

## ✓ MNIST Handwritten Digit Recognition - Google Colab Notebook

This notebook uses Keras's built-in MNIST dataset for training and testing, ensuring both sets are available. It also includes the optional CSV upload for custom test data.

```
# Step 1: Import Libraries
!pip install -q gradio
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten
from sklearn.metrics import classification_report, confusion_matrix
import gradio as gr
```



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```
# Step 2: Load MNIST from Keras
(X_train, y_train), (X_test, y_test) = tf.keras.datasets.mnist.load_data()
print(f"Training set shape: {X_train.shape}, {y_train.shape}")
print(f"Test set shape: {X_test.shape}, {y_test.shape}")
```



Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz>  
11490434/11490434 ————— 0s 0us/step  
Training set shape: (60000, 28, 28), (60000,)  
Test set shape: (10000, 28, 28), (10000,)

```
# Optional: Load custom CSV test set
from google.colab import files
print("Upload 'mnist_test.csv' if you have a custom test set:")
uploaded = files.upload()
if 'mnist_test.csv' in uploaded:
    df_test = pd.read_csv('mnist_test.csv')
    print("Custom CSV loaded, shape:", df_test.shape)
```



Upload 'mnist\_test.csv' if you have a custom test set:  
 mnist\_test.csv  
• **mnist\_test.csv**(text/csv) - 18303650 bytes, last modified: 20/05/2025 - 100% done  
Saving mnist\_test.csv to mnist\_test.csv  
Custom CSV loaded, shape: (10000, 785)

```
# Step 3: Preprocess Data
# Normalize and reshape
```

```

X_train = X_train.reshape(-1, 28*28) / 255.0
X_test = X_test.reshape(-1, 28*28) / 255.0

# Data exploration

import matplotlib.pyplot as plt
import numpy as np
# Check the data types
print("\nData types of features:")
print("X_train dtype:", X_train.dtype)
print("y_train dtype:", y_train.dtype)
print("X_test dtype:", X_test.dtype)
print("y_test dtype:", y_test.dtype)

# Check for missing values
print("\nMissing values in training data:")
print("X_train missing:", np.isnan(X_train).sum())
print("y_train missing:", np.isnan(y_train).sum())
print("X_test missing:", np.isnan(X_test).sum())
print("y_test missing:", np.isnan(y_test).sum())

# Check the range of values in the features (after normalization)
print("\nRange of values in features:")
print("X_train min:", X_train.min(), "max:", X_train.max())
print("X_test min:", X_test.min(), "max:", X_test.max())

# Check the distribution of target classes
print("\nDistribution of target classes in training set:")
unique_train, counts_train = np.unique(y_train, return_counts=True)
print(dict(zip(unique_train, counts_train)))

print("\nDistribution of target classes in test set:")
unique_test, counts_test = np.unique(y_test, return_counts=True)
print(dict(zip(unique_test, counts_test)))

# Display some sample images (optional, requires reshaping back for plotting)
# Reshape back for plotting
X_train_img = X_train.reshape(-1, 28, 28)
X_test_img = X_test.reshape(-1, 28, 28)

plt.figure(figsize=(10, 10))
for i in range(25):
    plt.subplot(5, 5, i + 1)
    plt.imshow(X_train_img[i], cmap='gray')
    plt.title(f"Label: {y_train[i]}")
    plt.axis('off')
plt.suptitle("Sample Training Images")
plt.show()

if 'df_test' in globals():
    # If custom CSV was loaded, perform similar checks
    print("\n--- Custom CSV Data Exploration ---")
    print("Custom CSV columns:", df_test.columns)
    print("Custom CSV info:")
    df_test.info()
    print("\nMissing values in custom CSV:")
    print(df_test.isnull().sum().sum())

    # Assuming the first column is the label and the rest are pixel values
    # (This might need adjustment based on the actual CSV format)
    custom_X_test_raw = df_test.drop(df_test.columns[0], axis=1).values
    custom_y_test_raw = df_test[df_test.columns[0]].values

    # Check data types of custom data

```

```

print("\nData types of custom test data:")
print("custom_X_test_raw dtype:", custom_X_test_raw.dtype)
print("custom_y_test_raw dtype:", custom_y_test_raw.dtype)

# Check the range of values in the raw custom data
print("\nRange of values in raw custom test data:")
print("custom_X_test_raw min:", custom_X_test_raw.min(), "max:", custom_X_test_raw.m

# Check the distribution of target classes in custom test set
print("\nDistribution of target classes in custom test set:")
unique_custom, counts_custom = np.unique(custom_y_test_raw, return_counts=True)
print(dict(zip(unique_custom, counts_custom)))

# Display some sample custom images (optional, requires reshaping back for plotting)
custom_X_test_img = custom_X_test_raw.reshape(-1, 28, 28)

plt.figure(figsize=(10, 10))
num_samples_to_plot = min(25, custom_X_test_img.shape[0])
for i in range(num_samples_to_plot):
    plt.subplot(5, 5, i + 1)
    # Scale the pixel values to 0-255 for display if they are not already
    img_to_show = custom_X_test_img[i]
    if img_to_show.max() <= 1:
        img_to_show = img_to_show * 255
    plt.imshow(img_to_show.astype(np.uint8), cmap='gray')
    plt.title(f"Label: {custom_y_test_raw[i]}")
    plt.axis('off')
plt.suptitle("Sample Custom Test Images")
plt.show()

```



Data types of features:

X\_train dtype: float64

y\_train dtype: uint8

X\_test dtype: float64

y\_test dtype: uint8

Missing values in training data:

X\_train missing: 0

y\_train missing: 0

X\_test missing: 0

y\_test missing: 0

Range of values in features:

X\_train min: 0.0 max: 1.0

X\_test min: 0.0 max: 1.0

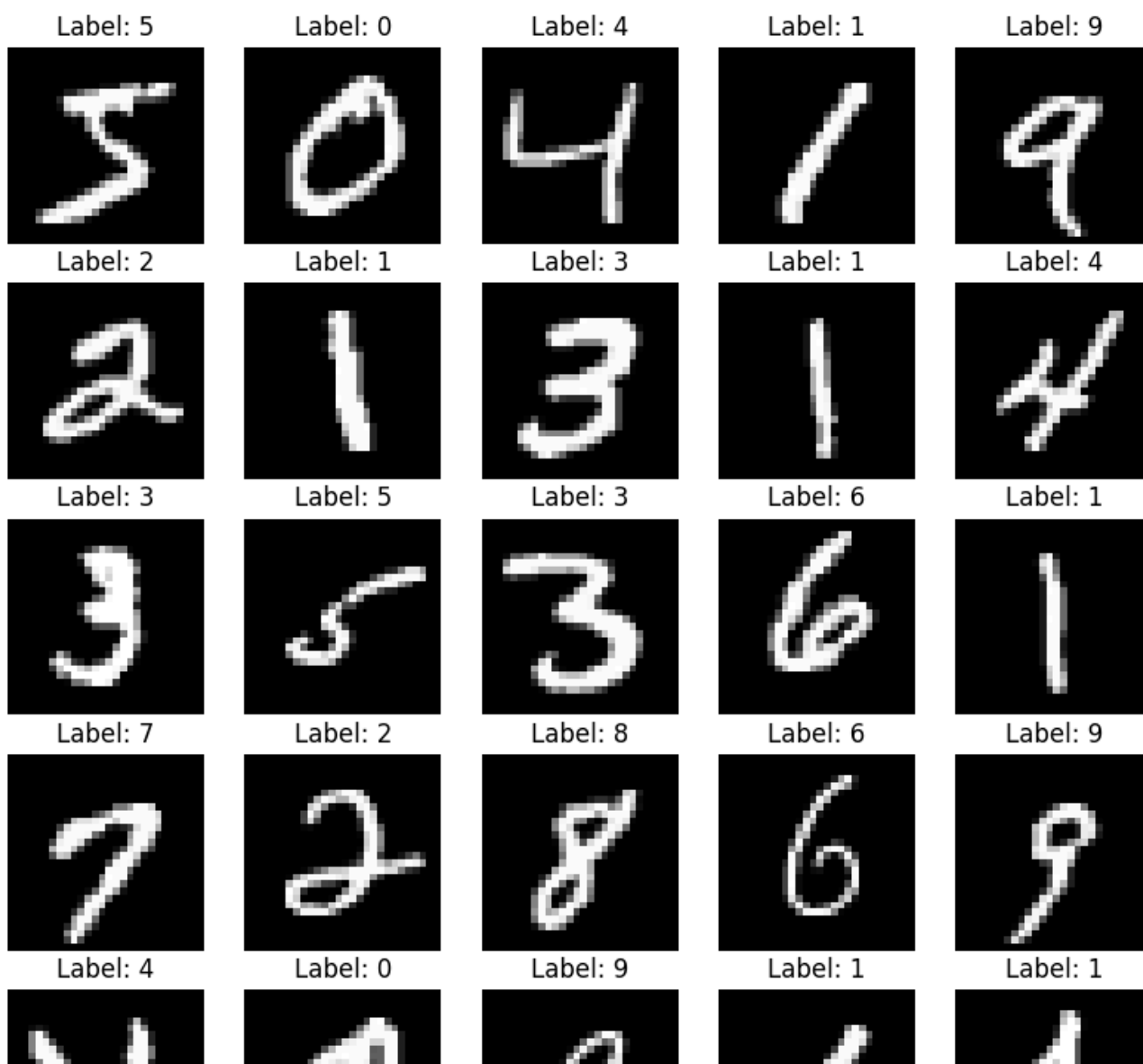
Distribution of target classes in training set:

{np.uint8(0): np.int64(5923), np.uint8(1): np.int64(6742), np.uint8(2): np.int64(5923), np.uint8(3): np.int64(5923), np.uint8(4): np.int64(5923), np.uint8(5): np.int64(5923), np.uint8(6): np.int64(5923), np.uint8(7): np.int64(5923), np.uint8(8): np.int64(5923), np.uint8(9): np.int64(5923)}

Distribution of target classes in test set:

{np.uint8(0): np.int64(980), np.uint8(1): np.int64(1135), np.uint8(2): np.int64(980), np.uint8(3): np.int64(980), np.uint8(4): np.int64(980), np.uint8(5): np.int64(980), np.uint8(6): np.int64(980), np.uint8(7): np.int64(980), np.uint8(8): np.int64(980), np.uint8(9): np.int64(980)}

### Sample Training Images





```

--- Custom CSV Data Exploration ---
Custom CSV columns: Index(['label', '1x1', '1x2', '1x3', '1x4', '1x5', '1x6',
...
'28x19', '28x20', '28x21', '28x22', '28x23', '28x24', '28x25', '28x26',
'28x27', '28x28'],
dtype='object', length=785)
Custom CSV info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Columns: 785 entries, label to 28x28
dtypes: int64(785)
memory usage: 59.9 MB

Missing values in custom CSV:
0

Data types of custom test data:
custom_X_test_raw dtype: int64
custom_y_test_raw dtype: int64

```

# prompt: Data analysis

```

import matplotlib.pyplot as plt
import numpy as np
# If a custom test set was uploaded, use it. Otherwise, use the Keras test set.
# files.upload() # Remove this duplicated call
from google.colab import files # Re-import files

```

```

if 'mnist_test.csv' in uploaded:
    # The first column is the label, the rest are pixel values
    y_test_custom = df_test.iloc[:, 0].values
    X_test_custom = df_test.iloc[:, 1:].values / 255.0 # Normalize
    X_test = X_test_custom
    y_test = y_test_custom
    print("Using custom test set.")
else:
    print("Using default Keras test set.")

```

```
print(f"Final Test set shape: {X_test.shape}, {y_test.shape}")
```

```

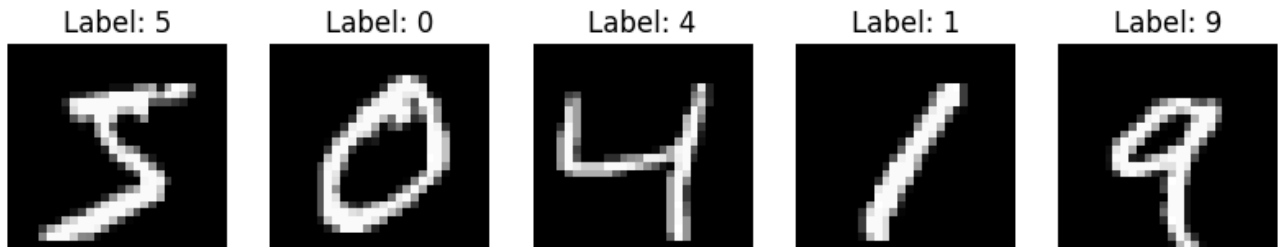
➡ Using custom test set.
Final Test set shape: (10000, 784), (10000,)

```

```

# Step 4: Visualize Sample Digits
plt.figure(figsize=(10,4))
for i in range(10):
    plt.subplot(2,5,i+1)
    plt.imshow(X_train[i].reshape(28,28), cmap='gray')
    plt.title(f"Label: {y_train[i]}")
    plt.axis('off')
plt.show()

```



# Step 5: Build Model

```
model = Sequential([
    Flatten(input_shape=(784,)),
    Dense(128, activation='relu'),
    Dense(64, activation='relu'),
    Dense(10, activation='softmax')
])
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
model.summary()
```



```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/resizing/flatten.py:
    super().__init__(**kwargs)
Model: "sequential"
```

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 784)	0
dense (Dense)	(None, 128)	100,480
dense_1 (Dense)	(None, 64)	8,256
dense_2 (Dense)	(None, 10)	650

```
Total params: 109,386 (427.29 KB)
Trainable params: 109,386 (427.29 KB)
Non-trainable params: 0 (0.00 B)
```

# Step 6: Train Model

```
history = model.fit(X_train, y_train, epochs=10, validation_split=0.1)
```



```
Epoch 1/10
1688/1688 ————— 16s 9ms/step - accuracy: 0.8638 - loss: 0.4
Epoch 2/10
1688/1688 ————— 15s 6ms/step - accuracy: 0.9661 - loss: 0.1
Epoch 3/10
1688/1688 ————— 9s 5ms/step - accuracy: 0.9777 - loss: 0.07
Epoch 4/10
1688/1688 ————— 7s 4ms/step - accuracy: 0.9818 - loss: 0.05
Epoch 5/10
1688/1688 ————— 10s 4ms/step - accuracy: 0.9868 - loss: 0.0
Epoch 6/10
1688/1688 ————— 8s 5ms/step - accuracy: 0.9900 - loss: 0.03
Epoch 7/10
1688/1688 ————— 10s 5ms/step - accuracy: 0.9913 - loss: 0.0
Epoch 8/10
1688/1688 ————— 7s 4ms/step - accuracy: 0.9930 - loss: 0.02
```

Epoch 9/10  
**1688/1688** ————— **8s** 5ms/step - accuracy: 0.9925 - loss: 0.02  
 Epoch 10/10  
**1688/1688** ————— **10s** 5ms/step - accuracy: 0.9940 - loss: 0.0

# Step 7: Evaluate Model

```
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {accuracy:.4f}")
```

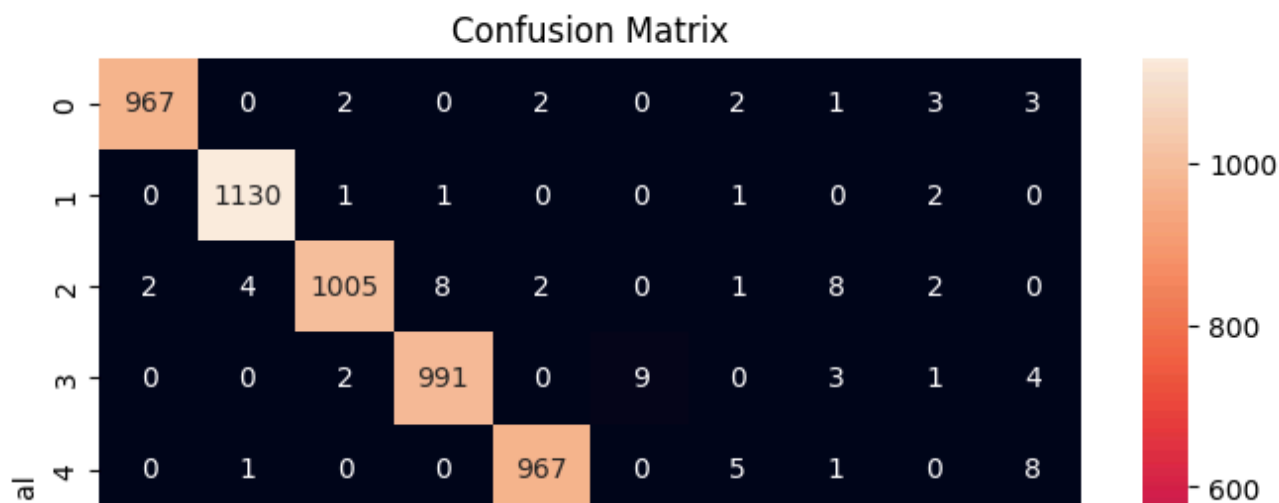
```
y_pred = np.argmax(model.predict(X_test), axis=1)
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
plt.figure(figsize=(8,6))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d')
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

↔ **313/313** ————— **1s** 2ms/step - accuracy: 0.9729 - loss: 0.1031  
 Test Accuracy: 0.9776  
**313/313** ————— **1s** 2ms/step

Classification Report:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	980
1	0.98	1.00	0.99	1135
2	0.98	0.97	0.98	1032
3	0.96	0.98	0.97	1010
4	0.97	0.98	0.98	982
5	0.96	0.98	0.97	892
6	0.99	0.98	0.98	958
7	0.97	0.98	0.98	1028
8	0.99	0.96	0.97	974
9	0.98	0.96	0.97	1009
accuracy			0.98	10000
macro avg	0.98	0.98	0.98	10000
weighted avg	0.98	0.98	0.98	10000



# Step 8: Deploy with Gradio

```
def gradio_interface(img):
    img = np.array(img.convert('L')).reshape(1,784)/255.0
```

```

pred = model.predict(img)
return {str(i): float(pred[0][i]) for i in range(10)}

interface = gr.Interface(fn=gradio_interface,
                        inputs=gr.Image(height=28, width=28, image_mode='L'), # Changed
                        outputs=gr.Label(num_top_classes=3),
                        live=True)

interface.launch()

```

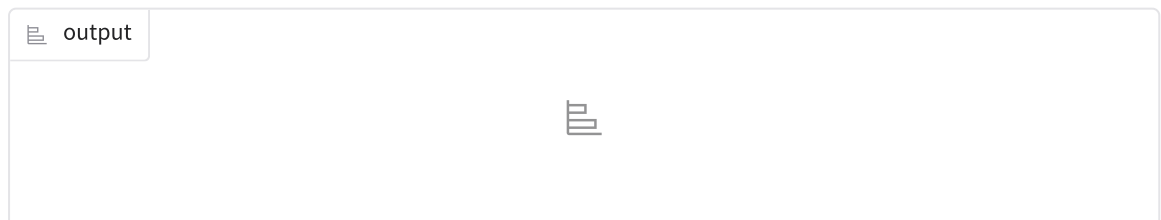
➡ It looks like you are running Gradio on a hosted Jupyter notebook. For the Colab notebook detected. To show errors in colab notebook, set debug=True in ]

\* Running on public URL: <https://813146c5cdf5aea22b.gradio.live>

This share link expires in 1 week. For free permanent hosting and GPU upgrades:



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