Optical Character Recognition (OCR) Model: Using TensorFlow and Keras API

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TensorFlow Documentation

Install TensorFlow & Configure Environment Locally

Youtube Tutorial & Steps

1. Youtube
2. Steps From Youtube Video

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1. Install Anaconda
2. Check System Requirement for TensorFlow
3. Check Software Requirement for TensorFlow
4. Build Configuration CPU
   - TF CPU Configuration
   - Create Conda Environment
   - Install dependancies

```
# Anything above 2.10 is not supported on the GPU on Windows Native
python -m pip install "tensorflow<2.11"
# Verify the installation:
python -c "import tensorflow as tf; print(tf.config.list_physical_devices('GPU'))"
```

5. Build Configuration GPU
   - Check if you GPU supports CUDA here
   - TF GPU Configuration
   - Nvidia CUDA toolkit
   - cuDNN Archive
   - Create Conda Environment
   - Install dependancies. Change CUDA toolkit, cuDNN version

```
conda install -c conda-forge cudatoolkit=11.2 cudnn=8.1.0
# Anything above 2.10 is not supported on the GPU on Windows Native
python -m pip install "tensorflow<2.11"
# Verify the installation:
python -c "import tensorflow as tf; print(tf.config.list_physical_devices('GPU'))"
```

1. Data Collection & Preparation

Data Sources

Kaggle

Hugging Face

NIST

EMNIST Dataset

Extended Modified NIST (EMNIST) Dataset

Derived from NIST Special Database 19

- EMNIST ByClass: 814,255 characters. 62 unbalanced classes.
- EMNIST ByMerge: 814,255 characters. 47 unbalanced classes.
- EMNIST Balanced: 131,600 characters. 47 balanced classes.
- EMNIST Letters: 145,600 characters. 26 balanced classes.
- EMNIST Digits: 280,000 characters. 10 balanced classes.
- EMNIST MNIST: 70,000 characters. 10 balanced classes.

Download & Inspect Data

1. Manual Download - Kaggle, Balanced EMNIST
    - Train CSV
    - Test CSV
    - Mapping

   Then, unzip the files in the root of project
2. From Terminal
    - Follow steps from here https://github.com/otenim/Python-EMNIST-Decoder
3. From IDE - NIST SD 19, ByMerge

```
import os
import pathlib

DOWNLOAD_DATA_DIR = 'C:\\Users\\User\\Desktop\\Python\\OCR_Workshop\\data'

download data, by_merge, unzip

download_data_dir = pathlib.Path(DOWNLOAD_DATA_DIR)
if not data_dir.exists():
  tf.keras.utils.get_file(
       'by_merge.zip',
       origin='https://s3.amazonaws.com/nist-srd/SD19/by_merge.zip',
       extract=True,
       cache_dir='.',
       cache_subdir='data'
   )
```

4. Online Google Colab/Jupyter Notebook

   Download train/test CSV files, ASCII mapping

```
!gdown 1ruHQJG2pPaeoSpvexdGgKQrwmZPE-Req
!gdown 1bHJFAdbKr_55HSVsjauuZpI9HGOO9UsZ
!gdown 1hf0mtpXwECXi_IvgwCQrgSzmPe-DHlaT
```

   Unzip the files

```
!unzip -q /content/emnist-balanced-train.csv.zip
!unzip -q /content/emnist-balanced-test.csv.zip
```

   See mapping

```
!cat /content/emnist-balanced-mapping.txt
```

```
# download
!gdown 1ruHQJG2pPaeoSpvexdGgKQrwmZPE-Req
!gdown 1bHJFAdbKr_55HSVsjauuZpI9HGOO9UsZ
!gdown 1hf0mtpXwECXi_IvgwCQrgSzmPe-DHlaT
```

```
Downloading...
From (original): https://drive.google.com/uc?id=1ruHQJG2pPaeoSpvexdGgKQrwmZPE-Req
From (redirected): https://drive.google.com/uc?id=1ruHQJG2pPaeoSpvexdGgKQrwmZPE-Req&confirm=t&uuid=a33ad1ee-cb33-4c0b-8878-e56f45108864
To: /content/emnist-balanced-train.csv.zip
100% 39.0M/39.0M [00:01<00:00, 19.7MB/s]
Downloading...
From: https://drive.google.com/uc?id=1bHJFAdbKr_55HSVsjauuZpI9HGOO9UsZ
To: /content/emnist-balanced-test.csv.zip
100% 6.53M/6.53M [00:00<00:00, 11.6MB/s]
Downloading...
From: https://drive.google.com/uc?id=1hf0mtpXwECXi_IvgwCQrgSzmPe-DHlaT
To: /content/emnist-balanced-mapping.txt
100% 326/326 [00:00<00:00, 1.31MB/s]
```

```
# unzip
!unzip -q /content/emnist-balanced-train.csv.zip
!unzip -q /content/emnist-balanced-test.csv.zip
```

```
# see mapping
!cat /content/emnist-balanced-mapping.txt
```

```
0 48
1 49
2 50
3 51
4 52
5 53
6 54
7 55
8 56
9 57
10 65
11 66
12 67
13 68
14 69
15 70
16 71
17 72
18 73
19 74
20 75
21 76
22 77
23 78
24 79
25 80
26 81
27 82
28 83
29 84
30 85
31 86
32 87
33 88
34 89
35 90
36 97
37 98
38 100
39 101
40 102
41 103
42 104
43 110
44 113
45 114
46 116
```

ASCII chart

Decimal - Binary - Octal - Hex – ASCII
Conversion Chart

Decimal	Binary	Octal	Hex	ASCII	Decimal	Binary	Octal	Hex	ASCII	Decimal	Binary	Octal	Hex	ASCII	Decimal	Binary	Octal	Hex	ASCII
0	00000000	000	00	NUL	32	00100000	040	20	SP	64	01000000	100	40	@	96	01100000	140	60	`
1	00000001	001	01	SOH	33	00100001	041	21	!	65	01000001	101	41	A	97	01100001	141	61	a
2	00000010	002	02	STX	34	00100010	042	22	“	66	01000010	102	42	B	98	01100010	142	62	b
3	00000011	003	03	ETX	35	00100011	043	23	#	67	01000011	103	43	C	99	01100011	143	63	c
4	00000100	004	04	EOT	36	00100100	044	24	$	68	01000100	104	44	D	100	01100100	144	64	d
5	00000101	005	05	ENQ	37	00100101	045	25	%	69	01000101	105	45	E	101	01100101	145	65	e
6	00000110	006	06	ACK	38	00100110	046	26	&	70	01000110	106	46	F	102	01100110	146	66	f
7	00000111	007	07	BEL	39	00100111	047	27	‘	71	01000111	107	47	G	103	01100111	147	67	g
8	00001000	010	08	BS	40	00101000	050	28	(	72	01001000	110	48	H	104	01101000	150	68	h
9	00001001	011	09	HT	41	00101001	051	29	)	73	01001001	111	49	I	105	01101001	151	69	i
10	00001010	012	0A	LF	42	00101010	052	2A	*	74	01001010	112	4A	J	106	01101010	152	6A	j
11	00001011	013	0B	VT	43	00101011	053	2B	+	75	01001011	113	4B	K	107	01101011	153	6B	k
12	00001100	014	0C	FF	44	00101100	054	2C	,	76	01001100	114	4C	L	108	01101100	154	6C	l
13	00001101	015	0D	CR	45	00101101	055	2D	-	77	01001101	115	4D	M	109	01101101	155	6D	m
14	00001110	016	0E	SO	46	00101110	056	2E	.	78	01001110	116	4E	N	110	01101110	156	6E	n
15	00001111	017	0F	SI	47	00101111	057	2F	/	79	01001111	117	4F	O	111	01101111	157	6F	o
16	00010000	020	10	DLE	48	00110000	060	30	0	80	01010000	120	50	P	112	01110000	160	70	p
17	00010001	021	11	DC1	49	00110001	061	31	1	81	01010001	121	51	Q	113	01110001	161	71	q
18	00010010	022	12	DC2	50	00110010	062	32	2	82	01010010	122	52	R	114	01110010	162	72	r
19	00010011	023	13	DC3	51	00110011	063	33	3	83	01010011	123	53	S	115	01110011	163	73	s
20	00010100	024	14	DC4	52	00110100	064	34	4	84	01010100	124	54	T	116	01110100	164	74	t
21	00010101	025	15	NAK	53	00110101	065	35	5	85	01010101	125	55	U	117	01110101	165	75	u
22	00010110	026	16	SYN	54	00110110	066	36	6	86	01010110	126	56	V	118	01110110	166	76	v
23	00010111	027	17	ETB	55	00110111	067	37	7	87	01010111	127	57	W	119	01110111	167	77	w
24	00011000	030	18	CAN	56	00111000	070	38	8	88	01011000	130	58	X	120	01111000	170	78	x
25	00011001	031	19	EM	57	00111001	071	39	9	89	01011001	131	59	Y	121	01111001	171	79	y
26	00011010	032	1A	SUB	58	00111010	072	3A	:	90	01011010	132	5A	Z	122	01111010	172	7A	z
27	00011011	033	1B	ESC	59	00111011	073	3B	;	91	01011011	133	5B	[	123	01111011	173	7B	{
28	00011100	034	1C	FS	60	00111100	074	3C	<	92	01011100	134	5C	\	124	01111100	174	7C	|
29	00011101	035	1D	GS	61	00111101	075	3D	=	93	01011101	135	5D	]	125	01111101	175	7D	}
30	00011110	036	1E	RS	62	00111110	076	3E	>	94	01011110	136	5E	^	126	01111110	176	7E	~
31	00011111	037	1F	US	63	00111111	077	3F	?	95	01011111	137	5F	_	127	01111111	177	7F	DEL

Prepare Data for TensorFlow

Determine Load Function

pd.read_csv

Read a comma-separated values (csv) file into DataFrame. pd.read_csv

```
pandas.read_csv(
  filepath_or_buffer
  )
```

tf.keras.utils.image_dataset_from_directory

Require directory structure for tf.keras.utils.image_dataset_from_directory:

```
main_directory/
...class_a/
......a_image_1.jpg
......a_image_2.jpg
...class_b/
......b_image_1.jpg
......b_image_2.jpg
```

2. Visualize Data & Preprocessing

Load Data & Inspect Shape

```
import gc

import tensorflow as tf
import numpy as np
import pandas as pd

import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline

from keras import layers
from keras.models import Sequential
from IPython.display import display, clear_output

gc.collect()
# add any additional imports after this line ----------------------------------
```

```
4
```

```
# declare global variables
SEED = 42
tf.random.set_seed(SEED)
np.random.seed(SEED)
```

```
train_dataframe = pd.read_csv('emnist-balanced-train.csv')
test_dataframe = pd.read_csv('emnist-balanced-test.csv')
mapping = pd.read_csv('emnist-balanced-mapping.txt', sep=' ', header=None)
```

```
display(train_dataframe.head())
train_dataframe.info()
print(f"train_dataframe shape: {train_dataframe.shape}")
```

	45	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	...	0.524	0.525	0.526	0.527	0.528
0	36	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
1	43	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
2	15	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
3	4	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
4	42	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0

5 rows × 785 columns

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 112799 entries, 0 to 112798
Columns: 785 entries, 45 to 0.533
dtypes: int64(785)
memory usage: 675.6 MB
```

[Kaggle EMNIST]

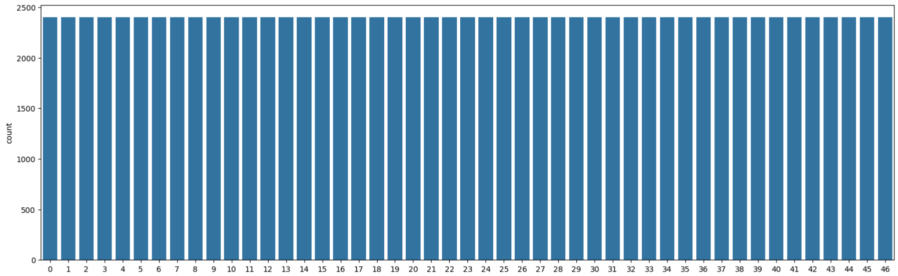
Format

There are six different splits provided in this dataset and each are provided in two formats:

- Binary (see emnist_source_files.zip)
- CSV (combined labels and images)
    - Each row is a separate image
    - 785 columns
    - First column = class_label (see mappings.txt for class label definitions)
    - Each column after represents one pixel value (784 total for a 28 x 28 image)

```
labels = train_dataframe["45"].values

plt.figure(figsize=(20, 6))
sns.countplot(x=labels)

del labels
gc.collect()
```

```
22296
```




```
def get_mapping(m):
  class_mapping = {}
  ascii_code = m[1].values
  for i, code in enumerate(ascii_code):
    class_mapping[i] = chr(code)

  return class_mapping


class_mapping = get_mapping(mapping)
print(f"Class Map: {class_mapping}")
```

```
Class Map: {0: '0', 1: '1', 2: '2', 3: '3', 4: '4', 5: '5', 6: '6', 7: '7', 8: '8', 9: '9', 10: 'A', 11: 'B', 12: 'C', 13: 'D', 14: 'E',
```

Preprocessing

Refering to [EMNSIT research paper]()

- CSV (combined labels and images)
  - Each row is a separate image
  - 785 columns
  - First column = class_label (see mappings.txt for class label definitions)
  - Each column after represents one pixel value (784 total for a 28 x 28 image)

```
# extract label and training data
y_train = np.array(train_dataframe.iloc[:,0].values)
x_train = np.array(train_dataframe.iloc[:,1:].values)

y_test = np.array(test_dataframe.iloc[:,0].values)
x_test = np.array(test_dataframe.iloc[:,1:].values)

print(f"Extracted Labels: {y_train}\n")
print(f"Train data shape: {x_train.shape}")
print(f"Train data shape: {x_test.shape}\n")

del train_dataframe
del test_dataframe
gc.collect()
```

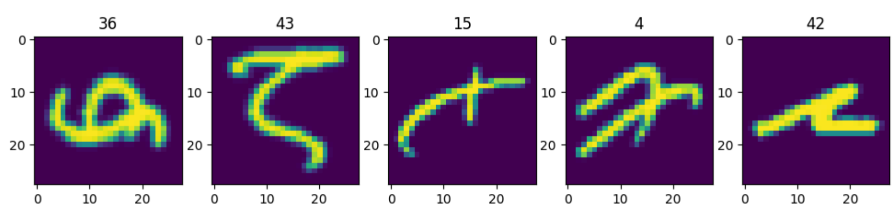
```
Extracted Labels: [36 43 15 ... 23 31  8]

Train data shape: (112799, 784)
Train data shape: (18799, 784)

9898
```

```
# normalize
x_train = x_train.astype('float32') / 255
x_test = x_test.astype('float32') / 255

# Reshape the data to have a single color channel (since EMNIST is grayscale)
# and match the input shape expected by the model
x_train = x_train.reshape((-1, 28, 28, 1))
x_test = x_test.reshape((-1, 28, 28, 1))
print(f"Shape before transpose: {x_train.shape}")
print(f"Mean before transpose: {np.mean(x_train[116])}\n")
```

```
Shape before transpose: (112799, 28, 28, 1)
Mean before transpose: 0.11454582214355469
```

Show 5 samples from original data

```
fig, axes = plt.subplots(1, 5, figsize=(12, 12))

for i, ax in enumerate(axes.flatten()):
  ax.imshow(x_train[i])
  ax.set_title(y_train[i])
```




```
# transpose to reverse effect from converting png to csv (2D -> 1D)
def transpose_data(x):
    return np.transpose(np.squeeze(x))[..., np.newaxis]

x_train = np.array([transpose_data(x) for x in x_train])
x_test = np.array([transpose_data(x) for x in x_test])
print(f"Shape after transpose: {x_train.shape}")
print(f"Mean after transpose: {np.mean(x_train[116])}\n")
```

```
Shape after transpose: (112799, 28, 28, 1)
Mean after transpose: 0.11454582214355469
```

```
# get a sample image for future comparison
sample_image = x_train[116]
sample_label = y_train[116]
print(f"Sample image shape: {sample_image.shape}")
print(f"Sample label: {class_mapping.get(sample_label)}")
```

```
Sample image shape: (28, 28, 1)
Sample label: F
```

```
train_dataset = tf.data.Dataset.from_tensor_slices((x_train, y_train))
test_dataset = tf.data.Dataset.from_tensor_slices((x_test, y_test))
print(f"train_dataset shape: {train_dataset.element_spec}")
```

```
train_dataset shape: (TensorSpec(shape=(28, 28, 1), dtype=tf.float32, name=None), TensorSpec(shape=(), dtype=tf.int64, name=None))
```

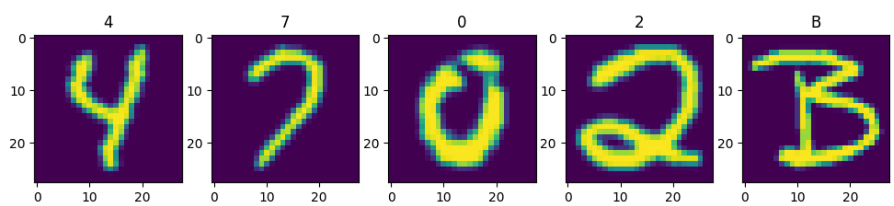
```
del x_train
del x_test
del y_train
del y_test
gc.collect()
```

```
25271
```

```
train_dataset = train_dataset.cache().shuffle(10000).batch(16).prefetch(tf.data.AUTOTUNE)
test_dataset = test_dataset.cache().batch(16)
```

Show 5 samples from preprocessed data

```
for img_ds, labels_ds in train_dataset.take(1):
  fig, axes = plt.subplots(1, 5, figsize=(12, 12))

  for i, ax in enumerate(axes.flatten()):
    ax.imshow(img_ds[i])
    ax.set_title(class_mapping.get(labels_ds[i].numpy()))
```



3. Build Model

Neural Network (NN)

Convolutional Neural Network (CNN)

Build Sequential Model

```
input_shape = img_ds.shape[1:]
num_classes = len(class_mapping)

model = Sequential([
    layers.Input(shape=input_shape),
    layers.Conv2D(filters=32, kernel_size=(6, 6), activation='relu', padding='same'),
    layers.MaxPooling2D((3, 3)),
    layers.Conv2D(filters=64, kernel_size=(4, 4), activation='relu', padding='same'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(filters=128, kernel_size=(3, 3), activation='relu'),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(64, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(num_classes)
])
```

4. Compile, Fit & Save Model

Compile: specifying a loss, metrics, and an optimizer

Optimizers

Adam

Adaptive Moment Estimation is an algorithm for optimization technique for gradient descent. Read more here

RMSprop

RMSprop (Root Mean Squared Propagation) is an adaptive learning rate optimization algorithm. Read more here

Loss Functions

Categorical Cross-Entropy

Computes the crossentropy loss between the labels **(one-hot encoded vectors)** and predictions. Read more here

Sparse Categorical Cross-Entropy

Computes the crossentropy loss between the labels **(integer values)** and predictions. Read more here

Metrics

Accuracy

Loss

Val Accuracy

Val Loss

Compile

```
model.compile(
    optimizer='adam',
    loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
    metrics=['accuracy']
)
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 28, 28, 32)        1184

 max_pooling2d (MaxPooling2  (None, 9, 9, 32)          0
 D)

 conv2d_1 (Conv2D)           (None, 9, 9, 64)          32832

 max_pooling2d_1 (MaxPoolin  (None, 4, 4, 64)          0
 g2D)

 conv2d_2 (Conv2D)           (None, 2, 2, 128)         73856

 flatten (Flatten)           (None, 512)               0

 dense (Dense)               (None, 64)                32832

 dense_1 (Dense)             (None, 64)                4160

 dropout (Dropout)           (None, 64)                0

 dense_2 (Dense)             (None, 47)                3055

=================================================================
Total params: 147919 (577.81 KB)
Trainable params: 147919 (577.81 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Fit Model

```
EPOCHS = 5

early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor='val_accuracy',
    patience=3,
    restore_best_weights=True,
    min_delta=0,
    mode='max',
    verbose=0
)


history = model.fit(
    train_dataset,
    validation_data=test_dataset,
    epochs=EPOCHS,
    callbacks=[early_stopping]
)
```

```
Epoch 1/5
7050/7050 [==============================] - 42s 5ms/step - loss: 0.9275 - accuracy: 0.7156 - val_loss: 0.4725 - val_accuracy: 0.8402
Epoch 2/5
7050/7050 [==============================] - 34s 5ms/step - loss: 0.5264 - accuracy: 0.8308 - val_loss: 0.4435 - val_accuracy: 0.8516
Epoch 3/5
7050/7050 [==============================] - 36s 5ms/step - loss: 0.4604 - accuracy: 0.8495 - val_loss: 0.4475 - val_accuracy: 0.8569
Epoch 4/5
7050/7050 [==============================] - 33s 5ms/step - loss: 0.4265 - accuracy: 0.8593 - val_loss: 0.4141 - val_accuracy: 0.8632
Epoch 5/5
7050/7050 [==============================] - 34s 5ms/step - loss: 0.4003 - accuracy: 0.8667 - val_loss: 0.4314 - val_accuracy: 0.8661
```

Save Model

```
model.save('ocr_model')
```

5. Test Accuracy of Model

Evaluate

Evaluate Function

```
model.evaluate(test_dataset)
```

```
1175/1175 [==============================] - 3s 2ms/step - loss: 0.4314 - accuracy: 0.8661
[0.43141597509384155, 0.8661099076271057]
```

6. Export Model

Python Module

```
class OCDModel(tf.Module):
  def __init__(self, model):
    self.model = model
    self.class_mapping = {0: '0', 1: '1', 2: '2', 3: '3', 4: '4', 5: '5', 6: '6', 7: '7', 8: '8', 9: '9',
                          10: 'A', 11: 'B', 12: 'C', 13: 'D', 14: 'E', 15: 'F', 16: 'G', 17: 'H', 18: 'I',
                          19: 'J', 20: 'K', 21: 'L', 22: 'M', 23: 'N', 24: 'O', 25: 'P', 26: 'Q', 27: 'R',
                          28: 'S', 29: 'T', 30: 'U', 31: 'V', 32: 'W', 33: 'X', 34: 'Y', 35: 'Z', 36: 'a',
                          37: 'b', 38: 'd', 39: 'e', 40: 'f', 41: 'g', 42: 'h', 43: 'n', 44: 'q', 45: 'r',
                          46: 't'}

  @tf.function
  def predict(self, data):
    if isinstance(data, tf.float32):
      result = self.model(data, training=False)
    elif isinstance(data, str):
      img = preprocess_image(data, 'preprocessed_input_img.png')
      result = self.model(img, training=False)
    else:
      raise ValueError("Unsurported data type.\nPlease pass preprocessed image using preprocess_image function.\nOr pass path to image file"

    return result

  def __call__(self, data):
    pred = self.predict(data)
    return self.class_mapping.get(np.argmax(pred.numpy()[0]))
```

TensorFlow Lite for Flutter

TensorFlow Lite

- TensorFlow Lite is a way to run TensorFlow models on devices locally, supporting mobile, embedded, web, and edge devices. [Read more here]
- Convert model to TFLite [Documentation]

```
Start coding or generate with AI.
```

7. UI, Input & Preprocessing Pipeline

Preprocessing pipeline

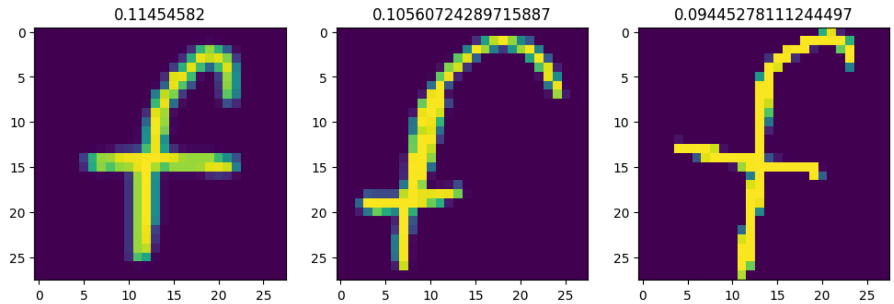
```
!gdown 1-cTOocQVoNPAl4u5oxu6eBgIUG5jg4y3
!gdown 12NGQvSBp0hBIbiFidPYAyjKhX17ooJGn
```

```
Downloading...
From: https://drive.google.com/uc?id=1-cTOocQVoNPAl4u5oxu6eBgIUG5jg4y3
To: /content/random_scale_img_f.png
100% 14.1k/14.1k [00:00<00:00, 36.0MB/s]
Downloading...
From: https://drive.google.com/uc?id=12NGQvSBp0hBIbiFidPYAyjKhX17ooJGn
```

```
To: /content/sample_input.png
100% 793/793 [00:00<00:00, 4.22MB/s]
```

```
import cv2
from scipy.ndimage import gaussian_filter


def preprocess_image(input_image_path, output_image_path):
    # read the original image
    image = cv2.imread(input_image_path, cv2.IMREAD_GRAYSCALE)
    if image is None:
        raise ValueError("Image not found or the path is incorrect")

    # invert the colors of the image
    image = 255 - image

    # apply Gaussian filter with σ = 1
    image = gaussian_filter(image, sigma=1)

    # extract the region around the character
    # find non-zero pixels (characters)
    coords = cv2.findNonZero(image)
    x, y, w, h = cv2.boundingRect(coords)

    # crop the image to the bounding box
    cropped_image = image[y:y+h, x:x+w]

    # center the character in a square image
    # calculate the size of the new image (keeping the aspect ratio)
    max_side = max(w, h)
    square_image = np.zeros((max_side, max_side), dtype=np.uint8)

    # compute the offset to center the character
    x_offset = (max_side - w) // 2
    y_offset = (max_side - h) // 2

    # place the cropped image in the center of the square image
    square_image[y_offset:y_offset+h, x_offset:x_offset+w] = cropped_image

    # add a 2-pixel border
    padded_image = cv2.copyMakeBorder(square_image, 2, 2, 2, 2, cv2.BORDER_CONSTANT, value=0)

    # down-sample to 28x28 using bi-cubic interpolation
    downsampled_image = cv2.resize(padded_image, (28, 28), interpolation=cv2.INTER_CUBIC)

    # scale intensity values to [0, 255]
    # convert image to have values in range [0, 255]
    final_image = cv2.normalize(downsampled_image, None, 0, 255, cv2.NORM_MINMAX)

    # normalize values between [0, 1]
    final_image = final_image/255.0

    # verify that preprocessing is consistant with data
    print(f"Mean input image: {np.mean(final_image)}\n")
    plt.imshow(final_image[..., np.newaxis])

    # save the final processed image
    cv2.imwrite(output_image_path, final_image[..., np.newaxis])

    # add batch shape, and channel
    return final_image[np.newaxis, ..., np.newaxis]


# compare sample from dataset & preprocessed input image
fig, axes = plt.subplots(1, 3, figsize=(12, 8))
axes[0].imshow(sample_image)
axes[0].set_title(np.mean(sample_image));

preprocessed_img_nist = preprocess_image('sample_input.png', 'preprocessed_sample_input.png')
img1 = np.squeeze(preprocessed_img_nist, axis=0)
axes[1].imshow(img1)
axes[1].set_title(np.mean(img1));

preprocessed_img_f = preprocess_image('random_scale_img_f.png', 'preprocessed_random_scale_img_f.png')
img2 = np.squeeze(preprocessed_img_f, axis=0)
axes[2].imshow(img2)
axes[2].set_title(np.mean(img2));
```

```
Mean input image: 0.10560724289715887

Mean input image: 0.09445278111244497
```



8. Load & Use Pretrained Model

Run prediction on Google Colab

```
model = tf.keras.models.load_model('ocr_model')
pred = model.predict(preprocessed_img_f)
print(f"Prediction: {class_mapping.get(np.argmax(pred[0]))}")

plt.figure()
plt.imshow(np.squeeze(preprocessed_img_f, axis=0))
plt.title(class_mapping.get(np.argmax(pred[0])));
```

```
WARNING:tensorflow:5 out of the last 5 calls to <function Model.make_predict_function.<l
1/1 [==============================] - 0s 118ms/step
Prediction: F
```