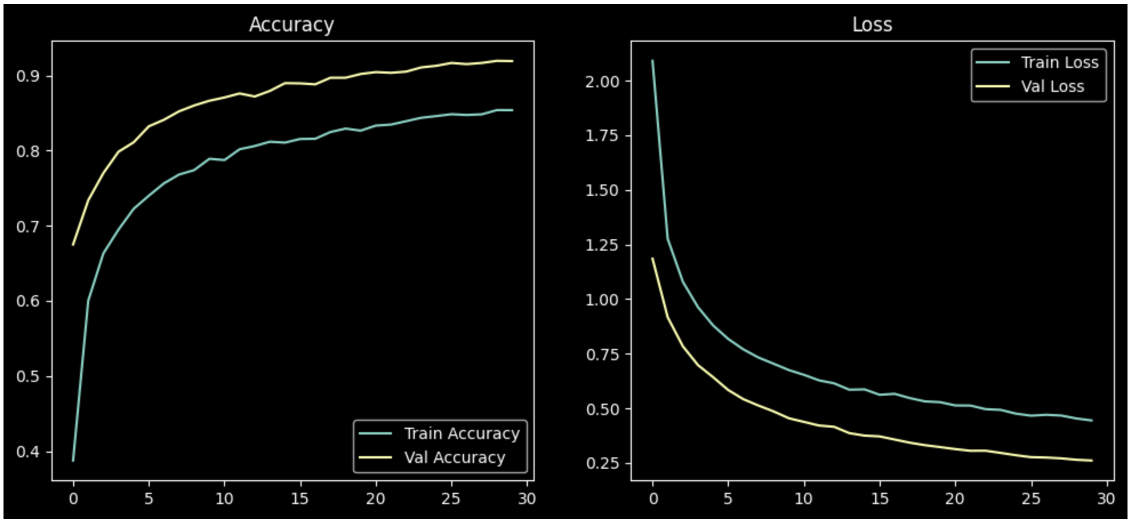
```
125/125              0s 2ms/step -
accuracy: 0.9279 - loss: 0.2520
Test Accuracy: 0.93
```

[8]:

```python
#  Step 8: Plot Training Curves
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.legend()
plt.title("Accuracy")

plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.legend()
plt.title("Loss")

plt.show()
```



[9]:
```
#   Step 9: Make Predictions (optional)
predictions = model.predict(X_test)
pred_classes = np.argmax(predictions, axis=1)
true_classes = np.argmax(y_test, axis=1)

# Decode class labels
pred_labels = le.inverse_transform(pred_classes)
true_labels = le.inverse_transform(true_classes)

# Show some predictions
for i in range(5):
    print(f"True: {true_labels[i]} | Predicted: {pred_labels[i]}")
```

```
125/125              0s 1ms/step
True: T | Predicted: X
True: L | Predicted: L
True: A | Predicted: A
True: E | Predicted: E
True: Q | Predicted: Q
```