Homework 1 of CS330

```
import os
import time
from google_drive_downloader import GoogleDriveDownloader as gdd

# Need to download the Omniglot dataset -- DON'T MODIFY THIS CELL
if not os.path.isdir('./omniglot_resized'):
    gdd.download_file_from_google_drive(file_id='1iaSFXIYC3AB8q9K_M-
oVMa4pmB7yKMtI',
                                        dest_path='./omniglot_resized.zip',
                                        unzip=True)

assert os.path.isdir('./omniglot_resized')
```

```
Downloading 1iaSFXIYC3AB8q9K_M-oVMa4pmB7yKMtI into ./omniglot_resized.zip...
Done.
Unzipping...Done.
```

Problem 1

```
import numpy as np
import os
import random
import tensorflow as tf
from scipy import misc


def get_images(paths, labels, nb_samples=None, shuffle=True):
    """
    Takes a set of character folders and labels and returns paths to image files
    paired with labels.
    Args:
        paths: A list of character folders
        labels: List or numpy array of same length as paths
        nb_samples: Number of images to retrieve per character
    Returns:
        List of (label, image_path) tuples
    """
    if nb_samples is not None:
        sampler = lambda x: random.sample(x, nb_samples)
    else:
        sampler = lambda x: x
    images_labels = [(i, os.path.join(path, image))
                     for i, path in zip(labels, paths)
                     for image in sampler(os.listdir(path))]
    if shuffle:
        random.shuffle(images_labels)
    return images_labels
```

```python
def image_file_to_array(filename, dim_input):
    """
    Takes an image path and returns numpy array
    Args:
        filename: Image filename
        dim_input: Flattened shape of image
    Returns:
        1 channel image
    """
    import imageio
    image = imageio.imread(filename)  # misc.imread(filename)
    image = image.reshape([dim_input])
    image = image.astype(np.float32) / 255.0
    image = 1.0 - image
    return image


class DataGenerator(object):
    """
    Data Generator capable of generating batches of Omniglot data.
    A "class" is considered a class of omniglot digits.
    """

    def __init__(self, num_classes, num_samples_per_class, config={}):
        """
        Args:
            num_classes: Number of classes for classification (K-way)
            num_samples_per_class: num samples to generate per class in one
batch
            batch_size: size of meta batch size (e.g. number of functions)
        """
        self.num_samples_per_class = num_samples_per_class
        self.num_classes = num_classes

        data_folder = config.get('data_folder', './omniglot_resized')
        self.img_size = config.get('img_size', (28, 28))

        self.dim_input = np.prod(self.img_size)
        self.dim_output = self.num_classes

        character_folders = [os.path.join(data_folder, family, character)
                             for family in os.listdir(data_folder)
                             if os.path.isdir(os.path.join(data_folder, family))
                             for character in
os.listdir(os.path.join(data_folder, family))
                             if os.path.isdir(os.path.join(data_folder, family,
character))]

        random.seed(1)
        random.shuffle(character_folders)
        num_val = 100
        num_train = 1100
        self.metatrain_character_folders = character_folders[: num_train]
        self.metaval_character_folders = character_folders[
            num_train:num_train + num_val]
        self.metatest_character_folders = character_folders[
            num_train + num_val:]
```

```
    def sample_batch(self, batch_type, batch_size):
        """
        Samples a batch for training, validation, or testing
        Args:
            batch_type: train/val/test
        Returns:
            A a tuple of (1) Image batch and (2) Label batch where
            image batch has shape [B, K, N, 784] and label batch has shape [B, K,
N, N]
            where B is batch size, K is number of samples per class, N is number
of classes
        """
        if batch_type == "train":
            folders = self.metatrain_character_folders
        elif batch_type == "val":
            folders = self.metaval_character_folders
        else:
            folders = self.metatest_character_folders
        # initialization
        image_batch = np.zeros((batch_size, self.num_samples_per_class,
self.num_classes, 784))
        label_batch = np.zeros((batch_size, self.num_samples_per_class,
self.num_classes, self.num_classes))
        # assert true labels for every picture
        #
label_batch[:,:,np.arange(self.num_classes),np.arange(self.num_classes)] = 1
        # create image batch
        for batch_index in range(batch_size):
          selected_folders = np.random.choice(folders, self.num_classes)
          image_names = get_images(selected_folders, labels =
range(self.num_classes), nb_samples = self.num_samples_per_class, shuffle=False)
          # filling images and labels here, extra careful here so code sould be
clear and detailed
          # keep track of number of samples per class
          samples_recorded = {}
          for c in range(self.num_classes): samples_recorded[c] = 0
          # iterate through image names
          for image_name in image_names:
            class_num = image_name[0]
            file_name = image_name[1]
            image_array = image_file_to_array(file_name, self.dim_input)
            # set values
            image_batch[batch_index,samples_recorded[class_num],class_num,:] =
image_array

 label_batch[batch_index,samples_recorded[class_num],class_num,class_num] = 1
            # update dict
            samples_recorded[class_num] += 1
          # shuffle the test images and test labels
          shuffled = list(range(self.num_classes))
          random.shuffle(shuffled)
          image_batch[batch_index,-1,:,:] =
image_batch[batch_index,-1,shuffled,:]
          label_batch[batch_index,-1,:,:] =
label_batch[batch_index,-1,shuffled,:]
        # convert to tf
        image_batch = tf.constant(image_batch, dtype='float64')
        label_batch = tf.constant(label_batch, dtype='float64')
```

```
        return image_batch, label_batch
```

Problem 2

```
import numpy as np
import random
import tensorflow as tf
from tensorflow.keras import layers


class MANN(tf.keras.Model):

    def __init__(self, num_classes, samples_per_class):
        super(MANN, self).__init__()
        self.num_classes = num_classes
        self.samples_per_class = samples_per_class
        self.layer1 = tf.keras.layers.LSTM(128, return_sequences=True)
        self.layer2 = tf.keras.layers.LSTM(num_classes, return_sequences=True)
        self.__getLabelMask__()

    def __getLabelMask__(self):
        mask =
np.ones((self.samples_per_class,self.num_classes,self.num_classes))
        mask[self.samples_per_class-1,:,:] = 0
        self.label_mask = tf.constant(mask)

    def call(self, input_images, input_labels):
        """
        MANN
        Args:
            input_images: [B, K+1, N, 784] flattened images
            labels: [B, K+1, N, N] ground truth labels
        Returns:
            [B, K+1, N, N] predictions
        """
        # mask labels (during training time)
        train_mask =
tf.repeat(tf.expand_dims(self.label_mask,axis=0),repeats=input_labels.shape[0],a
xis=0)
        train_labels = tf.math.multiply(input_labels, train_mask)
        # input tensor
        input_images = tf.cast(input_images, dtype='float64')
        input_4dim = tf.concat([input_images, train_labels], axis=3)
        three_dim_shape =
(input_4dim.shape[0],input_4dim.shape[1]*input_4dim.shape[2],input_4dim.shape[3]
)
        input_3dim = tf.reshape(input_4dim, three_dim_shape)
        # calculations
        a1 = self.layer1(input_3dim)
        output_3dim = self.layer2(a1)
        output_4dim = tf.reshape(output_3dim, input_labels.shape)
        return output_4dim

    def loss_function(self, preds, labels):
        """
        Computes MANN loss
        Args:
```

```
            preds: [B, K+1, N, N] network output
            labels: [B, K+1, N, N] labels
        Returns:
            scalar loss
        """
        # label tensor
        preds = tf.cast(preds, dtype='float64')
        lossFun = tf.keras.losses.CategoricalCrossentropy(from_logits=True)
        return lossFun(labels[:,-1,:,:], preds[:,-1,:,:])


@tf.function
def train_step(images, labels, model, optim, eval=False):
    with tf.GradientTape() as tape:
        predictions = model(images, labels)
        loss = model.loss_function(predictions, labels)
    if not eval:
        gradients = tape.gradient(loss, model.trainable_variables)
        optim.apply_gradients(zip(gradients, model.trainable_variables))
    return predictions, loss


def main(num_classes=5, num_samples=1, meta_batch_size=16, random_seed=1234):
    random.seed(random_seed)
    np.random.seed(random_seed)
    tf.random.set_seed(random_seed)

    data_generator = DataGenerator(num_classes, num_samples + 1)

    o = MANN(num_classes, num_samples + 1)
    optim = tf.keras.optimizers.Adam(learning_rate=0.001)
    result = []
    for step in range(25000):
        input, label = data_generator.sample_batch('train', meta_batch_size)
        _, ls = train_step(input, label, o, optim)
        if (step + 1) % 100 == 0:
            print("*" * 5 + "Iter " + str(step + 1) + "*" * 5)
            input, label = data_generator.sample_batch('test', 100)
            pred, tls = train_step(input, label, o, optim, eval=True)
            print("Train Loss:", ls.numpy(), "Test Loss:", tls.numpy())
            pred = tf.reshape(pred, [-1, num_samples + 1, num_classes,
num_classes])
            pred = tf.math.argmax(pred[:, -1, :, :], axis=2)
            label = tf.math.argmax(label[:, -1, :, :], axis=2)
            test_acc = tf.reduce_mean(tf.cast(tf.math.equal(pred, label),
tf.float32)).numpy()
            result.append(test_acc)
            print("Test Accuracy", test_acc)
    return result
```

Problem 3

```python
# training: K = 1, N = 2
tik = time.time()
result1 = main(num_classes=2, num_samples=1, meta_batch_size=16,
random_seed=1234)
tok = time.time()
print("{} minutes".format((tok-tik)/60))
```

```
*****Iter 25000*****
Train Loss: 0.3172699213027954 Test Loss: 0.3556191325187683
Test Accuracy 0.92
12.105502327283224 minutes
```

```python
# training: K = 1, N = 3
tik = time.time()
result2 = main(num_classes=3, num_samples=1, meta_batch_size=16,
random_seed=2345)
tok = time.time()
print("{} minutes".format((tok-tik)/60))
```

```
*****Iter 25000*****
Train Loss: 0.7330042719841003 Test Loss: 0.7626179456710815
Test Accuracy 0.6533333
15.872245995203654 minutes
```

```python
# training: K = 1, N = 4
tik = time.time()
result3 = main(num_classes=4, num_samples=1, meta_batch_size=32,
random_seed=1234)
tok = time.time()
print("{} minutes".format((tok-tik)/60))
```

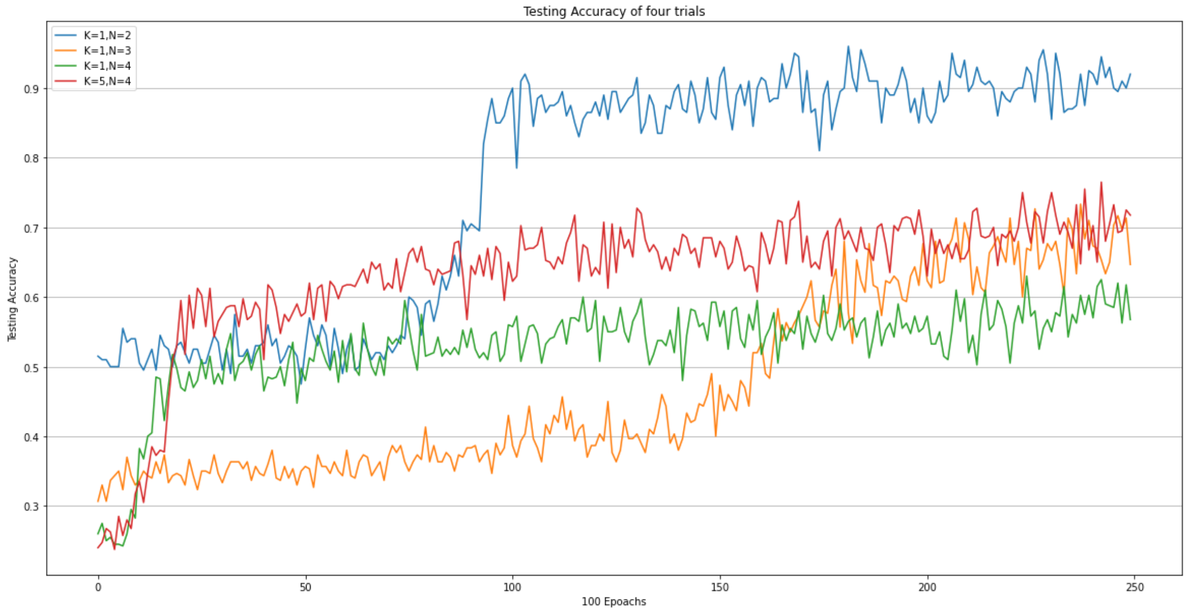
```
*****Iter 25000*****
Train Loss: 0.9981169700622559 Test Loss: 1.1085859537124634
Test Accuracy 0.5675
38.417714615662895 minutes
```

```python
# training: K = 5, N = 4
tik = time.time()
result4 = main(num_classes=4, num_samples=5, meta_batch_size=64,
random_seed=1234)
tok = time.time()
print("{} minutes".format((tok-tik)/60))
```

```
*****Iter 25000*****
Train Loss: 0.8135148882865906 Test Loss: 0.9396679401397705
Test Accuracy 0.7175
192.3871466477712 minutes
```

```python
import matplotlib.pyplot as plt
plt.figure(figsize=(20,10))
plt.plot(result1, label='K=1,N=2')
plt.plot(result2, label='K=1,N=3')
plt.plot(result3, label='K=1,N=4')
plt.plot(result4, label='K=5,N=4')
plt.legend()
plt.grid(which='both', axis='y')
plt.title('Testing Accuracy of four trials')
plt.xlabel('100 Epoachs')
plt.ylabel('Testing Accuracy')
```

```
Text(0, 0.5, 'Testing Accuracy')
```



Problem 4

4A

The hyperparameter that I choose to tune one is: number of layers

Tryouts:

- Layer = 1
- Layer = 2 (original structure)
- Layer = 3

```python
# one layer model
```

```
class MANN_1layer(tf.keras.Model):

    def __init__(self, num_classes, samples_per_class):
        super(MANN_1layer, self).__init__()
        self.num_classes = num_classes
        self.samples_per_class = samples_per_class
        self.layer1 = tf.keras.layers.LSTM(num_classes, return_sequences=True)
        self.__getLabelMask__()

    def __getLabelMask__(self):
        mask =
np.ones((self.samples_per_class,self.num_classes,self.num_classes))
        mask[self.samples_per_class-1,:,:] = 0
        self.label_mask = tf.constant(mask)

    def call(self, input_images, input_labels):
        """
        MANN
        Args:
            input_images: [B, K+1, N, 784] flattened images
            labels: [B, K+1, N, N] ground truth labels
        Returns:
            [B, K+1, N, N] predictions
        """
        # mask labels (during training time)
        train_mask =
tf.repeat(tf.expand_dims(self.label_mask,axis=0),repeats=input_labels.shape[0],a
xis=0)
        train_labels = tf.math.multiply(input_labels, train_mask)
        # input tensor
        input_images = tf.cast(input_images, dtype='float64')
        input_4dim = tf.concat([input_images, train_labels], axis=3)
        three_dim_shape =
(input_4dim.shape[0],input_4dim.shape[1]*input_4dim.shape[2],input_4dim.shape[3]
)
        input_3dim = tf.reshape(input_4dim, three_dim_shape)
        # calculations
        output_3dim = self.layer1(input_3dim)
        output_4dim = tf.reshape(output_3dim, input_labels.shape)
        return output_4dim

    def loss_function(self, preds, labels):
        """
        Computes MANN loss
        Args:
            preds: [B, K+1, N, N] network output
            labels: [B, K+1, N, N] labels
        Returns:
            scalar loss
        """
        # label tensor
        preds = tf.cast(preds, dtype='float64')
        lossFun = tf.keras.losses.CategoricalCrossentropy(from_logits=True)
        return lossFun(labels[:,-1,:,:], preds[:,-1,:,:])

# two layers model is just MANN

# three layers model
```

```
class MANN_3layers(tf.keras.Model):

    def __init__(self, num_classes, samples_per_class):
        super(MANN_3layers, self).__init__()
        self.num_classes = num_classes
        self.samples_per_class = samples_per_class
        self.layer1 = tf.keras.layers.LSTM(128, return_sequences=True)
        self.layer2 = tf.keras.layers.LSTM(64, return_sequences=True)
        self.layer3 = tf.keras.layers.LSTM(self.num_classes,
return_sequences=True)
        self.__getLabelMask__()

    def __getLabelMask__(self):
        mask =
np.ones((self.samples_per_class,self.num_classes,self.num_classes))
        mask[self.samples_per_class-1,:,:] = 0
        self.label_mask = tf.constant(mask)

    def call(self, input_images, input_labels):
        """
        MANN
        Args:
            input_images: [B, K+1, N, 784] flattened images
            labels: [B, K+1, N, N] ground truth labels
        Returns:
            [B, K+1, N, N] predictions
        """
        # mask labels (during training time)
        train_mask =
tf.repeat(tf.expand_dims(self.label_mask,axis=0),repeats=input_labels.shape[0],a
xis=0)
        train_labels = tf.math.multiply(input_labels, train_mask)
        # input tensor
        input_images = tf.cast(input_images, dtype='float64')
        input_4dim = tf.concat([input_images, train_labels], axis=3)
        three_dim_shape =
(input_4dim.shape[0],input_4dim.shape[1]*input_4dim.shape[2],input_4dim.shape[3]
)
        input_3dim = tf.reshape(input_4dim, three_dim_shape)
        # calculations
        a1 = self.layer1(input_3dim)
        a2 = self.layer2(a1)
        output_3dim = self.layer3(a2)
        output_4dim = tf.reshape(output_3dim, input_labels.shape)
        return output_4dim

    def loss_function(self, preds, labels):
        """
        Computes MANN loss
        Args:
            preds: [B, K+1, N, N] network output
            labels: [B, K+1, N, N] labels
        Returns:
            scalar loss
        """
        # label tensor
        preds = tf.cast(preds, dtype='float64')
        lossFun = tf.keras.losses.CategoricalCrossentropy(from_logits=True)
```

```python
        return lossFun(labels[:,-1,:,:], preds[:,-1,:,:])

@tf.function
def train_step(images, labels, model, optim, eval=False):
    with tf.GradientTape() as tape:
        predictions = model(images, labels)
        loss = model.loss_function(predictions, labels)
    if not eval:
        gradients = tape.gradient(loss, model.trainable_variables)
        optim.apply_gradients(zip(gradients, model.trainable_variables))
    return predictions, loss

def main_v2(model, num_classes=5, num_samples=1, meta_batch_size=16,
random_seed=1234):
    random.seed(random_seed)
    np.random.seed(random_seed)
    tf.random.set_seed(random_seed)

    data_generator = DataGenerator(num_classes, num_samples + 1)

    o = model(num_classes, num_samples + 1)
    optim = tf.keras.optimizers.Adam(learning_rate=0.001)
    result = []
    for step in range(25000):
        input, label = data_generator.sample_batch('train', meta_batch_size)
        _, ls = train_step(input, label, o, optim)
        if (step + 1) % 100 == 0:
            print("*" * 5 + "Iter " + str(step + 1) + "*" * 5)
            input, label = data_generator.sample_batch('test', 100)
            pred, tls = train_step(input, label, o, optim, eval=True)
            print("Train Loss:", ls.numpy(), "Test Loss:", tls.numpy())
            pred = tf.reshape(pred, [-1, num_samples + 1, num_classes,
num_classes])
            pred = tf.math.argmax(pred[:, -1, :, :], axis=2)
            label = tf.math.argmax(label[:, -1, :, :], axis=2)
            test_acc = tf.reduce_mean(tf.cast(tf.math.equal(pred, label),
tf.float32)).numpy()
            result.append(test_acc)
            print("Test Accuracy", test_acc)
    return result
```

```python
# training: 1 layer model. K = 1, N = 3
import time
tik = time.time()
result5 = main_v2(MANN_1layer, num_classes=3, num_samples=1, meta_batch_size=64,
random_seed=1234)
tok = time.time()
print("{} minutes".format((tok-tik)/60))
```

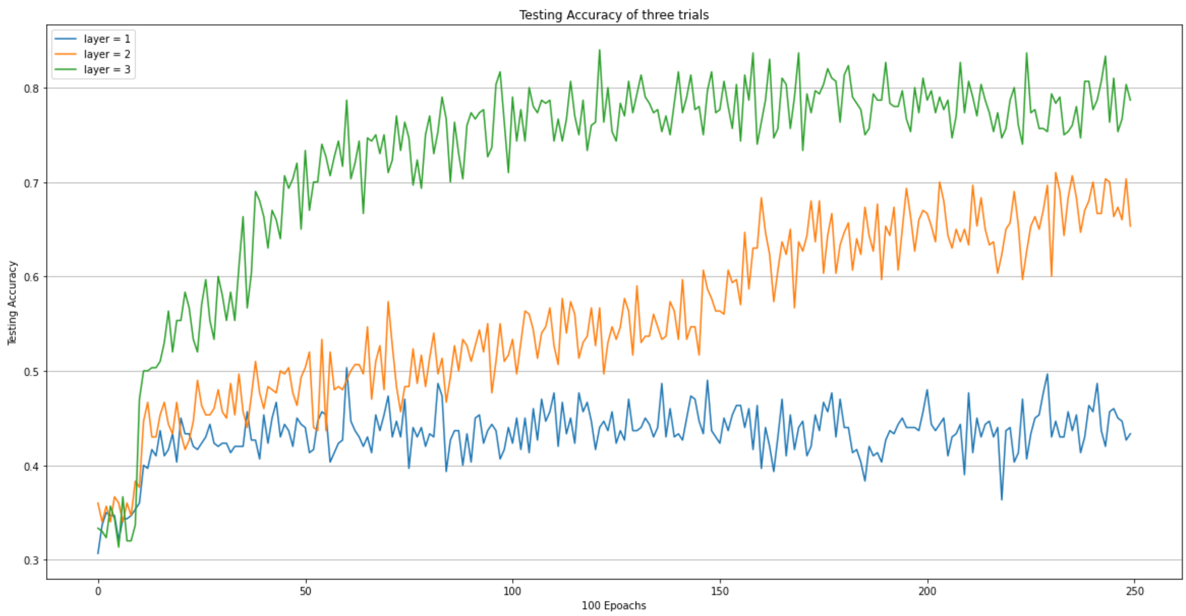
```
*****Iter 25000*****
Train Loss: 0.9720925688743591 Test Loss: 1.0167109966278076
Test Accuracy 0.43333334
56.81088780959447 minutes
```

```python
# training: 3 layer model. K = 1, N = 3
import time
tik = time.time()
result6 = main_v2(MANN_3layers, num_classes=3, num_samples=1,
meta_batch_size=64, random_seed=1234)
tok = time.time()
print("{} minutes".format((tok-tik)/60))
```

```
*****Iter 25000*****
Train Loss: 0.42669305205345154 Test Loss: 0.6496610641479492
Test Accuracy 0.7866667
58.341820776462555 minutes
```

```python
import matplotlib.pyplot as plt
plt.figure(figsize=(20,10))
plt.plot(result5, label='layer = 1')
plt.plot(result2, label='layer = 2')
plt.plot(result6, label='layer = 3')
plt.legend()
plt.grid(which='both', axis='y')
plt.title('Testing Accuracy of three trials')
plt.xlabel('100 Epoachs')
plt.ylabel('Testing Accuracy')
```

```
Text(0, 0.5, 'Testing Accuracy')
```



Observations

Using more `LSTM` layers in the model would incease the model's flexibility, meaning the model could learn more complex structures and tasks.

By choosing layers = `1, 2, 3`, from the testing accuracy plot, we can observe that the model of different layers performed differently:

Layers of the Model	Testing Accuracy
1	43.3%
2	65.3%
3	78.7%

The model performance increases with the number of layers, which indicates that task is more complicated for a one-layer or two-layer MANN model to study, trying higher number of layers may increase the predicting performance the model. And the final number of layer and be dicided through balancing the training time comsumption and the testing accuracy.

4B

Try changing the architecture of the model

```
# three layers model
class MANN_new(tf.keras.Model):

    def __init__(self, num_classes, samples_per_class):
        super(MANN_new, self).__init__()
        self.num_classes = num_classes
        self.samples_per_class = samples_per_class
        self.layer1 = tf.keras.layers.Conv1D(128, 32, padding='same',
activation='relu')
        self.layer2 = tf.keras.layers.Conv1D(64, 32, padding='same',
activation='relu')
        forward_layer = tf.keras.layers.LSTM(self.num_classes,
return_sequences=True)
        backward_layer = tf.keras.layers.LSTM(self.num_classes,
activation='relu',
                                              go_backwards=True,
return_sequences=True)
        self.layer3 = tf.keras.layers.Bidirectional(forward_layer,
                                                    merge_mode='sum',

 backward_layer=backward_layer)
        self.__getLabelMask__()

    def __getLabelMask__(self):
        mask =
np.ones((self.samples_per_class,self.num_classes,self.num_classes))
        mask[self.samples_per_class-1,:,:] = 0
        self.label_mask = tf.constant(mask)

    def call(self, input_images, input_labels):
        """
```

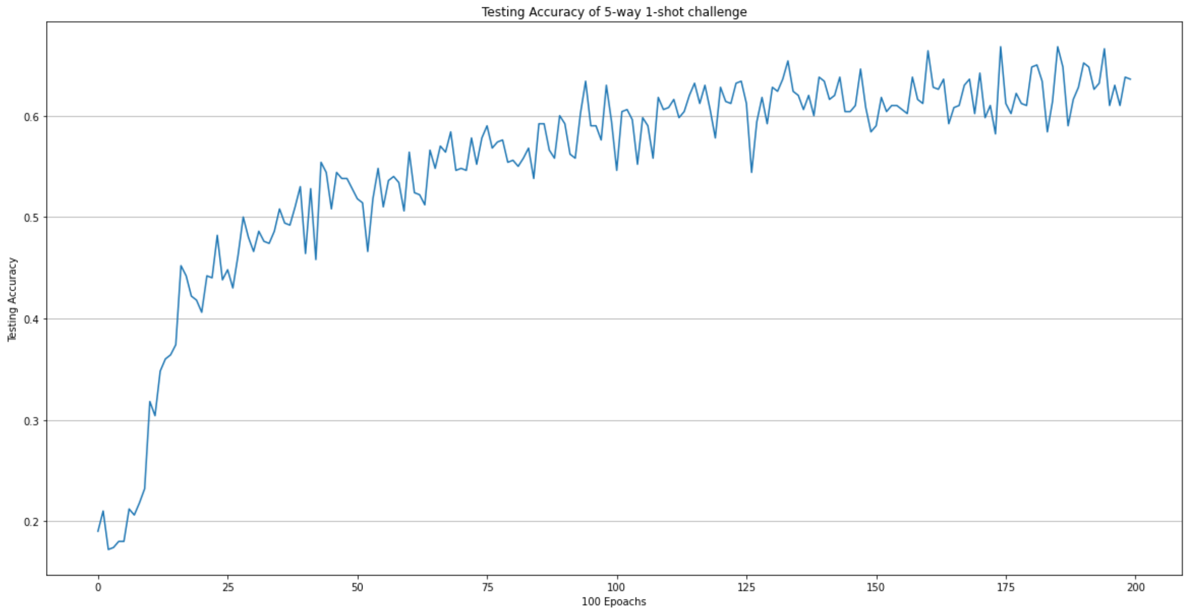
```
        MANN
        Args:
            input_images: [B, K+1, N, 784] flattened images
            labels: [B, K+1, N, N] ground truth labels
        Returns:
            [B, K+1, N, N] predictions
        """
        # mask labels (during training time)
        train_mask =
tf.repeat(tf.expand_dims(self.label_mask,axis=0),repeats=input_labels.shape[0],a
xis=0)
        train_labels = tf.math.multiply(input_labels, train_mask)
        # input tensor
        input_images = tf.cast(input_images, dtype='float64')
        input_4dim = tf.concat([input_images, train_labels], axis=3)
        three_dim_shape =
(input_4dim.shape[0],input_4dim.shape[1]*input_4dim.shape[2],input_4dim.shape[3]
)
        input_3dim = tf.reshape(input_4dim, three_dim_shape)
        # calculations
        a1 = self.layer1(input_3dim)
        a2 = self.layer2(a1)
        output_3dim = self.layer3(a2)
        output_4dim = tf.reshape(output_3dim, input_labels.shape)
        return output_4dim

    def loss_function(self, preds, labels):
        """
        Computes MANN loss
        Args:
            preds: [B, K+1, N, N] network output
            labels: [B, K+1, N, N] labels
        Returns:
            scalar loss
        """
        # label tensor
        preds = tf.cast(preds, dtype='float64')
        lossFun = tf.keras.losses.CategoricalCrossentropy(from_logits=True)
        return lossFun(labels[:,-1,:,:], preds[:,-1,:,:])

@tf.function
def train_step(images, labels, model, optim, eval=False):
    with tf.GradientTape() as tape:
        predictions = model(images, labels)
        loss = model.loss_function(predictions, labels)
    if not eval:
        gradients = tape.gradient(loss, model.trainable_variables)
        optim.apply_gradients(zip(gradients, model.trainable_variables))
    return predictions, loss

def main_v4(model, num_classes=5, num_samples=1, meta_batch_size=16,
random_seed=1234):
    random.seed(random_seed)
    np.random.seed(random_seed)
    tf.random.set_seed(random_seed)

    data_generator = DataGenerator(num_classes, num_samples + 1)
```

```
    o = model(num_classes, num_samples + 1)
    optim = tf.keras.optimizers.Adam(learning_rate=0.0002)
    result = []
    for step in range(20000):
        input, label = data_generator.sample_batch('train', meta_batch_size)
        _, ls = train_step(input, label, o, optim)
        if (step + 1) % 100 == 0:
            print("*" * 5 + "Iter " + str(step + 1) + "*" * 5)
            input, label = data_generator.sample_batch('test', 100)
            pred, tls = train_step(input, label, o, optim, eval=True)
            print("Train Loss:", ls.numpy(), "Test Loss:", tls.numpy())
            pred = tf.reshape(pred, [-1, num_samples + 1, num_classes,
num_classes])
            pred = tf.math.argmax(pred[:, -1, :, :], axis=2)
            label = tf.math.argmax(label[:, -1, :, :], axis=2)
            test_acc = tf.reduce_mean(tf.cast(tf.math.equal(pred, label),
tf.float32)).numpy()
            result.append(test_acc)
            print("Test Accuracy", test_acc)
    return result
```

```
# train for 1-shot, 5-way task for 20000 epoch
tik = time.time()
result7 = main_v4(MANN_new, num_classes=5, num_samples=1, meta_batch_size=64,
random_seed=2345)
tok = time.time()
print("{} minutes".format((tok-tik)/60))
```

```
*****Iter 20000*****
Train Loss: 0.8358861804008484 Test Loss: 0.880961000919342
Test Accuracy 0.636
73.72812336683273 minutes
```

```
import matplotlib.pyplot as plt
plt.figure(figsize=(20,10))
plt.plot(result7)
plt.grid(which='both', axis='y')
plt.title('Testing Accuracy of 5-way 1-shot challenge')
plt.xlabel('100 Epoachs')
plt.ylabel('Testing Accuracy')
```



Changes of Architecture

1. 1D convolutional layer $\times$ 2
2. Bi-directional LSTM layer