DSC680-Handwritten Character Recognition – Devnagari -cnn

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${f 1}$ DSC680-Devnagari-Handwritten-Chars-Classification-CNN

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- 1.0.4 Introduction -

This handwritten Devanagari character classification project by Sheetal Munjewar utilizes TensorFlow and Keras to build a model capable of recognizing handwritten characters. The dataset, sourced from the "DevanagariHandwrittenCharacterDataset," contains training and testing data that is loaded and preprocessed using Python libraries such as TensorFlow, Keras, and PIL. Data augmentation techniques, including rotations, shifts, and changes in brightness, are applied to enhance the dataset and improve model generalization. A convolutional neural network (CNN) model is built with multiple convolutional layers, max-pooling layers, and fully connected layers. The model is compiled using Adam optimizer and sparse categorical cross-entropy as the loss function. It is then trained using batches of images and labels, with an additional validation set created from the test dataset. The model's architecture and performance are visualized using plot_model. Data is preprocessed with TensorFlow's Rescaling and StringLookup layers, and the datasets are loaded into TensorFlow's Dataset API for efficient training. The project demonstrates a common pipeline for image classification tasks using deep learning techniques.

1.1 Import Libraries

```
[2]: # !pip install git+https://github.com/tensorflow/examples.git
    # !pip install keras
    import os
    import tensorflow as tf
# from tensorflow.keras.layers.experimental import preprocessing
# from tensorflow.keras.preprocessing.image import ImageDataGenerator
    from tensorflow.keras.layers import Rescaling, Normalization
    from IPython.display import clear_output
    import matplotlib.pyplot as plt
    import PIL
    from PIL import Image
    import numpy as np
    from tqdm import tqdm
    import random
```

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
# from keras.preprocessing.image import ImageDataGenerator
```

1.2 Specify data source paths.

```
[3]: base_path = "DevanagariHandwrittenCharacterDataset"

#base_path = "../input/devnagrihandwrittenchars/

DevanagariHandwrittenCharacterDataset"

train_path = os.path.join(base_path, "Train")

test_path = os.path.join(base_path, "Test")
```

1.3 A function to traverse directories and load images into an array.

```
[4]: def load_image_to_array(file_path):
         with open(file_path, "rb") as f:
             img = PIL.Image.open(f)
             nparr = np.asarray(img)
             # plt.imshow(nparr)
             nparr = nparr[:, :, np.newaxis]
             return nparr
     def read_data_from_folder(folder_path, read_first_record_only=False):
         imgs = []
         labels = []
         for folder in tqdm(os.listdir(folder_path)):
             sub_folder = os.path.join(folder_path, folder)
             for f in os.listdir(sub folder):
                 img = load_image_to_array(os.path.join(sub_folder, f))
                 imgs.append(img)
                 labels.append(folder)
                 if read_first_record_only:
                     break
         return np.asarray(imgs), np.asarray(labels)
```

1.4 Select images from each source folder.

```
[5]: sample_imgs, sample_labels = read_data_from_folder(train_path, True)
sample_imgs.shape

100%|

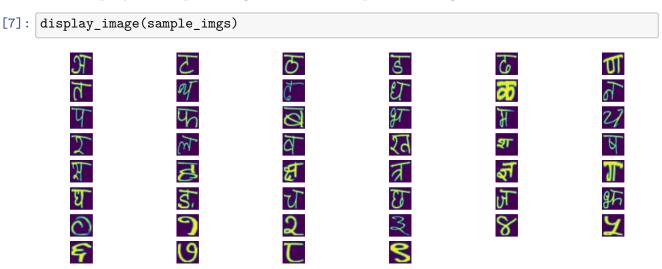
| 46/46 [00:00<00:00, 104.10it/s]

[5]: (46, 32, 32, 1)
```

1.5 Function to showcase images.

```
[6]: def display_image(imgarr):
    plt.figure(figsize=(20, 40))
    for i in range(len(imgarr)):
        plt.subplot(46, 6, i+1)
        img = tf.image.resize(imgarr[i], [100, 100])
        plt.imshow(img)
        plt.axis('off')
    plt.show()
```

1.6 Display a sample image from each input training folder.



1.7 Load the training and testing datasets.

1.8 Show the shapes of the datasets.

```
[9]: print("Training data imgs shape", train_data_img.shape)
    print("Training data labels shape", train_data_labels.shape)
    print("Test data imgs shape", test_data_imgs.shape)
    print("Test data labels shape", test_data_labels.shape)

Training data imgs shape (78200, 32, 32, 1)
Training data labels shape (78200,)
Test data imgs shape (13800, 32, 32, 1)
Test data labels shape (13800,)
```

1.9 Display a few sample images from the training dataset.

```
[10]: def display_image(imgarr):
    plt.figure(figsize=(20, 20))
    for i in range(len(imgarr)):
        plt.subplot(1, len(imgarr), i+1)
        plt.imshow(imgarr[i])
        plt.axis('off')
    plt.show()
rand = [random.randrange(1, 78200) for i in range(1, 20)]
display_image(train_data_img[rand])
```



1.10 Include additional augmented images in the training set.

```
[11]: def augment_data(images, labels):
    imgs = []
    labs = []
    data_gen = ImageDataGenerator(
        rotation_range=10,
        width_shift_range=0.1,
        height_shift_range=0.1,
        shear_range=0.1,
        brightness_range=(0.3, 1.0),
        fill_mode="nearest",
)

# generate samples and plot
for i in range(images.shape[0]):
    # generate batch of images
```



```
[13]: imgs, labels = augment_data(train_data_img, train_data_labels)
    train_data_img = np.concatenate((train_data_img, imgs))
    train_data_labels = np.concatenate((train_data_labels, labels))
```

```
[14]: print("Training dataset shape after augmentation:", train_data_img.shape)
print("Training dataset labels shape after augmentation:", train_data_labels.

shape)
```

Training dataset shape after augmentation: (156400, 32, 32, 1) Training dataset labels shape after augmentation: (156400,)

```
[15]: TRAIN_LENGTH = train_data_img.shape[0]
```

1.11 Create a vocabulary for labels to map label strings to integers.

```
[16]: # vocab = np.unique(train_data_labels)

# label_to_int = tf.keras.layers.StringLookup(vocabulary=vocab, invert=False)

# train_data_labels = label_to_int(train_data_labels)

# test_data_labels = label_to_int(test_data_labels)

import tensorflow as tf
import numpy as np

# Ensure labels are NumPy arrays and strings
train_data_labels = np.array(train_data_labels, dtype=str)
test_data_labels = np.array(test_data_labels, dtype=str)
```

```
# Create vocabulary and StringLookup layer
vocab = np.unique(train_data_labels)
label_to_int = tf.keras.layers.StringLookup(vocabulary=vocab, invert=False)

# Convert labels to integer representation
train_data_labels = label_to_int(tf.convert_to_tensor(train_data_labels))
test_data_labels = label_to_int(tf.convert_to_tensor(test_data_labels))
```

1.12 Load the datasets into a TensorSliceDataset.

1.13 Divide the test dataset into test and validation datasets.

```
[18]: ds_size = 13800
ds = test_val_images_ds.shuffle(10000, seed=12)

test_size = int(0.5 * ds_size)
val_size = int(0.5 * ds_size)

test_images_ds = ds.take(test_size)
val_images_ds = ds.skip(test_size).take(val_size)
```

1.14 Specify the batch size.

```
[19]: BUFFER_SIZE = TRAIN_LENGTH
BATCH_SIZE = 32
input_shape = (32, 32)
```

1.15 Generate batches for all three datasets.

```
test_batches = test_images_ds.batch(BATCH_SIZE)
val_batches = val_images_ds.batch(BATCH_SIZE)
```

1.16 Define the CNN model architecture.

```
[21]: OUTPUT_CLASSES = 47

model = tf.keras.models.Sequential([
    tf.keras.layers.Rescaling(1./255, input_shape=(32, 32, 1)),
    tf.keras.layers.Conv2D(16, 2, padding='same', activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(32, 3, padding='same', activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(64, 4, padding='same', activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(OUTPUT_CLASSES)
])
```

C:\Users\munje\anaconda3\lib\site-

packages\keras\src\layers\preprocessing\tf_data_layer.py:19: 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.

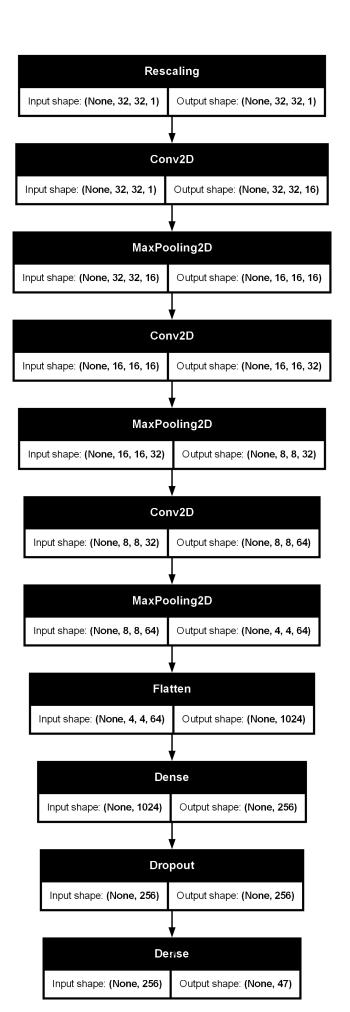
```
super().__init__(**kwargs)
```

1.17 Compile model

```
[23]: tf.keras.utils.plot_model(model, show_shapes=True)

[23]:
```

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1.18 Callback functions for early stopping and displaying information.

```
[24]: int_to_label = tf.keras.layers.StringLookup(vocabulary=vocab, invert=True)
      def show_images_predictions(imgs, pred):
          plt.figure(figsize=(15, 40))
          for i in range(len(imgs)):
              plt.subplot(32, 2, i+1)
              plt.imshow(imgs[i])
              lab = int_to_label([np.argmax(pred[i])]).numpy()[0]
              conf = np.max(tf.nn.softmax(pred[i])) * 100
              plt.title("Label:{} with confidence:{:.2f}%".format(lab, conf))
              plt.axis('off')
          plt.show()
      def show_predictions(dataset=None, num=1, rec=BATCH_SIZE):
          for image_batch, label_batch in dataset.take(num):
              pred_batch = model.predict(image_batch[:rec])
              show_images_predictions(image_batch[:rec], pred_batch)
              # print(np.argmax(pred_batch[0]))
[25]: earlyStopCallback = tf.keras.callbacks.EarlyStopping(
          monitor='val_loss', patience=5, min_delta=0.0001, restore_best_weights=True)
      for image_batch, label_batch in val_batches.take(1):
          sample_images = image_batch[:2]
      class DisplayCallback(tf.keras.callbacks.Callback):
          def on_epoch_end(self, epoch, logs=None):
              # clear_output(wait=True)
              print('\nSample Prediction after epoch {}\n'.format(epoch+1))
              pred_batch = model.predict(sample_images)
              show_images_predictions(sample_images, pred_batch)
```

print("epoch {}, the {} is {:7.2f}.".format(

(epoch+1), key, logs[key]))

for key in logs.keys():

print(logs.keys())

1.19 Train the model

Epoch 1/30

4883/4887 Os 8ms/step - accuracy: 0.6653 - loss: 1.2184
Sample Prediction after epoch 1

1/1 0s 129ms/step

Label:b'character_11_taamatar' with confidence:100.00%



Label:b'character_4_gha' with confidence:99.55%



4887/4887 41s 8ms/step -

accuracy: 0.6654 - loss: 1.2178 - val_accuracy: 0.9680 - val_loss: 0.0977

Epoch 2/30

4883/4887 Os 8ms/step - accuracy: 0.9291 - loss: 0.2314
Sample Prediction after epoch 2

1/1 0s 38ms/step

Label:b'character_11_taamatar' with confidence:100.00%



 $Label: b'character_4_gha' \ with \ confidence: 99.81\%$



4887/4887 39s 8ms/step -

accuracy: 0.9291 - loss: 0.2314 - val_accuracy: 0.9789 - val_loss: 0.0668

Epoch 3/30

4883/4887 Os 8ms/step - accuracy: 0.9511 - loss: 0.1609
Sample Prediction after epoch 3

1/1 0s 37ms/step

Label:b'character_11_taamatar' with confidence:100.00%



 $Label: b'character_4_gha' \ with \ confidence: 99.89\%$



4887/4887 40s 8ms/step -

accuracy: 0.9511 - loss: 0.1609 - val_accuracy: 0.9862 - val_loss: 0.0342

Epoch 4/30

4886/4887 Os 8ms/step - accuracy: 0.9618 - loss: 0.1204
Sample Prediction after epoch 4

1/1 0s 39ms/step

Label:b'character_11_taamatar' with confidence:99.99%



Label:b'character_4_gha' with confidence:97.21%



4887/4887 39s 8ms/step -

accuracy: 0.9618 - loss: 0.1204 - val_accuracy: 0.9811 - val_loss: 0.0792

Epoch 5/30

4884/4887 Os 8ms/step - accuracy: 0.9675 - loss: 0.1018
Sample Prediction after epoch 5

1/1 0s 24ms/step

 $Label: b'character_11_ta\underline{amatar'\ w} ith\ confidence: 100.00\%$



 $Label: b'character_4_gha' \ with \ confidence: 99.99\%$



4887/4887 39s 8ms/step -

accuracy: 0.9675 - loss: 0.1018 - val_accuracy: 0.9855 - val_loss: 0.0470

Epoch 6/30

4887/4887 Os 8ms/step - accuracy: 0.9728 - loss: 0.0859
Sample Prediction after epoch 6

1/1 0s 42ms/step





4887/4887 39s 8ms/step -

accuracy: 0.9728 - loss: 0.0859 - val_accuracy: 0.9898 - val_loss: 0.0362

Epoch 7/30

4883/4887 Os 8ms/step - accuracy: 0.9758 - loss: 0.0760 Sample Prediction after epoch 7

1/1 0s 37ms/step

Label:b'character_11_taamatar' with confidence:100.00%



Label:b'character_4_gha' with confidence:99.96%



4887/4887 40s 8ms/step -

accuracy: 0.9758 - loss: 0.0760 - val_accuracy: 0.9876 - val_loss: 0.0535

Epoch 8/30

4885/4887 Os 8ms/step - accuracy: 0.9783 - loss: 0.0690 Sample Prediction after epoch 8

1/1 0s 39ms/step

 $Label: b'character_11_taamatar' \ with \ confidence: 100.00\%$



Label:b'character_4_gha' with confidence:97.88%



4887/4887 39s 8ms/step -

accuracy: 0.9783 - loss: 0.0690 - val_accuracy: 0.9891 - val_loss: 0.0583

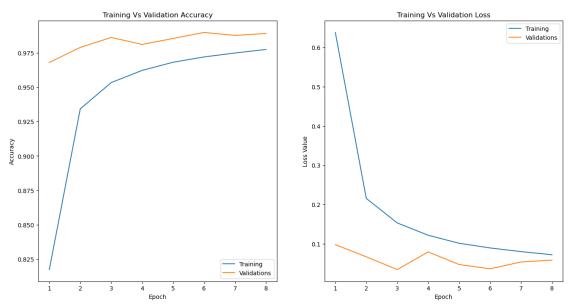
1.20 Plot the accuracy and loss for both training and validation.

```
[27]: length = len(model_history.history["accuracy"])+1

fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(16, 8))
  titles = ['Training Vs Validation Accuracy', 'Training Vs Validation Loss']
  ax[0].set_title(titles[0])
```

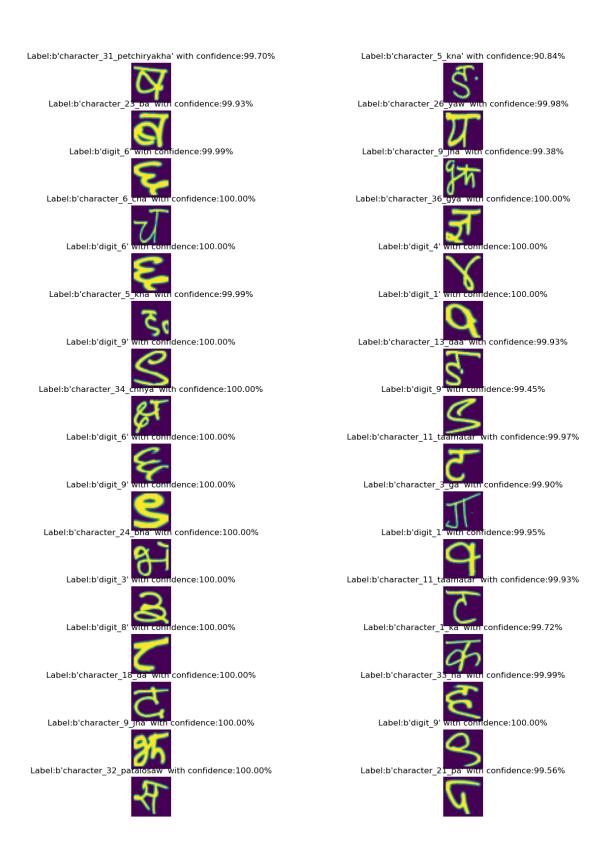
```
ax[0].plot(range(1, length), model_history.history["accuracy"])
ax[0].plot(range(1, length), model_history.history["val_accuracy"])
ax[0].set_xlabel('Epoch')
ax[0].set_ylabel('Accuracy')
ax[0].legend(["Training", "Validations"])

ax[1].set_title(titles[1])
ax[1].plot(range(1, length), model_history.history["loss"])
ax[1].plot(range(1, length), model_history.history["val_loss"])
ax[1].set_xlabel('Epoch')
ax[1].set_ylabel('Loss Value')
ax[1].legend(["Training", "Validations"])
plt.show()
```



1.21 Evaluate the model on the test dataset.

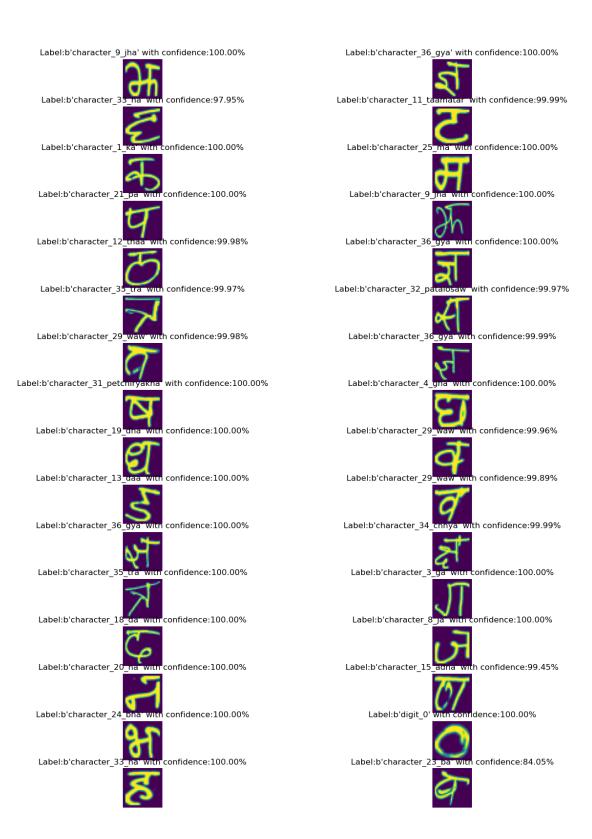
1.22 Select sample predictions from the validation dataset.



1.23 Select sample predictions from the test dataset.



1/1 0s 19ms/step



[]: