***Abstract*—This paper is a report for Project A of ECE1512 2022W, University of Toronto. In the paper, we described four assigned tasks with detail, including CNN construction and training, statistic assessment, XAI based interpretation and Quantitative evaluation. For the attribution methods, we choose Grad-CAM, Grad-CAM++ and Ablation-CAM as a group of two, and we reviewed their paper and implemented corresponding functions. Moreover, we tried to analyze the performance of the XAI methods based on quantitative evaluation and gave our explanations towards the experiment.**

I. Task 1: 1-Dimensional digit classification

In this task, we basically train an one-hot 1-D CNN model following typical procedure, including network construction, training and evaluation.

A. Question 1

In this section, we build a one-hot ConvNet, including three convolutional layer, one flatten layer and one dense layer. The network structure is plotted by $model.summary()$ and shown as Fig. 1.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 40, 25)	150
conv1d_1 (Conv1D)	(None, 40, 25)	1900
conv1d_2 (Conv1D)	(None, 40, 25)	1900
flatten (Flatten)	(None, 1000)	0
dense (Dense)	(None, 10)	10010

Total params: 13,960
Trainable params: 13,960
Non-trainable params: 0

Fig. 1. Task1-Question1: ConvNet Model

This is not a complex network, since there are only three sequential convolution layer for feature extracting and no additional structures. The implementation code is as followed.

```
weight_decay = 5e-4
model = Sequential()
#Your code starts from here
model.add(Input(shape=(40,1)))
model.add(Conv1D(25, kernel_size=5, padding
    ='same', activation='relu',
    kernel_regularizer=regularizers.l2(
    weight_decay)))
model.add(Conv1D(25, kernel_size=3, padding
    ='same', activation='relu',
    kernel_regularizer=regularizers.l2(
    weight_decay)))
model.add(Conv1D(25, kernel_size=3, padding
    ='same', activation='relu',
    kernel_regularizer=regularizers.l2(
    weight_decay)))
model.add(Flatten())
model.add(Dense(10, activation='softmax',
    kernel_initializer=keras.initializers.
    RandomNormal(mean=0.0, stddev=0.5),
            bias_initializer=keras.
                initializers.Zeros(),
                kernel_regularizer=
                regularizers.l2(
                weight_decay)))

model.summary()
```

B. Question 2

In this section, we applied the model constructed in the previous section to the MNIST1D dataset.

In this part, we use the TensorBoard to record the training procedure, which we also found could be standalone execute as a TensorFlow based analyzing tool which is running on localhost with port 6006 by default.

As a standard procedure using TensorFlow, first of all, we compile this model and set the loss function to cross-entropy, the optimizer to Stochastic Gradient Descent(SGD) and the target metrics to accuracy as required.

Then we define a LearningRateScheduler, in order to control the learning rate during the training process. Learning rate is similar to a "step" of training process, which is typically set to 0.01 or 0.001. Learning rate only care about the magnitude, it somehow determine the precision of fitting parameters. In this part, we declare a dynamic learning rate to increase it speed to fit, while setting the magnitude to 0,01 according to the direction.

For the next step, we declare the object of TensorBoard, along with the EarlyStopping to accomplish a speed-up of training working with the dynamic learning rate. Then, in order

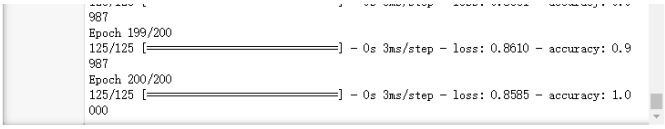


Fig. 2. Task1-Question2: Training Process Log

to be convenient for the following steps, we extract the dataset into several lists, and handle the data into correct form. Finally, we feed the data with the facilities into the model to execute training process and save the model as a static file afterwards.

A screen shot of the training log generated by TensorFlow is shown in Fig. 2.

```
model.compile(loss=keras.losses.
    categorical_crossentropy,
        optimizer=tensorflow.keras.
            optimizers.SGD(),
        metrics=['accuracy'])

def lr_scheduler(epoch):
   base_ep = 15
   return 1e-3 * (.5 ** (epoch // base_ep))
```

```
lr_reduce_cb = keras.callbacks.
    LearningRateScheduler(lr_scheduler)
tensorboard_cb = keras.callbacks.
    TensorBoard(log_dir='log2', write_graph
    =True)
early_stopping_cb = keras.callbacks.
    EarlyStopping(patience=8, min_delta=0.)

# X = tensorflow.expand_dims(dataset['x'],
    axis=2)
train_x=dataset['x']
train_y=dataset['y']
train_x=train_x.reshape(4000,40,1)
train_y=tensorflow.keras.utils.
    to_categorical(train_y, num_classes=10)

# print(X.shape)
history=model.fit(x=train_x,y=train_y,
    epochs=200,
#                 steps_per_epoch=len(X) //
    32,
                callbacks=[tensorboard_cb],
                shuffle = True,
                verbose=1)
model.save('MNIST1D.h5')
```

C. Question 3

In this section, we finish the typical model evaluation by extracting several significant statistics. As well-known and commonly used metrics, those statistics all have easy-to-run function to achieve, and most of them are from $scikit-learn$.

1) SubQuestion a: We firstly plot the loss curve and accuracy curve of the training process. As implementation, we extract the data using the training history, which is a return value of $model.fit()$. This is a modification of the original notebook since the $model.fit_generator()$ is deprecated in TensorFlow 2.7.0 which is the version we used for this project, and it no longer saves training statistics of accuracy and loss during the training process in the log, which could be extracted by $tf_record.tf_record_iterator()$ in the past.

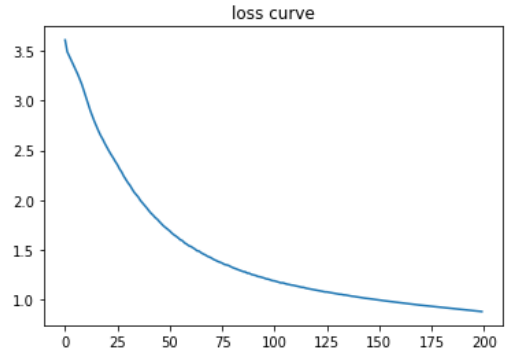
As a matter of fact, this plot is generated only when we execute the training process (i.e. $model.fit()$ function). And it is shown in Fig. 3.

The code is quite simple as shown below, whose history object is define in the previous section as mentioned.

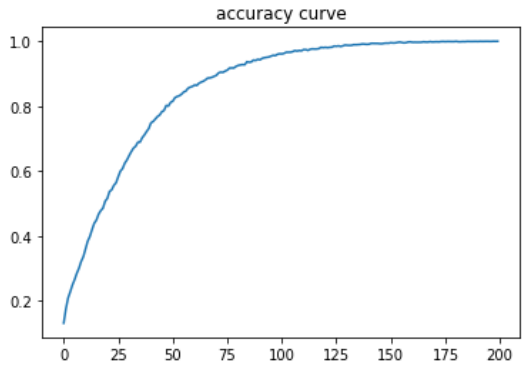
```
train_acc = history.history['accuracy']
train_loss = history.history['loss']
plt.plot(train_acc)
plt.figure()
plt.plot(train_loss)
```

2) SubQuestion b: This part talks about overall classification accuracy on the test set.

```
# Use Scikit-learn to calculate stats
from sklearn.metrics import accuracy_score,
     precision_score, recall_score,f1_score
from sklearn.metrics import
    classification_report
```



(a) Loss



(b) Accuracy

Fig. 3. Loss and Accuracy Curve Plots on MNIST-1D dataset

```
# Q3.b get the prediction from the test set
x_test = dataset['x_test']
y_test = dataset['y_test']
x_test=x_test.reshape(1000,40,1)
# predict_classes removed in tf 2.6.0
y_pred = model.predict(x_test)
y_predicted = np.argmax(y_pred,axis=1)
print('Overall classification accuracy for
    all classes:'+str(np.sum(y_predicted==
    y_test)/y_test.shape[0]))
```

We read the test set, fit the model on the set and calculate the accuracy by deciding the max prediction in every class and compare them with the ground truth. The result is 0.9194.

```
Overall classification accuracy for all classes:0.919
```

Fig. 4. Task1-Question3b: Overall accuracy

3) SubQuestion c: In this part, we calculated the class-wise accuracy for all classes.This is our code:

```
   # Q3.c class-wise classification
for i in range(10):
   true_i=np.where(y_test==i)[0]
   res=0
   for j in true_i:
      if y_predicted[j]==i:
         res=res+1
```

```
print('class '+str(i)+' accuracy:'+str(res/
    true_i.shape[0]))
```

We find out the lines which belongs to class i and find the ones which is correct in these lines to calculate the accuracy. The result is shown below5:

```
class 0 accuracy:0.9803921568627451
class 1 accuracy:0.8557692307692307
class 2 accuracy:0.898876404494382
class 3 accuracy:0.9811320754716981
class 4 accuracy:0.8962264150943396
class 5 accuracy:0.9183673469387755
class 6 accuracy:0.9595959595959596
class 7 accuracy:0.8958333333333334
class 8 accuracy:0.9795918367346939
class 9 accuracy:0.8235294117647058
```

Fig. 5. Task1-Question3b: class-wise accuracy

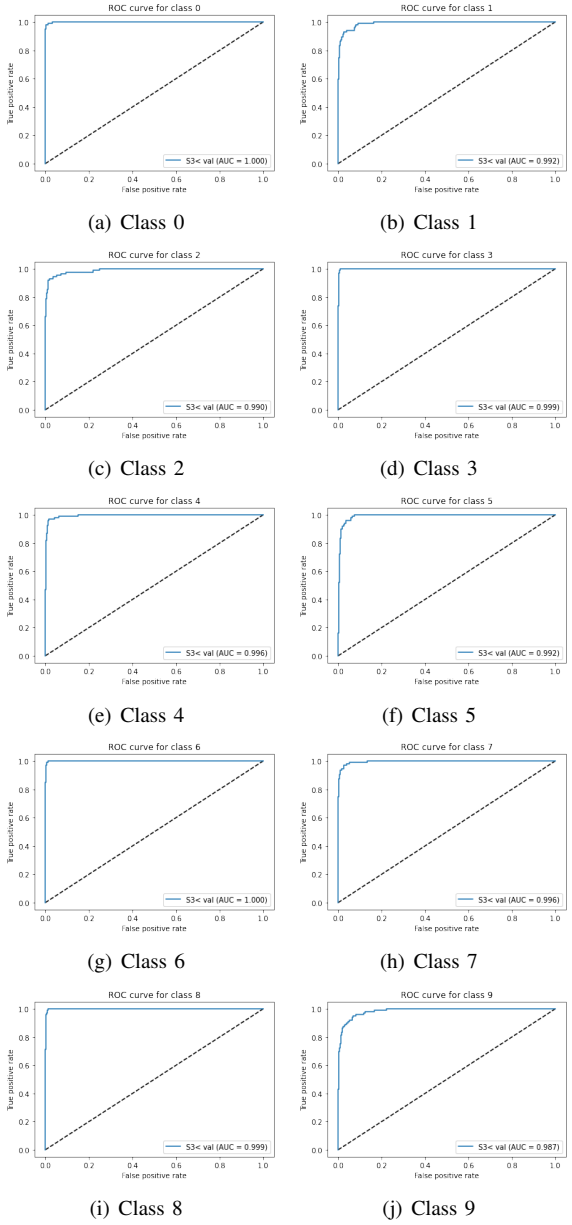
4) SubQuestion d: In this part, we will plot the ROC and AUC curves for each class. Here is the code:

```
# Q3.d ROC and AUC curve for every class
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
# print(dataset['y_test'].shape)
real_y=np.zeros((dataset['y_test'].size,10)
    )
for i in range(y_test.size):
   real_y[i,y_test[i]]=1
for i in range(10):
   FPR, TPR, thresholds_keras = roc_curve(
       real_y[:,i], y_pred[:,i])
   AUC = auc(FPR, TPR)
   print("AUC : ", AUC)
   plt.figure()
   plt.plot([0, 1], [0, 1], 'k--')
   plt.plot(FPR, TPR, label='S3< val (AUC =
       {:.3f})'.format(AUC))
   plt.xlabel('False positive rate')
   plt.ylabel('True positive rate')
   plt.title('ROC curve for class '+str(i))
   plt.legend(loc='best')
   plt.show()
```

In the code, we first reshape the test set to 2D set. Then we apply the test set and prediction set to roc_curve. Then we will calculate the auc number and plot the curve.The AUC and ROC curve is listed below:

5) SubQuestion e: This is the code for normalized confusion matrix.

```
from sklearn.metrics import
    confusion_matrix
cm=confusion_matrix(list(y_test),list(
    y_predicted))
cm_normalized = cm.astype('float') / cm.sum
    (axis=1)[:, np.newaxis]
fig, ax = plt.subplots()
im = ax.imshow(cm, interpolation='nearest',
     cmap=plt.cm.Blues)
ax.figure.colorbar(im, ax=ax)
classes=[0,1,2,3,4,5,6,7,8,9]
```



(a) Class 0 (b) Class 1

(c) Class 2 (d) Class 3

(e) Class 4 (f) Class 5

(g) Class 6 (h) Class 7

(i) Class 8 (j) Class 9

Fig. 6. Class-wise ROC Curve Plots on MNIST-1D dataset

```
# print(classes)
# We want to show all ticks...
ax.set(xticks=np.arange(cm_normalized.shape
    [1]),
   yticks=np.arange(cm_normalized.shape[0])
       ,
   # ... and label them with the respective
       list entries
   xticklabels=classes, yticklabels=classes
       ,
   ylabel='True label',
   xlabel='Predicted label')
plt.setp(ax.get_xticklabels(), ha="right",
         rotation_mode="anchor")
thresh = cm_normalized.max() / 2.
for i in range(cm_normalized.shape[0]):
   for j in range(cm_normalized.shape[1]):
```

```
        ax.text(j, i, format(cm_normalized[i,
            j], '.2f'),
                ha="center", va="center",
                color="white" if cm_normalized[
                    i, j] > thresh else "black"
                )
    fig.tight_layout()
```

The result plot is listed in Fig.7.

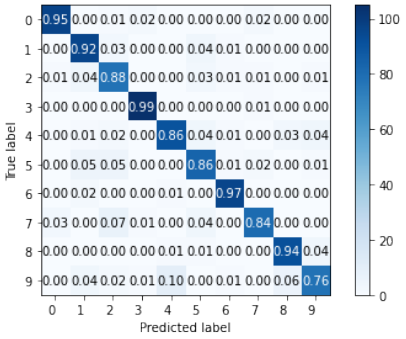


Fig. 7. normalized confusion matrix plot

6) SubQuestion f: This is the code for calculating Precision, Recall, and F-1 score on the test set.

```
    # Q3.f
    print(classification_report(y_true=y_test,
        y_pred=y_predicted))
```

This is the result for the plot8:

	precision	recall	f1-score	support
0	0.97	0.98	0.98	102
1	0.92	0.86	0.89	104
2	0.87	0.90	0.88	89
3	0.96	0.98	0.97	106
4	0.91	0.90	0.90	106
5	0.83	0.92	0.87	98
6	0.97	0.96	0.96	99
7	0.96	0.90	0.92	96
8	0.91	0.98	0.95	98
9	0.89	0.82	0.86	102
accuracy			0.92	1000
macro avg	0.92	0.92	0.92	1000
weighted avg	0.92	0.92	0.92	1000

Fig. 8. Precision,Recall and F-1 score

D. Question 4

To do this question, we did some coding in our program, the codes are listed below:

Success Examples:

```
    index 10 true class: 0 predicted class: 0
    index 412 true class: 1 predicted class: 1
    index 729 true class: 2 predicted class: 2
```

Failure Examples:

```
    index 236 true class: 0 predicted class: 7
    index 6 true class: 1 predicted class: 2
    index 25 true class: 1 predicted class: 4
```

All the concrete Success/Failure cases are listed in 'MNIST1D.ipynb', if you want to refer to more examples. The most misclassification lies in class 1 and 4. The reason for that is TODOOO: analyze

II. Task 2: CNN interprectation

This section introduces our interpretation of 1-D CNN model based on MNIST-1D dataset using 3 different attribution methods, including our literature review, discussion and implementation of the XAI attribute algorithms.

A. Grad-CAM

In the previous study, researchers introduced CAM to explain the CNN. However, CAM requires to modify the structure of original training models. It limits the usage of CAM greatly, because the cost of retraining the model is quite high for the published model. It is almost impossible to retrain them. To solve this problem, Grad-CAM was proposed, which is similar to CAM. It also gets the weight of every feature maps and calculate the results accordingly. The difference lies in the calculation of weights. CAM replaced full-connection layer with GAP layer and retrain this whole model. In contrast to that, Grad-CAM put forward a new way to do it. It calculates the weight by averaging the gradients which is equivalent to the CAM. It makes CAM applicable to all the existing models.

The core algorithm of Grad-CAM is based on CAM which proposed: class c gets the final classification score Y_c with a linear combination of its global average pooled last convolutional layer feature maps A_k.

$$Y^c = \Sigma_k w_k^c \Sigma_i \Sigma_j A_{ij}^k \tag{1}$$

So, first, it defines the weight of feature map k to class c as α_k^c, and it calculates the weight using the global gradients2:

$$\alpha_k^c = \frac{1}{Z} * \Sigma_i \Sigma_j \frac{\partial y^c}{\partial A_{ij}^k} \tag{2}$$

In which, y_c is the gradient of the score for class c, A_k is the feature map activation.$\frac{\partial y^c}{\partial A_{ij}^k}$ is the gradient achieved by backpropagating. $\frac{1}{Z}$ is global averaging. After calculating the α_k^c, the algorithm computed the weighted combination of forward activation maps, followed by a ReLU function:

$$L_{Grad-CAM}^c = ReLU(\Sigma_k \alpha_k^c A^k)$$

The advantages for Grad-CAM is quite obvious: First, compared with CAM, it does not need to change the model and retrain it which costs a lot of time and money. The novelty is the usage of propagation and gradients to compute the weights of feature maps.It makes the visualization of published models possible. Second is that the algorithm is quite easy to code and maintain.

The disadvantages for Grad-CAM is that: it considers the global features for all classes. As a result, Grad-CAM cannot localize the targets when faced with many targets of the same class. If there are many objects of the same class in an image, it cannot localize the targets well or it can only locate part of them.

B. Grad-CAM++

Grad-CAM++ is an algorithm based on Grad-CAM, aiming to get a better explanation for CNN models. It improves the performance of Grad-CAM when facing targets of the same class, and helps to better localize the targets.

It introduced a weighted combination of gradients of the output in the pixel level, which provides a measure of importance of every pixels to the feature maps. It introduced a closed-form solution for the pixels weights, thus making the improvement of explanation possible.

The core algorithm is shown below: First, as we have introduced above, class c gets the final classification score Y_c with a linear combination of its global average pooled last convolutional layer feature maps Ak in equation2. Grad-CAM calculates the weight w_k^c with equation**??**. To improve the performance, Grad-CAM++ changed this equation. Combine the equation2 and **??** together, we will get the equation3:

$$Y^c = \Sigma_k[\Sigma_i\Sigma_j(\Sigma_a\Sigma_b\alpha_{ab}^{kc}relu(\frac{\partial Y_c}{\partial A_{ab}^k}))A_{ij}^k] \tag{3}$$

Take partial derivative w.r.t. A_{ij}^k on both sides:

$$\frac{\partial Y_c}{\partial A_{ij}^k} = \Sigma_a\Sigma b\alpha_{ab}^{kc}\frac{\partial Y_c}{\partial A_{ab}^k} + \Sigma_a\Sigma bA_{ab}^k\{\alpha_{ij}^{kc}\frac{\partial^2 Y_c}{(\partial A_{ij}^k)^2}\} \tag{4}$$

Take a further partial derivative w.r.t. A_{ij}^k on both sides:

$$\frac{\partial^2 Y_c}{(\partial A_{ij}^k)^2} = 2\alpha_{ij}^{kc}\frac{\partial^2 Y_c}{(\partial A_{ij}^k)^2} + \Sigma_a\Sigma bA_{ab}^k\{\alpha_{ij}^{kc}\frac{\partial^3 Y_c}{(\partial A_{ij}^k)^3}\} \tag{5}$$

Rearrage equation5, we get:

$$\alpha_{ij}^{kc} = \frac{\frac{\partial^2 Y_c}{(\partial A_{ij}^k)^2}}{2\frac{\partial^2 Y_c}{(\partial A_{ij}^k)^2} + \Sigma_a\Sigma bA_{ab}^k\{\frac{\partial^3 Y_c}{(\partial A_{ij}^k)^3}\}} \tag{6}$$

So, we are able to get weight w_k with:

$$w_k^c = \Sigma_i\Sigma_j\alpha_{ij}^{kc}relu(\frac{\partial Y_c}{\partial A_{ij}^k}) \tag{7}$$

Applying equation7 to **??**, we will get final results. There are many advantages for Grad-CAM++: First, it clearly improved the performance of Grad-CAM when facing with many objects of the same class in an image. It helps us to localize the objects more accurately. Second is that it only adds tow partial derivative to the computation, and it uses backpropagation only once. So it does not increase the computation time a lot.

However, it still remains to be revised in some aspects: First, although it improved the performance of Grad-CAM in some degrees, its performance is far from perfect. The same problem remains and connot be solved completelly. Second, from my perspective, ignoring the relu function in the alpha calculation will decrease the precision.

Our implementation code is as followed:

```
ef grad_cam_plus_plus(input_model, image,
    layer_name, class_index=None):
# if class_index is None:
#    class_index=np.argmax(input_model.
    predict(np.array([image])), axis=-1)[0]
"""GradCAM method for visualizing input
    saliency."""
# cls = np.argmax(input_model.predict(image
    ))
y_c = input_model.output
conv_output = input_model.get_layer(
    layer_name).output
feedforward1 = keras.models.Model([
    input_model.input], [conv_output, y_c])
# with tf.GradientTape() as tape1:
#    with tf.GradientTape() as tape2:
#       with tf.GradientTape() as tape3:
#          ff_results = feedforward1([image
    ])
#          all_fmap_masks, predictions =
    ff_results[0], ff_results[-1]
if class_index==None:
   cls=np.argmax(input_model.predict(image)
       )
else:
   cls=class_index
#          loss = predictions[:, cls]
#       grads_val = tape3.gradient(loss,
    all_fmap_masks)
#    grads_val2 = tape2.gradient(grads_val,
    all_fmap_masks)
# grads_val3 = tape1.gradient(grads_val2,
    all_fmap_masks)
with tf.GradientTape() as tape:
   ff_results=feedforward1([image])
   all_fmap_masks, predictions = ff_results
       [0], ff_results[-1]
   loss = predictions[:, cls]
grads_val = tape.gradient(loss,
    all_fmap_masks)
grads_val2=grads_val**2
grads_val3=grads_val2*grads_val
if len(image.shape) == 3:
   axis = (0, 1)
elif len(image.shape) == 4:
   axis = (0, 1, 2)
alpha_div=(2.0 * grads_val2 + grads_val3 *
    np.sum(all_fmap_masks, axis))
alpha_div = np.where(alpha_div != 0.0,
    alpha_div, 0)
alpha = grads_val2 / alpha_div
weights = np.maximum(grads_val, 0.0) *
    alpha
weights = np.sum(weights, axis=axis)
# weights = np.mean(grads_val, axis=axis)
cam = np.dot(all_fmap_masks[0], weights)
# print (cam)
H, W = image.shape[1:3]
cam = np.maximum(cam, 0)
# cam = resize(cam, (H, W))
cam = zoom(cam, H / cam.shape[0])
# cam = np.maximum(cam, 0)
```

```
    cam = cam / cam.max()
    return cam
```

C. Ablation-CAM

The Ablation-CAM creatively uses ablation analysis to determine the importance of individual feature map units for different classes. It proposes a novel "gradient-free" visualization approach which avoids use of gradients and at the same time, produce high quality class-discriminative localization maps.

The core algorithm of Ablation-CAM is not complex: it uses the value of slope to describe the effect of ablation of individual unit k by the following formula:

$$slope = \frac{y^c - y^c_k}{||A_k||}$$

In the formula, y^c stands for activation score of class c, which represent the entire class activation status. y^c_k indicates the value of the function for absence of unit k, where A_k is the baseline. Those concepts lead us to ablation study, which is the basic principle of the method.

Ablation study is a method to distribute the influencing importance of different factors by controlling the variable while switching the combination of potential factors, and also their standalone. For example, if we'd like to know whether A or B component of medicine could improve the effect of an old medicine C. We could compare $C + A$, $C + B$ and also $C+A+B$ with the baseline of C. We could know if the A or B or they together are able to improve the effect. In the instance of Ablation-CAM, different unit k is the "component", and the whole feature map is so-called baseline, A_k. Thus, using slope described in the previous formula could represent the importance of a single unit to the feature map.

However practically, norm $||A_k||$ is hard to compute due to its large size and hence the slope could be approximately presented by the following formula, assuming a very small value.

$$w^c_k = \frac{y^c - y^c_k}{y^c}$$

As the algorithm, Ablation-CAM can then be obtained as weighted linear combination of activation maps and corresponding weights from the formula above, which is somehow similar to that of Grad-CAM.

$$L^C_{Ablation-CAM} = ReLU(\sum_k w^c_k A_k)$$

There are a number of advantages and features of Ablation-CAM. Firstly, a significant contribution and novelty of the Ablation-CAM is the ablation analysis it used to decide the weights of feature map units. Secondly, it could produce a coarse localization map highlighting the regions in the image for prediction. Thirdly, compare to other CAM methods, this approach works essentially better when it is full connected to obtain the result, which is known as final linear classifier, and have as good performance as other gradient-based CAM methods when evaluating other CNNs. Last but not the least, the approach introduce a gradient-free principle which avoids use of gradient as Grad-CAM does and produce a high-quality class-wise localization maps, which helps it to adapt into any CNN based architecture.

However, the approach have some limitations as well. First of all, the computational time required to generate a single Ablation-CAM is much grater than the required for Grad-CAM, as it has to iterate over each feature map to ablate it and check the drop in class activation score correspondingly. On the hand, the Ablation-CAM only benefits the interpretation where last convolutional layer is not followed immediately by decision nodes, yet show the same performance statistically as other CAM methods.

Our implementation code is as followed.

```
def extract_feature_map(img, model,
    class_index=None, layer_name="conv1d_2"):
    # Get gradients for the class on the last
        conv layer
    gradModel = tf.keras.models.Model([model.
        inputs],[model.get_layer(layer_name).
        output, model.output])
    print("gradModel = ")
    print(gradModel)
    # Get Activation Map on the last conv layer
    with tf.GradientTape() as tape:
        # Get Prediction on the last conv layer
        convOutputs, predictions = gradModel(np.
            array([img]))
        output = convOutputs[0]
        print("#prediction#")
        print(predictions)
        print("OUTPUT")
        print(output)

    if class_index is None:
        class_index = np.argmax(model.predict(np
            .array([img])), axis = -1)[0]
        y_class = np.max(model.predict(np.array
            ([img])))
    else:
        y_class = model.predict(np.array([img]))
            [0][class_index]

    # Get Weights on the layer
    weights = np.zeros(model.get_layer(
        layer_name).get_weights()[1].shape)
    # Get Weights for the maps
    allWeights = model.get_layer(layer_name).
        get_weights().copy()
    zeroWeight = allWeights[0][:,:,:,0]*0
    localWeight = [np.zeros(allWeights[0].shape
        )]
    localWeight.append(np.zeros(allWeights[1].
        shape))

    for i in range(weights.shape[0]):
        localWeight[0] = allWeights[0].copy()
        localWeight[0][:,:,:,i] = zeroWeight
        model.get_layer(layer_name).set_weights(
            localWeight)
        y_pred = model.predict(np.array([img]))
```

```
            [0][class_index]
        weights[i] = (y_class - y_pred)/y_class
            # Simplified Formula
        model.get_layer(layer_name).set_weights(
            allWeights)

    outputMean = np.mean([output[:,:,i] for i
        in range(output.shape[2])], axis = 0)
    outputMean = np.maximum(outputMean, 0.0)
    outMeanMask = np.zeros(output.shape[0:2],
        dtype = np.float32)
    for i in range(output.shape[0]):
        for j in range(output.shape[1]):
            if outputMean[i][j] < np.mean(
                outputMean[:,:]):
                outMeanMask[i][j] = 255
            else:
                outMeanMask[i][j] = 0
    return weights, output, outputMean,
        outMeanMask

def ablation_cam(weights, output):
    ablationMap = weights * output
    ablationCam = np.sum(ablationMap, axis=(2))

    ablationMask = np.zeros(ablationMap.shape
        [0:2], dtype = np.float32)
    for i in range(ablationMap.shape[0]):
        for j in range(ablationMap.shape[1]):
            if ablationCam[i][j] < np.mean(
                ablationCam[:,:]):
                ablationMask[i][j] = 255
            else:
                ablationMask[i][j] = 0

    return ablationCam, ablationMask
```

III. Task 3: Biomedical Image Classification and Interpretation

A. Question 1

1) Overall classification accuracy: Here we calculate the overall classification accuracy, here is the code:

```
    from sklearn.metrics import accuracy_score,
        precision_score, recall_score,f1_score
    from sklearn.metrics import
        classification_report
    from sklearn.metrics import roc_curve, auc
    from sklearn.metrics import
        confusion_matrix

    test_generator.reset()
    y_test=test_generator.classes
    y_pred=model.predict(test_generator)
    y_predicted=np.argmax(y_pred, axis=1)
    print('Overall classification accuracy for
        all classes:'+str(np.sum(y_predicted==
        y_test)/y_test.shape[0]))
```

The result is 83.06%, as is shown in Fig9:

2) class-wise classification accuracy: In this part, we discuss the classification accuracy for every class.Here is the code:

```
Overall classification accuracy for all classes:0.8306451612903226
```

Fig. 9. Overall classification accuracy

```
    for i in range(8):
    true_i=np.where(y_test==i)[0]
    res=0
    for j in true_i:
        if y_predicted[j]==i:
            res=res+1
    print('class '+str(i)+' accuracy:'+str(res/
        true_i.shape[0]))
```

The results are shown in Fig10:

```
class 0 accuracy:0.9193548387096774
class 1 accuracy:0.8709677419354839
class 2 accuracy:0.5967741935483871
class 3 accuracy:0.8870967741935484
class 4 accuracy:0.45161290322580644
class 5 accuracy:0.9516129032258065
class 6 accuracy:0.967741935483871
class 7 accuracy:1.0
```

Fig. 10. class-wise classification accuracy

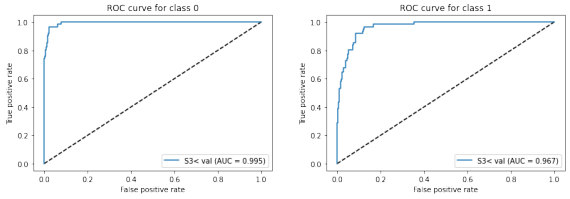
3) AUC-ROC curve: In this part, we discuss the AUC and ROC curve.Here is the code:

```
    real_y=np.zeros((y_test.size,8))
    for i in range(y_test.size):
        real_y[i,y_test[i]]=1
    for i in range(8):
        FPR, TPR, thresholds_keras = roc_curve(
            real_y[:,i], y_pred[:,i])
        AUC = auc(FPR, TPR)
        print("AUC for class "+str(i)+": ", AUC)
        plt.figure()
        plt.plot([0, 1], [0, 1], 'k--')
        plt.plot(FPR, TPR, label='S3< val (AUC =
            {:.3f})'.format(AUC))
        plt.xlabel('False positive rate')
        plt.ylabel('True positive rate')
        plt.title('ROC curve for class '+str(i))
        plt.legend(loc='best')
        plt.show()
```

The plots are shown in Fig. 11.

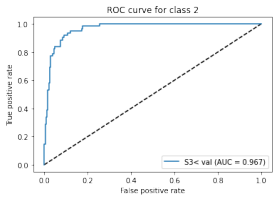
4) normalized confusion matrix: In this part, we discuss the normalized confusion matrix plot.Here is the code:

```
    cm=confusion_matrix(list(y_test),list(
        y_predicted))
    cm_normalized = cm.astype('float') / cm.sum
        (axis=1)[:, np.newaxis]
    fig, ax = plt.subplots()
    im = ax.imshow(cm, interpolation='nearest',
        cmap=plt.cm.Blues)
    ax.figure.colorbar(im, ax=ax)
    classes=[0,1,2,3,4,5,6,7]
    # print(classes)
```

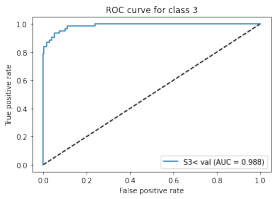


(a) Class 0

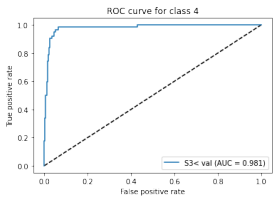
(b) Class 1



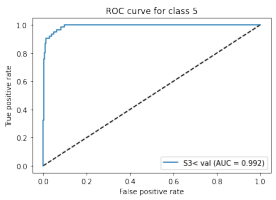
(c) Class 2



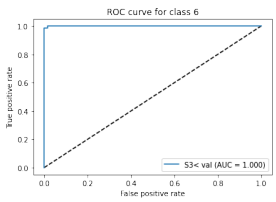
(d) Class 3



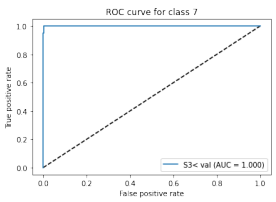
(e) Class 4



(f) Class 5



(g) Class 6



(h) Class 7

Fig. 11. Class-wise ROC Curve Plots of HMT dataset

```
# We want to show all ticks...
ax.set(xticks=np.arange(cm_normalized.shape
    [1]),
   yticks=np.arange(cm_normalized.shape[0])
       ,
   # ... and label them with the respective
       list entries
   xticklabels=classes, yticklabels=classes
       ,
   ylabel='True label',
   xlabel='Predicted label')
plt.setp(ax.get_xticklabels(), ha="right",
         rotation_mode="anchor")
thresh = cm_normalized.max() / 2.
for i in range(cm_normalized.shape[0]):
   for j in range(cm_normalized.shape[1]):
      ax.text(j, i, format(cm_normalized[i,
           j], '.2f'),
            ha="center", va="center",
            color="white" if cm_normalized[
                i, j] > thresh else "black"
                )
fig.tight_layout()
```

The result plot is shown in Fig.12.

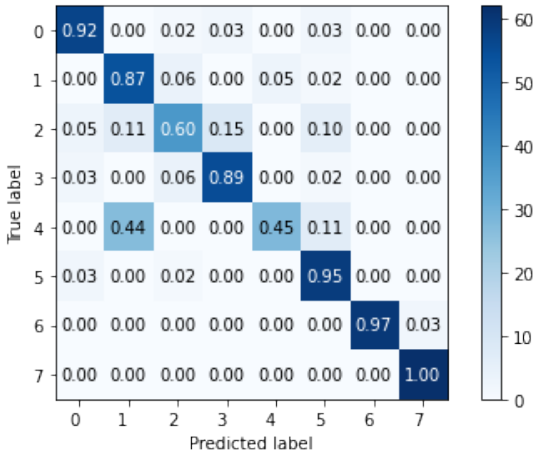


Fig. 12. normalized confusion matrix plot

5) Precision, Recall, and F-1 score: In this part, we discuss the normalized confusion matrix plot. Here is the code:

```
print(classification_report(y_true=y_test,
    y_pred=y_predicted))
```

The result plot is shown in Fig.13.

	precision	recall	f1-score	support
0	0.89	0.92	0.90	62
1	0.61	0.87	0.72	62
2	0.79	0.60	0.68	62
3	0.83	0.89	0.86	62
4	0.90	0.45	0.60	62
5	0.78	0.95	0.86	62
6	1.00	0.97	0.98	62
7	0.97	1.00	0.98	62
accuracy			0.83	496
macro avg	0.85	0.83	0.82	496
weighted avg	0.85	0.83	0.82	496

Fig. 13. Precision, Recall, and F-1 score

B. Question 2

In this section, we describe the implementation of attribution methods application in HMT. As mentioned before, HMT is a 2-Dimensional based dataset, and therefore we need to either develop a capable XAI methods taking both 3-Dimensional and 4-dimensional tensor corresponding to 1-D and 2-D dataset, or we set up separate methods dealing with 2-Dimensional dataset, HMT. In our implementation, we choose different option for the two methods.

Our Grad-CAM++ implementation is a capable function whose code is as followed.

```
def grad_cam_plus_plus(input_model, image,
    layer_name, class_index=None):
```

```
# if class_index is None:
#    class_index=np.argmax(input_model.
    predict(np.array([image])), axis=-1)[0]
"""GradCAM method for visualizing input
    saliency."""
cls = np.argmax(input_model.predict(image))
y_c = input_model.output
conv_output = input_model.get_layer(
    layer_name).output
feedforward1 = keras.models.Model([
    input_model.input], [conv_output, y_c])
# with tf.GradientTape() as tape1:
#    with tf.GradientTape() as tape2:
#       with tf.GradientTape() as tape3:
#          ff_results = feedforward1([image
    ])
#          all_fmap_masks, predictions =
    ff_results[0], ff_results[-1]
if class_index==None:
   cls=np.argmax(input_model.predict(image)
       )
else:
   cls=class_index
#          loss = predictions[:, cls]
#       grads_val = tape3.gradient(loss,
    all_fmap_masks)
#    grads_val2 = tape2.gradient(grads_val,
    all_fmap_masks)
# grads_val3 = tape1.gradient(grads_val2,
    all_fmap_masks)
with tf.GradientTape() as tape:
   ff_results=feedforward1([image])
   all_fmap_masks, predictions = ff_results
       [0], ff_results[-1]
   loss = predictions[:, cls]
grads_val = tape.gradient(loss,
    all_fmap_masks)
grads_val2=grads_val**2
grads_val3=grads_val2*grads_val
if len(image.shape) == 3:
   axis = (0, 1)
elif len(image.shape) == 4:
   axis = (0, 1, 2)
alpha_div=(2.0 * grads_val2 + grads_val3 *
    np.sum(all_fmap_masks, axis))
alpha_div = np.where(alpha_div != 0.0,
    alpha_div, 0)
alpha = grads_val2 / alpha_div
weights = np.maximum(grads_val, 0.0) *
    alpha
weights = np.sum(weights, axis=axis)
# weights = np.mean(grads_val, axis=axis)
cam = np.dot(all_fmap_masks[0], weights)
# print (cam)
H, W = image.shape[1:3]
cam = np.maximum(cam, 0)
# cam = resize(cam, (H, W))
cam = zoom(cam, H / cam.shape[0])
# cam = np.maximum(cam, 0)
cam = cam / cam.max()
return cam
```

The capability is achieved by the code of branch,

```
if len(image.shape) == 3:
   axis = (0, 1)
elif len(image.shape) == 4:
   axis = (0, 1, 2)
```

and hence it can process both 3-Dimensional and 4-Dimensional tensors.

Another modification needs to be mentioned is that

IV. Task 4: Quantitative evaluation of the attribution methods

In this task, we use two rates, decrease rate and increase rate, to evaluate the explanation map generated by the attribution methods, in order to assess the performance of the methods we implemented. Besides, we would like to use some subjective observation to evaluate the performance as a support.

A. Experiment

The calculator function is already provided in the notebook, which takes in a 3-Dimensional map for MNIST-1D dataset and deals with a 4-Dimensional explanation map for HMT dataset. However, we have the processing codes slightly modified, which is shown below.

An example of Grad-CAM++ rate calculation procedure in MNIST-1D dataset is as followed.

An example of Grad-CAM rate calculation procedure in HMT dataset is as followed. Similar to the procedure structure in MNIST-1D, we firstly initialize the variables and reset the generator. Then recursively, we generate explanation map for 15 batches, and 32 samples per batch, and calculate both the drop and increase rate by the calculator function. To get the averaged value, which is the rate, we firstly add them up to the variable and finally divided by the total running times. Specifically, we set the parameter $frac$ to 0.9 as required in HMT datasets.

```
test_generator.reset()
drop_rate = 0.
increase_rate = 0.
for i in range(15):
   image_batch,label_batch=test_generator.next
       ()
   # print("Current Round:", i)
   for index in range(32):
      # print(i, index)
      prediction=model(image_batch)
      explanation_map_GradCAM = grad_cam(model
          , np.expand_dims(image_batch[index],
           axis=0), 'max_pooling2d_1')
      res = calculate_drop_increase(np.
          expand_dims(image_batch[index], axis
          =0), model, explanation_map_GradCAM,
           class_index=np.argmax(prediction[
          index]), frac=0.9)

      drop_rate += res[0]
      increase_rate += res[1]

drop_rate /= (15*32)
increase_rate /= (15*32)
print("======Grad-CAM======")
print(drop_rate, increase_rate)
```

Specially, for the ablation-CAM, we could only implement it and generate explanation map in the last convolution layer which is different with other maps and have a different size (112,112) correspondingly. So alternatively, the calculation process of ablation-CAM is shown as followed, in which we add a resize function to force it fit in the layer size.

```
drop_rate = 0.
increase_rate = 0.

for i in range(15):
   image_batch,label_batch=test_generator.next
       ()
   print("Current Round:", i)
   for index in range(32):
      # print(i, index)
      prediction=model(image_batch)
      explanation_map_ablation_cam =
          ablation_cam_2d(model, np.
          expand_dims(image_batch[index], axis
          =0), 'conv2d_3')
      explanation_map_ablation_cam = cv2.
          resize(explanation_map_ablation_cam,
           (224,224), interpolation=cv.
          INTER_AREA)
      res = calculate_drop_increase(np.
          expand_dims(image_batch[index], axis
          =0), model,
          explanation_map_ablation_cam,
          class_index=np.argmax(prediction[
          index]), frac=0.9)

      drop_rate += res[0]
      increase_rate += res[1]

drop_rate /= (15*32)
increase_rate /= (15*32)
print("======Ablation-CAM======")
print(drop_rate, increase_rate)
```

We can get all the rates after rounds of experiment, and the data is shown in the table.

TABLE I
DROP AND INCREASE RATES OF DIFFERENT ATTRIBUTION METHODS IN MNIST-1D AND HMT

Rate	Drop Rate (%)	Increase Rate (%)
Grad-CAM (MNIST-1D)	0	0
Grad-CAM++ (MNIST-1D)	0	0
Ablation-CAM (MNIST-1D)	0	0
Grad-CAM (HMT)	47.436	22.083
Grad-CAM++ (HMT)	50.921	19.792
Ablation-CAM (HMT)	43.341	30.469

From the table we could know that in HMT, Ablation-CAM works best, as it has lowest drop rate among the algorithms and highest increase rate. Besides in MNIST-1D dataset,

We will further discuss the evaluation result in the next section.

B. Discussion

data analysis

successful? compare to benchmark

fail?

Two methods comparasion.

REFERENCES

[1] Y. Gilad, R. Hemo, S. Micali, G. Vlachos, and N. Zeldovich, “Algorand: Scaling Byzantine Agreements for Cryptocurrencies,” in Proceedings of the 26th Symposium on operating systems principles, 2017, pp. 51–68. doi: 10.1145/3132747.3132757.

[2] King, Sunny, and Scott Nadal. ”Ppcoin: Peer-to-peer crypto-currency with proof-of-stake.” self-published paper, August 19.1, 2012.