

BeFree-3class-gru

September 18, 2024

1 Evaluation using the BeFree corpus

1.0.1 GAD dataset

To obtain a large benchmark of Gene Disease Associations along with associated sentences from literature, we used the corpus generated by BeFree system based on Genetic Association Database (GAD)

2

3 imports

```
[1]: import tensorflow as tf
import keras
from keras.models import load_model
from keras.callbacks import ModelCheckpoint, EarlyStopping
from keras_tqdm import TQDMNotebookCallback
import numpy as np
np.random.seed(1337)
from keras_tqdm import TQDMNotebookCallback
import nltk
import xml.etree.ElementTree as ET
import pandas as pd
import os
import string
from nltk.tokenize import TreebankWordTokenizer
from numpy.random import random_sample
import re
import pickle
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report

from keras.layers import Embedding, Flatten, LSTM, GRU
from keras.layers.convolutional import Conv2D, MaxPooling2D
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential, Model
```

```

from keras.layers import Dense, Dropout, Activation, Input, merge, Conv1D, MaxPooling1D, GlobalMaxPooling1D, Convolution1D
from keras import regularizers
from sklearn.metrics import precision_recall_fscore_support
from sklearn.model_selection import StratifiedKFold
import matplotlib.pyplot as plt
from keras.layers import Concatenate, concatenate
from keras import backend as K
from keras.layers import multiply
from keras.layers import merge
from keras.layers.core import *
from keras.layers.recurrent import LSTM
from keras.models import *
random_seed=1337

```

Using TensorFlow backend.

3.0.1 Define Callback functions to generate Measures

```

[2]: from keras import backend as K

def f1(y_true, y_pred):
    def recall(y_true, y_pred):
        true_positives = K.sum(K.round(K.clip(y_true * y_pred, 0, 1)))
        possible_positives = K.sum(K.round(K.clip(y_true, 0, 1)))
        recall = true_positives / (possible_positives + K.epsilon())
        return recall

    def precision(y_true, y_pred):
        true_positives = K.sum(K.round(K.clip(y_true * y_pred, 0, 1)))
        predicted_positives = K.sum(K.round(K.clip(y_pred, 0, 1)))
        precision = true_positives / (predicted_positives + K.epsilon())
        return precision
    precision = precision(y_true, y_pred)
    recall = recall(y_true, y_pred)
    return 2*((precision*recall)/(precision+recall+K.epsilon()))

```

4 Experiments to reproduce the results of Table 7

4.0.1 Evaluation results for multi-class classification

4.0.2 Load Prerocssed Data

```

[3]: with open('../data/pickles/befree_3class_crawl-300d-2M.pickle', 'rb') as handle:
    gene_id_list = pickle.load(handle)
    gene_symbol_list = pickle.load(handle)
    disease_id_list = pickle.load(handle)
    X_train = pickle.load(handle)

```

```

distance1_vectors = pickle.load(handle)
distance2_vectors = pickle.load(handle)
Y_train = pickle.load(handle)
word_list = pickle.load(handle)
word_vectors = pickle.load(handle)
word_dict = pickle.load(handle)
distance1_dict = pickle.load(handle)
distance2_dict = pickle.load(handle)
label_dict = pickle.load(handle)
MAX_SEQUENCE_LENGTH = pickle.load(handle)
print ("word_vectors",len(word_vectors))

```

word_vectors 6766

4.0.3 Create Position Embedding Vectors

```

[4]: import keras
from keras_pos_embd import TrigPosEmbedding

model = keras.models.Sequential()
model.add(TrigPosEmbedding(
    input_shape=(None,),
    output_dim=20,
    mode=TrigPosEmbedding.MODE_EXPAND,
    name='Pos-Embd',
))
model.compile('adam', keras.losses.mae, {})

d1_train_embedded=model.predict(distance1_vectors)

d1_train_embedded.shape

d2_train_embedded=model.predict(distance2_vectors)

d2_train_embedded.shape

```

[4]: (5330, 81, 20)

4.0.4 Prepare Word Embedding Layer

```

[5]: EMBEDDING_DIM=word_vectors.shape[1]
print("EMBEDDING_DIM=",EMBEDDING_DIM)
embedding_matrix=word_vectors

def create_embedding_layer(l2_reg=0.01,use_pretrained=True,is_trainable=False):

    if use_pretrained:

```

```

        return Embedding(len(word_dict)␣
↪, EMBEDDING_DIM, weights=[embedding_matrix], input_length=MAX_SEQUENCE_LENGTH, trainable=is_trainable)
↪l2(12_reg))

    else:
        return Embedding(len(word_dict)␣
↪, EMBEDDING_DIM, input_length=MAX_SEQUENCE_LENGTH)

```

EMBEDDING_DIM= 300

4.0.5 Prepare Attention Mechanism

```

[6]: INPUT_DIM = 2
TIME_STEPS = MAX_SEQUENCE_LENGTH
def attentionNew(inputs):
    inputs = Lambda(lambda x: tf.keras.backend.tanh(x))(inputs)
    input_dim = int(inputs.shape[2])
    a = Permute((2, 1))(inputs)
    a = Dense(TIME_STEPS, activation='softmax')(a)
    a_probs = Permute((2, 1))(a)
    output_attention_mul = multiply([inputs, a_probs])
    output_attention_mul = Lambda(lambda x: tf.keras.backend.
↪tanh(x))(output_attention_mul)
    return output_attention_mul

```

4.0.6 Create the Model

```

[7]: # set parameter for metric calculation, 'macro' for multiclass classification
param='macro'
def build_model():

    sequence_input = Input(shape=(MAX_SEQUENCE_LENGTH,), dtype='int32')
    ␣
↪embedding_layer=create_embedding_layer(use_pretrained=True,is_trainable=False)
    embedded_sequences = embedding_layer(sequence_input)

    pos_embedd_1=Input(shape=(MAX_SEQUENCE_LENGTH,20), dtype='float32')
    pos_embedd_2=Input(shape=(MAX_SEQUENCE_LENGTH,20), dtype='float32')

    embedded_sequences =␣
↪concatenate([embedded_sequences,pos_embedd_1,pos_embedd_2])

    x = Conv1D(32, 5, activation='relu')(embedded_sequences)

```

```

x = MaxPooling1D(3)(x)
x = Dropout(0.1)(x)
conv_sequence_w5=GlobalMaxPooling1D()(x)      #x = Flatten()(x)

x = Conv1D(64, 3, activation='relu')(embedded_sequences)
x = MaxPooling1D(3)(x)
x = Dropout(0.1)(x)
conv_sequence_w4=GlobalMaxPooling1D()(x)      #x = Flatten()(x)

x = Conv1D(128, 3, activation='relu')(embedded_sequences)
x = MaxPooling1D(3)(x)
x = Dropout(0.1)(x)
conv_sequence_w3=GlobalMaxPooling1D()(x)      #x = Flatten()(x)

forward = GRU(100, recurrent_dropout=0.
↪05,return_sequences=True)(embedded_sequences)
backward = GRU(100, go_backwards=True,recurrent_dropout=0.
↪05,return_sequences=True)(embedded_sequences)
attention_forward=attentionNew(forward)
attention_backward=attentionNew(backward)
lstm_sequence = concatenate([attention_forward,attention_backward])

lstm_sequence = Flatten()(lstm_sequence)
merge = ␣
↪concatenate([conv_sequence_w5,conv_sequence_w4,conv_sequence_w3,lstm_sequence])
x = Dense(64, activation='relu', kernel_regularizer=regularizers.l2(0.
↪1))(merge)
x = Dropout(0.1)(x)
preds = Dense(3, activation='softmax')(x)
model = Model(inputs=[sequence_input,␣
↪pos_embedd_1,pos_embedd_2],outputs=preds)
opt=tf.keras.optimizers.Adam()
model.
↪compile(loss='categorical_crossentropy',optimizer=opt,metrics=['acc',f1])
return model

```

```

[8]: model = build_model()
model.summary()

```

```

Model: "model_1"

```

```

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```

Layer (type)	Output Shape	Param #	Connected to
=====			
input_1 (InputLayer)	(None, 81)	0	

embedding_1 (Embedding)	(None, 81, 300)	2029800	input_1[0][0]

input_2 (InputLayer)	(None, 81, 20)	0	

input_3 (InputLayer)	(None, 81, 20)	0	

concatenate_1 (Concatenate)	(None, 81, 340)	0	
embedding_1[0][0]			input_2[0][0]
			input_3[0][0]

gru_1 (GRU)	(None, 81, 100)	132300	
concatenate_1[0][0]			

gru_2 (GRU)	(None, 81, 100)	132300	
concatenate_1[0][0]			

lambda_1 (Lambda)	(None, 81, 100)	0	gru_1[0][0]

lambda_3 (Lambda)	(None, 81, 100)	0	gru_2[0][0]

permute_1 (Permute)	(None, 100, 81)	0	lambda_1[0][0]

permute_3 (Permute)	(None, 100, 81)	0	lambda_3[0][0]

dense_1 (Dense)	(None, 100, 81)	6642	permute_1[0][0]

dense_2 (Dense)	(None, 100, 81)	6642	permute_3[0][0]

permute_2 (Permute)	(None, 81, 100)	0	dense_1[0][0]

permute_4 (Permute)	(None, 81, 100)	0	dense_2[0][0]
conv1d_1 (Conv1D) concatenate_1[0][0]	(None, 77, 32)	54432	
conv1d_2 (Conv1D) concatenate_1[0][0]	(None, 79, 64)	65344	
conv1d_3 (Conv1D) concatenate_1[0][0]	(None, 79, 128)	130688	
multiply_1 (Multiply)	(None, 81, 100)	0	lambda_1[0][0] permute_2[0][0]
multiply_2 (Multiply)	(None, 81, 100)	0	lambda_3[0][0] permute_4[0][0]
max_pooling1d_1 (MaxPooling1D)	(None, 25, 32)	0	conv1d_1[0][0]
max_pooling1d_2 (MaxPooling1D)	(None, 26, 64)	0	conv1d_2[0][0]
max_pooling1d_3 (MaxPooling1D)	(None, 26, 128)	0	conv1d_3[0][0]
lambda_2 (Lambda) multiply_1[0][0]	(None, 81, 100)	0	
lambda_4 (Lambda) multiply_2[0][0]	(None, 81, 100)	0	
dropout_1 (Dropout) max_pooling1d_1[0][0]	(None, 25, 32)	0	
dropout_2 (Dropout) max_pooling1d_2[0][0]	(None, 26, 64)	0	

```

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-----
dropout_3 (Dropout)          (None, 26, 128)      0
max_pooling1d_3[0][0]
-----
-----
concatenate_2 (Concatenate)  (None, 81, 200)      0          lambda_2[0][0]
                                          lambda_4[0][0]
-----
-----
global_max_pooling1d_1 (GlobalM (None, 32)      0          dropout_1[0][0]
-----
-----
global_max_pooling1d_2 (GlobalM (None, 64)      0          dropout_2[0][0]
-----
-----
global_max_pooling1d_3 (GlobalM (None, 128)      0          dropout_3[0][0]
-----
-----
flatten_1 (Flatten)          (None, 16200)        0
concatenate_2[0][0]
-----
-----
concatenate_3 (Concatenate)  (None, 16424)        0
global_max_pooling1d_1[0][0]
global_max_pooling1d_2[0][0]
global_max_pooling1d_3[0][0]
                                          flatten_1[0][0]
-----
-----
dense_3 (Dense)              (None, 64)           1051200
concatenate_3[0][0]
-----
-----
dropout_4 (Dropout)          (None, 64)           0          dense_3[0][0]
-----
-----
dense_4 (Dense)              (None, 3)             195        dropout_4[0][0]
=====
=====
Total params: 3,609,543
Trainable params: 1,579,743
Non-trainable params: 2,029,800
-----
-----

```



```

[9]: validation_split_rate = 0.1
skf = StratifiedKFold(n_splits=5,shuffle=True, random_state=42)
Y = [np.argmax(y, axis=None, out=None) for y in Y_train]
for tr_index, te_index in skf.split(X_train,Y):
    test_index = te_index
    train_index = tr_index

trainRate = (len(train_index)/len(Y))*100
testRate = (len(test_index)/len(Y))*100
print ("TrainRate:{:.2f}% testRate:{:.2f}% validation:{:.2f}% ".
    ↪format(trainRate,testRate, trainRate*validation_split_rate))
X_train, X_test = X_train[train_index], X_train[test_index]
pos_train1, pos_test1 = d1_train_embedded[train_index], ↵
    ↪d1_train_embedded[test_index]
pos_train2, pos_test2 = d2_train_embedded[train_index], ↵
    ↪d2_train_embedded[test_index]
y_train, y_test = Y_train[train_index], Y_train[test_index]

# # Saving the training data split as a pickle file
# training_data = {
#     'X_train': X_train,
#     'pos_train1': pos_train1,
#     'pos_train2': pos_train2,
#     'y_train': y_train
# }

# with open('training_data12.pkl', 'wb') as f:
#     pickle.dump(training_data, f)

# # Saving the testing data split as a pickle file
# testing_data = {
#     'X_test': X_test,
#     'pos_test1': pos_test1,
#     'pos_test2': pos_test2,
#     'y_test': y_test
# }

# with open('testing_data12.pkl', 'wb') as f:
#     pickle.dump(testing_data, f)

```

TrainRate:80.00% testRate:20.00% validation:8.00%

```

[10]: # Load the training data from the pickle file
with open('training_data.pkl', 'rb') as f:

```

```

train_data = pickle.load(f)

# Load the testing data from the pickle file
with open('testing_data.pkl', 'rb') as f:
    test_data = pickle.load(f)

# Extract data from the loaded dictionaries
X_train = train_data['X_train']
pos_train1 = train_data['pos_train1']
pos_train2 = train_data['pos_train2']
y_train = train_data['y_train']

X_test = test_data['X_test']
pos_test1 = test_data['pos_test1']
pos_test2 = test_data['pos_test2']
y_test = test_data['y_test']
print(X_train.shape)
print(X_test.shape)

```

(4264, 81)

(1066, 81)

4.0.7 Run the Evaluation using 10 fold Cross Validation

```

[11]: MaxEpochs =50
batchsize =32
validation_split_rate = 0.1
history=model.fit([X_train,pos_train1,pos_train2],
    ↪y_train,validation_split=validation_split_rate ,epochs=MaxEpochs,
    ↪batch_size=batchsize,verbose=1)

```

Train on 3837 samples, validate on 427 samples

Epoch 1/50

3837/3837 [=====] - 87s 23ms/step - loss: 2780.3121 -
acc: 0.4454 - f1: 0.1384 - val_loss: 2779.7211 - val_acc: 0.4333 - val_f1:
0.0397

Epoch 2/50

3837/3837 [=====] - 21s 5ms/step - loss: 2779.6360 -
acc: 0.4699 - f1: 0.1608 - val_loss: 2779.6530 - val_acc: 0.4333 - val_f1:
0.1856

Epoch 3/50

3837/3837 [=====] - 21s 5ms/step - loss: 2779.5958 -
acc: 0.4788 - f1: 0.2140 - val_loss: 2779.6675 - val_acc: 0.4450 - val_f1:

0.0709
Epoch 4/50
3837/3837 [=====] - 21s 5ms/step - loss: 2779.5398 -
acc: 0.4827 - f1: 0.2854 - val_loss: 2779.7274 - val_acc: 0.5012 - val_f1:
0.3381
Epoch 5/50
3837/3837 [=====] - 21s 5ms/step - loss: 2779.4688 -
acc: 0.5442 - f1: 0.4584 - val_loss: 2779.6347 - val_acc: 0.4567 - val_f1:
0.4231
Epoch 6/50
3837/3837 [=====] - 21s 5ms/step - loss: 2779.4364 -
acc: 0.5603 - f1: 0.5021 - val_loss: 2779.5545 - val_acc: 0.5363 - val_f1:
0.5024
Epoch 7/50
3837/3837 [=====] - 21s 6ms/step - loss: 2779.4069 -
acc: 0.6185 - f1: 0.5916 - val_loss: 2779.6308 - val_acc: 0.5480 - val_f1:
0.5146
Epoch 8/50
3837/3837 [=====] - 21s 5ms/step - loss: 2779.3545 -
acc: 0.6706 - f1: 0.6566 - val_loss: 2779.5228 - val_acc: 0.5386 - val_f1:
0.5019
Epoch 9/50
3837/3837 [=====] - 21s 5ms/step - loss: 2779.3112 -
acc: 0.7047 - f1: 0.6950 - val_loss: 2779.6049 - val_acc: 0.6136 - val_f1:
0.5956
Epoch 10/50
3837/3837 [=====] - 21s 6ms/step - loss: 2779.2644 -
acc: 0.7415 - f1: 0.7366 - val_loss: 2779.6261 - val_acc: 0.5504 - val_f1:
0.5353
Epoch 11/50
3837/3837 [=====] - 23s 6ms/step - loss: 2779.2131 -
acc: 0.7709 - f1: 0.7635 - val_loss: 2779.4703 - val_acc: 0.6253 - val_f1:
0.6110
Epoch 12/50
3837/3837 [=====] - 21s 6ms/step - loss: 2779.1677 -
acc: 0.7965 - f1: 0.7918 - val_loss: 2779.5100 - val_acc: 0.6183 - val_f1:
0.6134
Epoch 13/50
3837/3837 [=====] - 21s 6ms/step - loss: 2779.1289 -
acc: 0.8144 - f1: 0.8134 - val_loss: 2779.4898 - val_acc: 0.6323 - val_f1:
0.6286
Epoch 14/50
3837/3837 [=====] - 21s 5ms/step - loss: 2779.1118 -
acc: 0.8210 - f1: 0.8216 - val_loss: 2779.7811 - val_acc: 0.5761 - val_f1:
0.5672
Epoch 15/50
3837/3837 [=====] - 21s 6ms/step - loss: 2779.0709 -
acc: 0.8455 - f1: 0.8457 - val_loss: 2779.5833 - val_acc: 0.6393 - val_f1:

0.6329
Epoch 16/50
3837/3837 [=====] - 21s 5ms/step - loss: 2779.0282 -
acc: 0.8598 - f1: 0.8580 - val_loss: 2779.7611 - val_acc: 0.6323 - val_f1:
0.6300
Epoch 17/50
3837/3837 [=====] - 21s 6ms/step - loss: 2779.0035 -
acc: 0.8791 - f1: 0.8780 - val_loss: 2779.5790 - val_acc: 0.6347 - val_f1:
0.6281
Epoch 18/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.9785 -
acc: 0.8861 - f1: 0.8858 - val_loss: 2779.6440 - val_acc: 0.6323 - val_f1:
0.6332
Epoch 19/50
3837/3837 [=====] - 22s 6ms/step - loss: 2778.9699 -
acc: 0.8887 - f1: 0.8867 - val_loss: 2779.5114 - val_acc: 0.6534 - val_f1:
0.6472
Epoch 20/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.9397 -
acc: 0.9080 - f1: 0.9064 - val_loss: 2779.6474 - val_acc: 0.6464 - val_f1:
0.6400
Epoch 21/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.9134 -
acc: 0.9150 - f1: 0.9139 - val_loss: 2779.7363 - val_acc: 0.6370 - val_f1:
0.6327
Epoch 22/50
3837/3837 [=====] - 21s 6ms/step - loss: 2778.8974 -
acc: 0.9223 - f1: 0.9212 - val_loss: 2779.7114 - val_acc: 0.6370 - val_f1:
0.6398
Epoch 23/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.9171 -
acc: 0.9208 - f1: 0.9202 - val_loss: 2779.9166 - val_acc: 0.6534 - val_f1:
0.6350
Epoch 24/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.8707 -
acc: 0.9302 - f1: 0.9302 - val_loss: 2779.7252 - val_acc: 0.6674 - val_f1:
0.6565
Epoch 25/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.8636 -
acc: 0.9317 - f1: 0.9309 - val_loss: 2779.5980 - val_acc: 0.6768 - val_f1:
0.6812
Epoch 26/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.8377 -
acc: 0.9416 - f1: 0.9413 - val_loss: 2779.8469 - val_acc: 0.6417 - val_f1:
0.6401
Epoch 27/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.8694 -
acc: 0.9445 - f1: 0.9445 - val_loss: 2780.0383 - val_acc: 0.6276 - val_f1:

0.6256
Epoch 28/50
3837/3837 [=====] - 22s 6ms/step - loss: 2778.8163 -
acc: 0.9481 - f1: 0.9484 - val_loss: 2779.6181 - val_acc: 0.7073 - val_f1:
0.7038
Epoch 29/50
3837/3837 [=====] - 21s 6ms/step - loss: 2778.7988 -
acc: 0.9533 - f1: 0.9529 - val_loss: 2779.8841 - val_acc: 0.6393 - val_f1:
0.6300
Epoch 30/50
3837/3837 [=====] - 22s 6ms/step - loss: 2778.7978 -
acc: 0.9526 - f1: 0.9523 - val_loss: 2779.6721 - val_acc: 0.6698 - val_f1:
0.6715
Epoch 31/50
3837/3837 [=====] - 21s 6ms/step - loss: 2778.8109 -
acc: 0.9523 - f1: 0.9527 - val_loss: 2780.1814 - val_acc: 0.6347 - val_f1:
0.6350
Epoch 32/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.8038 -
acc: 0.9520 - f1: 0.9520 - val_loss: 2779.7025 - val_acc: 0.6745 - val_f1:
0.6754
Epoch 33/50
3837/3837 [=====] - 21s 6ms/step - loss: 2778.8002 -
acc: 0.9547 - f1: 0.9547 - val_loss: 2779.7859 - val_acc: 0.6698 - val_f1:
0.6690
Epoch 34/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7823 -
acc: 0.9599 - f1: 0.9592 - val_loss: 2779.9133 - val_acc: 0.6581 - val_f1:
0.6506
Epoch 35/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7819 -
acc: 0.9601 - f1: 0.9594 - val_loss: 2779.8988 - val_acc: 0.6604 - val_f1:
0.6692
Epoch 36/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7786 -
acc: 0.9599 - f1: 0.9603 - val_loss: 2779.8131 - val_acc: 0.6393 - val_f1:
0.6195
Epoch 37/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7692 -
acc: 0.9640 - f1: 0.9651 - val_loss: 2779.9524 - val_acc: 0.6159 - val_f1:
0.6145
Epoch 38/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7633 -
acc: 0.9653 - f1: 0.9668 - val_loss: 2779.8813 - val_acc: 0.6440 - val_f1:
0.6390
Epoch 39/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7430 -
acc: 0.9724 - f1: 0.9723 - val_loss: 2780.0892 - val_acc: 0.6393 - val_f1:

0.6354
Epoch 40/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7247 -
acc: 0.9768 - f1: 0.9771 - val_loss: 2780.1236 - val_acc: 0.6183 - val_f1:
0.6168
Epoch 41/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7535 -
acc: 0.9669 - f1: 0.9679 - val_loss: 2779.8234 - val_acc: 0.6511 - val_f1:
0.6406
Epoch 42/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7365 -
acc: 0.9711 - f1: 0.9718 - val_loss: 2779.9257 - val_acc: 0.6440 - val_f1:
0.6478
Epoch 43/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7431 -
acc: 0.9708 - f1: 0.9711 - val_loss: 2780.0395 - val_acc: 0.6042 - val_f1:
0.5988
Epoch 44/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7754 -
acc: 0.9760 - f1: 0.9762 - val_loss: 2780.6627 - val_acc: 0.6323 - val_f1:
0.6211
Epoch 45/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7446 -
acc: 0.9742 - f1: 0.9740 - val_loss: 2780.4818 - val_acc: 0.6628 - val_f1:
0.6643
Epoch 46/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7396 -
acc: 0.9705 - f1: 0.9707 - val_loss: 2780.6776 - val_acc: 0.6112 - val_f1:
0.6029
Epoch 47/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7645 -
acc: 0.9692 - f1: 0.9695 - val_loss: 2780.0895 - val_acc: 0.6183 - val_f1:
0.6127
Epoch 48/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7295 -
acc: 0.9729 - f1: 0.9744 - val_loss: 2780.0008 - val_acc: 0.6487 - val_f1:
0.6466
Epoch 49/50
3837/3837 [=====] - 21s 5ms/step - loss: 2778.7011 -
acc: 0.9812 - f1: 0.9816 - val_loss: 2780.2382 - val_acc: 0.6581 - val_f1:
0.6499
Epoch 50/50
3837/3837 [=====] - 20s 5ms/step - loss: 2778.7253 -
acc: 0.9755 - f1: 0.9758 - val_loss: 2780.1437 - val_acc: 0.6300 - val_f1:
0.6374

```
[12]: import matplotlib.pyplot as plt

# Training & Validation accuracy
train_loss = history.history['loss']
val_loss = history.history['val_loss']
train_acc = history.history['acc']
val_acc = history.history['val_acc']
epochs = len(train_loss)

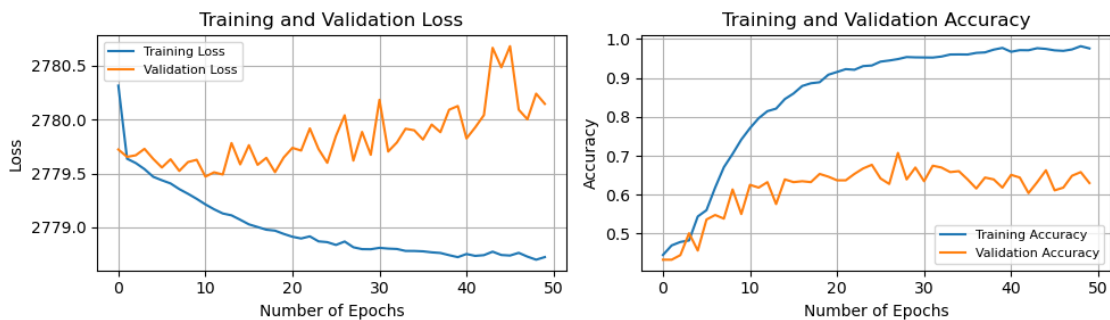
xc = range(epochs)

plt.figure(figsize=(10, 3))

# Loss subplot
plt.subplot(1, 2, 1)
plt.plot(xc, train_loss, label='Training Loss')
plt.plot(xc, val_loss, label='Validation Loss')
plt.xlabel('Number of Epochs', fontsize=10)
plt.ylabel('Loss', fontsize=10)
plt.title('Training and Validation Loss', fontsize=12)
plt.legend(fontsize=8)
plt.grid(True)

# Accuracy subplot
plt.subplot(1, 2, 2)
plt.plot(xc, train_acc, label='Training Accuracy')
plt.plot(xc, val_acc, label='Validation Accuracy')
plt.xlabel('Number of Epochs', fontsize=10)
plt.ylabel('Accuracy', fontsize=10)
plt.title('Training and Validation Accuracy', fontsize=12)
plt.legend(fontsize=8, loc='lower right') # Change position to lower right
plt.grid(True)

plt.tight_layout()
plt.show()
```



```
[13]: import torch
from sklearn.metrics import accuracy_score, classification_report,
precision_recall_fscore_support

# Predict on the training dataset
train_predicted = np.argmax(model.predict([X_train, pos_train1, pos_train2]),
axis=1)
y_train_to_label = np.argmax(y_train, axis=1)

# Calculate accuracy, precision, recall, and F1-score for the training data
train_accuracy = accuracy_score(y_train_to_label, train_predicted)
train_prec, train_reca, train_fscore, _ =
precision_recall_fscore_support(y_train_to_label, train_predicted,
average=param)

# Print the classification report for the training data
print("Training Classification Report:")
print(classification_report(y_train_to_label, train_predicted))

# Print the precision, recall, and F1-score for the training data
print("Training Accuracy: {:.2f}%".format(train_accuracy * 100))
print("Training Precision: {:.2f}%".format(train_prec * 100))
print("Training Recall: {:.2f}%".format(train_reca * 100))
print("Training F1 Score: {:.2f}%".format(train_fscore * 100))
```

Training Classification Report:

	precision	recall	f1-score	support
0	0.91	0.88	0.89	2023
1	0.86	0.95	0.90	1468
2	0.86	0.77	0.81	773
accuracy			0.88	4264
macro avg	0.88	0.86	0.87	4264
weighted avg	0.88	0.88	0.88	4264

Training Accuracy: 88.20%

Training Precision: 87.62%

Training Recall: 86.41%

Training F1 Score: 86.85%

```
[14]: predicted = np.argmax(model.predict([X_test, pos_test1, pos_test2]), axis=1)
y_test_to_label = np.argmax(y_test, axis=1)
prec, reca, fscore, sup = precision_recall_fscore_support(y_test_to_label,
predicted, average=param)
# Generate the classification report as a dictionary
```



```

report_dict = classification_report(y_test_to_label, predicted,
    ↪output_dict=True)

# Create a new dictionary to hold the formatted values
formatted_report_dict = {}

# Iterate over the items in the report dictionary
for key, value in report_dict.items():
    if isinstance(value, dict):
        # Format the nested dictionary values
        formatted_report_dict[key] = {sub_key: f"{sub_value:.4f}" for sub_key,
    ↪sub_value in value.items()}
    else:
        # Format the top-level dictionary values
        formatted_report_dict[key] = f"{value:.4f}"

# Create a string representation of the formatted dictionary
formatted_report_str = classification_report(y_test_to_label, predicted,
    ↪digits=4)

# Print the formatted classification report
print(formatted_report_str)
print(" Precision:{:.2f}% Recall:{:.2f}% Fscore:{:.2f}% ".format(prec*100,
    ↪reca*100, fscore*100))

```

	precision	recall	f1-score	support
0	0.7795	0.7689	0.7742	515
1	0.7473	0.8216	0.7827	342
2	0.7637	0.6651	0.7110	209
accuracy			0.7655	1066
macro avg	0.7635	0.7519	0.7560	1066
weighted avg	0.7661	0.7655	0.7645	1066

Precision:76.35% Recall:75.19% Fscore:75.60%

```

[15]: import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import classification_report, confusion_matrix,
    ↪precision_recall_fscore_support
from sklearn.model_selection import StratifiedKFold
# Calculate and visualize the confusion matrix
cm = confusion_matrix(y_test_to_label, predicted)
plt.figure(figsize=(10, 7))

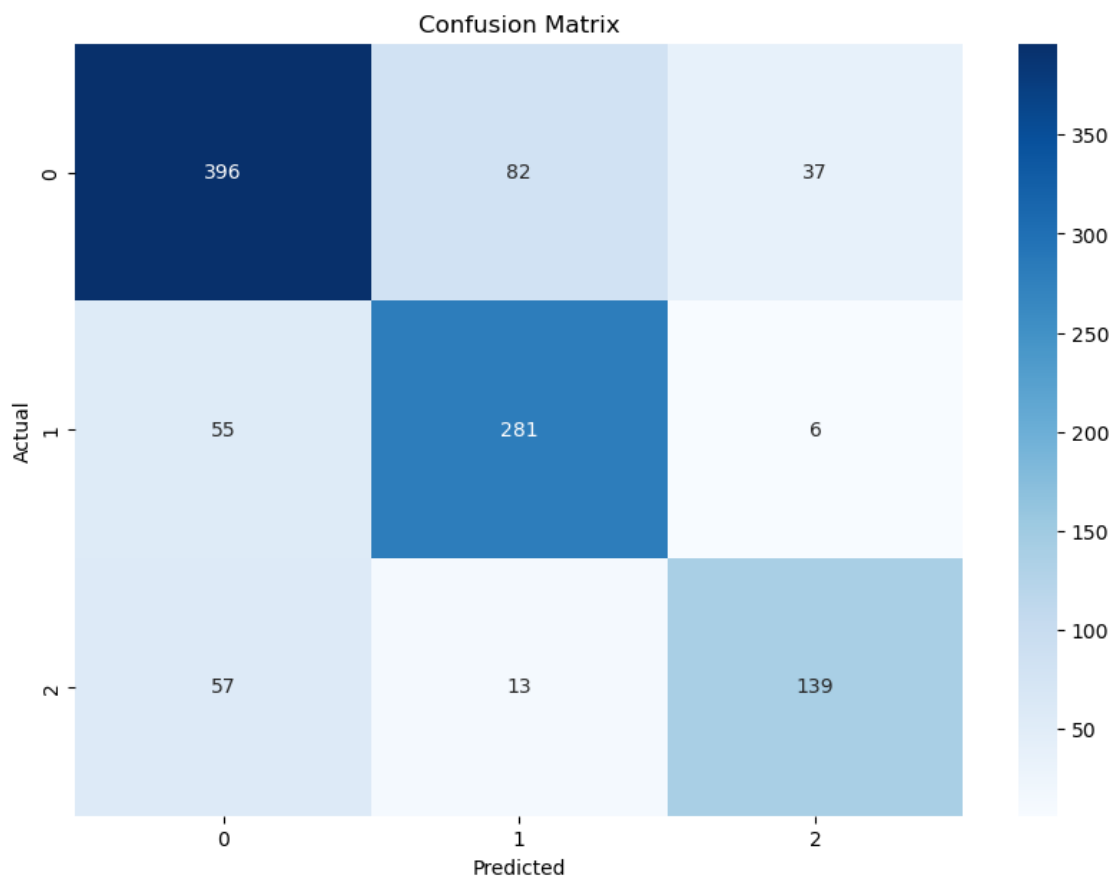
```

```

sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['0', '1', '2'],
            yticklabels=['0', '1', '2'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

# Print precision, recall, and f-score
prec, reca, fscore, sup = precision_recall_fscore_support(y_test_to_label,
            predicted, average=param)
print(" Precision:{:.2f}% Recall:{:.2f}% Fscore:{:.2f}% ".format(prec*100,
            reca*100, fscore*100))

```



Precision:76.35% Recall:75.19% Fscore:75.60%

[]: