In [1]:
```
import tensorflow as tf
import sys
import torch
from transformers import BertTokenizer, BertForSequenceClassification
from torch.utils.data import TensorDataset, DataLoader, RandomSampler, SequentialSa
from sklearn.model_selection import train_test_split
from keras.preprocessing.sequence import pad_sequences
from transformers import AdamW, get_linear_schedule_with_warmup
import numpy as np
import time
import datetime
import random
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
import os
```

```
WARNING:tensorflow:From C:\Users\tessa\anaconda3\Lib\site-packages\keras\src\losse
s.py:2976: The name tf.losses.sparse_softmax_cross_entropy is deprecated. Please u
se tf.compat.v1.losses.sparse_softmax_cross_entropy instead.
```

In [2]:
```
import pandas as pd
import numpy as np

# Define the path to your Excel file within the "Data" folder
file_path = "./15-12 Final Training data set.xlsx"


# Read the Excel file into a DataFrame
df = pd.read_excel(file_path)
df
```

Out[2]:

	Sentences	Label
0	A t-test confirmed that no significant differe...	Correct
1	No significant difference in HBP scores betwee...	Correct
2	No significant difference was found in any oth...	Correct
3	it was therefore assumed that this minimal var...	Correct
4	no significant differences were observed in th...	Correct
...	...	...
295	as compared with CHO, 12 while there was no di...	Incorrect
296	As shown in Table 1, there were no differences...	Incorrect
297	Also, there was no effect of time (p = 0.552) ...	Incorrect
298	NEFA concentrations dropped from the baseline ...	Incorrect
299	Insulin concentrations (Figure 3b) did not dif...	Incorrect

300 rows × 2 columns

In [3]:
```
label_mapping = {'Incorrect': 0, 'Correct': 1}
df['Label'] = df['Label'].replace(label_mapping)
df
```

Out[3]:

	Sentences	Label
0	A t-test confirmed that no significant differe...	1
1	No significant difference in HBP scores betwee...	1
2	No significant difference was found in any oth...	1
3	it was therefore assumed that this minimal var...	1
4	no significant differences were observed in th...	1
...	...	...
295	as compared with CHO, 12 while there was no di...	0
296	As shown in Table 1, there were no differences...	0
297	Also, there was no effect of time (p = 0.552) ...	0
298	NEFA concentrations dropped from the baseline ...	0
299	Insulin concentrations (Figure 3b) did not dif...	0

300 rows × 2 columns

In [4]:
```
print('Positive samples: %d of %d (%.2f%%)' % (df.Label.sum(), len(df.Label), (df.L
```

```
Positive samples: 150 of 300 (50.00%)
```

In [5]:
```
# Get the lists of sentences and their labels.
sentences = df.Sentences.values
labels = df.Label.values
```

In [6]:
```
print(labels.dtype)
```

```
int64
```

In [7]:
```
from transformers import BertTokenizer

tokenizer = BertTokenizer.from_pretrained('allenai/scibert_scivocab_uncased', do_lc
model = BertTokenizer.from_pretrained('allenai/scibert_scivocab_uncased')
```

In [8]:
```
# Print the original sentence.
print(' Original: ', sentences[0])

# Print the sentence split into tokens.
print('Tokenized: ', tokenizer.tokenize(sentences[0]))

# Print the sentence mapped to token ids.
print('Token IDs: ', tokenizer.convert_tokens_to_ids(tokenizer.tokenize(sentences[0
```

```
 Original:  A t-test confirmed that no significant difference existed between the
two groups ( t(30) = 0.74, P=0 .
Tokenized:  ['a', 't', '-', 'test', 'confirmed', 'that', 'no', 'significant', 'dif
ference', 'existed', 'between', 'the', 'two', 'groups', '(', 't', '(', '30', ')',
'=', '0', '.', '74', ',', 'p', '=', '0', '.']
Token IDs:  [106, 105, 579, 856, 3804, 198, 425, 684, 1673, 16158, 467, 111, 502,
1302, 145, 105, 145, 1339, 546, 275, 244, 205, 7667, 422, 118, 275, 244, 205]
```

In [9]:
```
# Tokenize all of the sentences and map the tokens to thier word IDs.
input_ids = []

# For every sentence...
for sent in sentences:
```

```
    # `encode` will:
    #   (1) Tokenize the sentence.
    #   (2) Prepend the `[CLS]` token to the start.
    #   (3) Append the `[SEP]` token to the end.
    #   (4) Map tokens to their IDs.
    encoded_sent = tokenizer.encode(
                        sent
                   )

    # Add the encoded sentence to the list.
    input_ids.append(encoded_sent)

# Print sentence 0, now as a list of IDs.
print('Original: ', sentences[0])
print('Token IDs:', input_ids[0])
```

```
Original:  A t-test confirmed that no significant difference existed between the t
wo groups ( t(30) = 0.74, P=0 .
Token IDs: [102, 106, 105, 579, 856, 3804, 198, 425, 684, 1673, 16158, 467, 111, 5
02, 1302, 145, 105, 145, 1339, 546, 275, 244, 205, 7667, 422, 118, 275, 244, 205,
103]
```

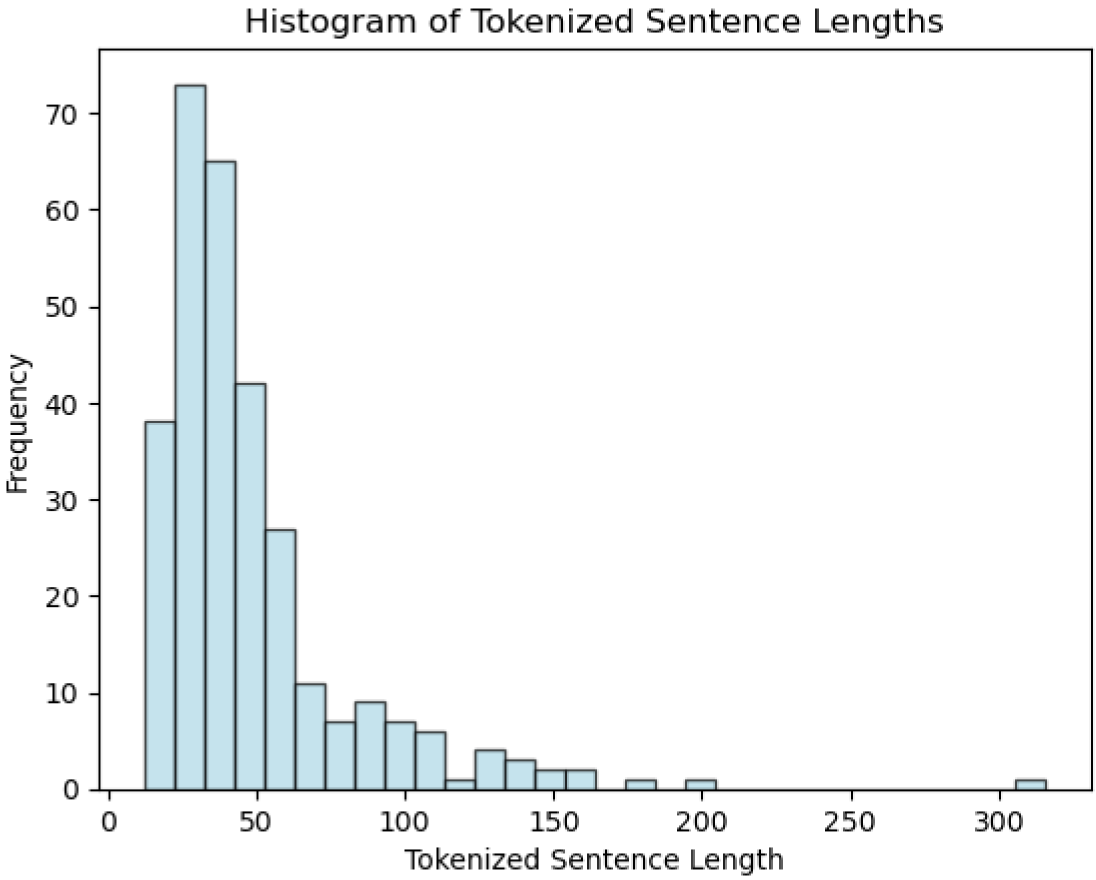
In [10]:
```
print('Max sentence length: ', max([len(sen) for sen in input_ids]))
```

```
Max sentence length:  316
```

In [11]:
```
average_length = sum(len(sen) for sen in input_ids) / len(input_ids)
print('Average sentence length:',average_length)
```

```
Average sentence length: 48.19
```

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

# Calculate the lengths of tokenized sentences
sentence_lengths = [len(sen) for sen in input_ids]

# Create a histogram
plt.hist(sentence_lengths, bins=30, color='lightblue', edgecolor='black', alpha=0.7
plt.xlabel('Tokenized Sentence Length')
plt.ylabel('Frequency')
plt.title('Histogram of Tokenized Sentence Lengths')
plt.show()
```



In [13]:

```
cutoff_length = 150

# Count the number of sentences below the cutoff
sentences_below_cutoff = sum(1 for length in sentence_lengths if length < cutoff_le

print(f'Number of sentences below {cutoff_length} tokens: {sentences_below_cutoff}'
```

```
Number of sentences below 150 tokens: 295
```

In [14]:

```
cutoff_length = 150

# Find the sentences above the cutoff
long_sentences = [sentences[i] for i, length in enumerate(sentence_lengths) if leng

# Print the long sentences with a line space between each
for idx, long_sentence in enumerate(long_sentences):
    print(f'Sentence {idx + 1} (Length: {len(long_sentence)}):\n{long_sentence}\n')
```

```
Sentence 1 (Length: 792):
Selfreport data and preliminary analyses  Oneway ANOVAs revealed no significant di
fferences between  groups in their ages (M 18-22 years, SD 1.23 -2.85), F (2, 4
6)  0.12, p F.05; weight (M 63.2 -68.4 kg, SD 9.60 -14.65), F (2, 46)  0.39, p
F.05; height (M 168.30 cm-171.07 cm, SD 9.07 -9.84), F (2,  46) 0.68, p F.05; t
raining hours/day (M 2.66 -2.90 h, SD  0.57 -2.00), F (2, 46) 0.65, p F.05; tra
ining days/week (M  3.10 -3.42, SD 0.71 -1.40), F (2, 46) 0.38, p F.05; year of
experience  (M 5.07 -5.86, SD 2.46 -4.05), F (2, 46) 0.30, p F.05; or MIQR  sco
res (M 15.9 -18.34, SD 2.08 -3.25), F (2, 46) 2.65, p F.05;  indicating no betw
eengroup differences in terms of age, weight, height,  training hours/day, trainin
g days/week, year of experience, and imagery ability.

Sentence 2 (Length: 396):
There was a small albeit significant increase in IL6,  8 and 10 concentrations  pr
e to postmatch in both PLB (IL6: 0.83±0.92 Vs 2.91±1.40, IL8: 2.16±1.22 Vs 3.91±1.
61  and IL10: 2.51±2.14 Vs 0.61±0.50 pg.mL1) and MC groups (IL6: 0.53±0.53 Vs 2.24
±1.73,  IL8: 1.85±0.96 Vs 3.46±1.12 and IL10: 0.48±0.50 Vs 2.54±2.10 pg.mL1), alth
ough there  were no significant differences between groups (P<0.05).

Sentence 3 (Length: 472):
The difference between means  were tested at a significance level of P<0.05.
13  Results   Match characteristics  There were no significant differences in abso
lute distance covered (6334±1924 vs 6596±177  m, P=0.75), relative distance covere
d (72.6±4.8 vs 79.3±5.5 m.min1, P=0.009), total collisions  (28±11 vs 29±13, P=0.8
9), high speed running (4457±1315 vs 4286±1532 m, P=0.78)  and  playing duration
(67:10±19:7 vs 67:10±19:3 min, P=0.99, between the two matches.

Sentence 4 (Length: 403):
Gender and EAMC History Results We did not observe an interaction between EAMC his
tory and gender for [Na+]sw,F(1, 313) = 0.02, p= .88, Na+ swcontent, F(1, 307) =
2.03, p= .16, [K+]sw,F(1, 314) = 0.75, p=. 3 9 ,K+ swcontent, F(1, 308) = 2.73, p
=. 0 9 , [ C l-]sw,F(1, 265) = 0.60, p=. 4 4 , C l- swcontent, F(1, 264) = 1.59, p
= .21, SR BSA,F(1, 346) = 0.44, p=. 5 1 , o r S R , F(1, 346) = 0.83, p= .36.

Sentence 5 (Length: 345):
We did not observe a main effect for “EAMC history ”for [Na+]sw,F(1, 181) = 0.36,
p= .55, Na+ swcontent, F(1, 180) = 0.30, p= .59, [K+]sw,F(1, 182) = 0.33, p= .57,
K+ swcontent, F(1, 180) = 0.46, p= .49, [Cl-]sw,F(1, 182) = 0.01, p= .94, Cl- swco
ntent, F(1, 181) = 0.36, p= .55, SR BSA, F(1, 194) = 0.01, p= .96, or SR, F(1, 19
4) = 0.01, p= .92.
```

In [15]:

```python
# We will use some utility function from tensorflow(Tensorflow was my first crush)
from keras.preprocessing.sequence import pad_sequences


MAX_LEN = 150

#Padding the input to the max length that is 150
input_ids = pad_sequences(input_ids, maxlen=MAX_LEN, dtype="long",
                          value=0, truncating="post", padding="post")
```

In [16]:

```python
# Creating the attention masks
attention_masks = []

# For each sentence...
for sent in input_ids:

    # Create the attention mask.
    #   - If a token ID is 0, then it's padding, set the mask to 0.
    #   - If a token ID is > 0, then it's a real token, set the mask to 1.
    att_mask = [int(token_id > 0) for token_id in sent]
```

```
    # Store the attention mask for this sentence.
    attention_masks.append(att_mask)
```

In [17]:
```
# # We will call the train_test_split() function from sklearn
# from sklearn.model_selection import train_test_split

# train_inputs, validation_inputs, train_labels, validation_labels = train_test_spl
#                                                             random_state=2018, te
# # Performing same steps on the attention masks
# train_masks, validation_masks, _, _ = train_test_split(attention_masks, labels,
#                                              random_state=2018, test_size=0.1)

from sklearn.model_selection import train_test_split

# Split into training and temporary (remaining) data
train_inputs, temp_inputs, train_labels, temp_labels = train_test_split(input_ids,
                                                                        random_stat

# Further split the remaining data into validation and test sets
validation_inputs, test_inputs, validation_labels, test_labels = train_test_split(t
                                                                                  r

# Repeat the same steps for attention masks
train_masks, temp_masks, _, _ = train_test_split(attention_masks, labels,
                                                 random_state=2018, test_size=0.2)
validation_masks, test_masks, _, _ = train_test_split(temp_masks, temp_labels,
                                                       random_state=2018, test_size=
```

In [18]:
```
import numpy as np

# Count the labels in each set
train_label_counts = np.bincount(train_labels)
validation_label_counts = np.bincount(validation_labels)
test_label_counts = np.bincount(test_labels)

# Print the counts
print("Train label counts:", train_label_counts)
print("Validation label counts:", validation_label_counts)
print("Test label counts:", test_label_counts)
```

```
Train label counts: [128 112]
Validation label counts: [10 20]
Test label counts: [12 18]
```

In [19]:
```
#Converting the input data to the tensor , which can be feeded to the model
train_inputs = torch.tensor(train_inputs)
validation_inputs = torch.tensor(validation_inputs)

train_labels = torch.tensor(train_labels, dtype=torch.long)
validation_labels = torch.tensor(validation_labels, dtype=torch.long)

train_masks = torch.tensor(train_masks)
validation_masks = torch.tensor(validation_masks)
```

In [20]:
```
from torch.utils.data import TensorDataset, DataLoader, RandomSampler, SequentialSa

#Creating the DataLoader which will help us to load data into the CPU
batch_size = 32

# Create the DataLoader for our training set.
train_data = TensorDataset(train_inputs, train_masks, train_labels)
train_sampler = RandomSampler(train_data)
train_dataloader = DataLoader(train_data, sampler=train_sampler, batch_size=batch_s
```

```
# Create the DataLoader for our validation set.
validation_data = TensorDataset(validation_inputs, validation_masks, validation_lab
validation_sampler = SequentialSampler(validation_data)
validation_dataloader = DataLoader(validation_data, sampler=validation_sampler, bat
```

In [21]:

```
from transformers import AutoTokenizer, AutoModelForSequenceClassification

from transformers import BertForSequenceClassification, BertTokenizer

# Specify the SciBERT model identifier
scibert_model_identifier = "allenai/scibert_scivocab_uncased"

# Load the SciBERT tokenizer
tokenizer = BertTokenizer.from_pretrained(scibert_model_identifier)

# Load the SciBERT model
model = BertForSequenceClassification.from_pretrained(
    scibert_model_identifier,
    num_labels=2,  # Adjust the number of labels based on your task
    output_attentions=True,
    output_hidden_states=False,
)
```

```
Some weights of BertForSequenceClassification were not initialized from the model
checkpoint at allenai/scibert_scivocab_uncased and are newly initialized: ['classi
fier.bias', 'classifier.weight']
You should probably TRAIN this model on a down-stream task to be able to use it fo
r predictions and inference.
```

In [22]:

```
# AdamW is an optimizer which is a Adam Optimzier with weight-decay-fix
from transformers.optimization import AdamW

optimizer = AdamW(model.parameters(),
                  lr = 3e-5,
                  eps = 1e-8,
                )
```

```
C:\Users\tessa\anaconda3\Lib\site-packages\transformers\optimization.py:411: Futur
eWarning: This implementation of AdamW is deprecated and will be removed in a futu
re version. Use the PyTorch implementation torch.optim.AdamW instead, or set `no_d
eprecation_warning=True` to disable this warning
  warnings.warn(
```

In [23]:

```
from transformers import get_linear_schedule_with_warmup

# Number of training epochs (authors recommend between 2 and 4)
epochs = 5

# Total number of training steps is number of batches * number of epochs.
total_steps = len(train_dataloader) * epochs

# Set the number of warm-up steps to 10% of the total steps
warmup_steps = int(0.1 * total_steps)

# Create the learning rate scheduler.
scheduler = get_linear_schedule_with_warmup(optimizer,
                                            num_warmup_steps = warmup_steps,
                                            num_training_steps = total_steps)
scheduler
```

Out[23]:

```
<torch.optim.lr_scheduler.LambdaLR at 0x16f5a5aa390>
```

In [ ]:

In [24]:
```
import numpy as np

# Function to calculate the accuracy of our predictions vs labels
def flat_accuracy(preds, labels):
    pred_flat = np.argmax(preds, axis=1).flatten()
    labels_flat = labels.flatten()
    return np.sum(pred_flat == labels_flat) / len(labels_flat)
```

In [25]:
```
#Creating the helper function to have a watch on elapsed time

import time
import datetime

def format_time(elapsed):
    '''
    Takes a time in seconds and returns a string hh:mm:ss
    '''
    # Round to the nearest second.
    elapsed_rounded = int(round((elapsed)))

    # Format as hh:mm:ss
    return str(datetime.timedelta(seconds=elapsed_rounded))
```

In [26]:
```
import random
import numpy as np
import torch
from transformers import BertForSequenceClassification, AdamW, BertTokenizer, get_l
from torch.utils.data import DataLoader, RandomSampler, SequentialSampler

# Set the seed value all over the place to make this reproducible.
seed_val = 42

random.seed(seed_val)
np.random.seed(seed_val)
torch.manual_seed(seed_val)
torch.cuda.manual_seed_all(seed_val)

# Store the average loss after each epoch so we can plot them.
loss_values = []

# For each epoch...
for epoch_i in range(0, epochs):

    # ========================================
    #               Training
    # ========================================

    # Perform one full pass over the training set.

    print("")
    print('======== Epoch {:} / {:} ========'.format(epoch_i + 1, epochs))
    print('Training...')

    # Measure how long the training epoch takes.
    t0 = time.time()

    # Reset the total loss for this epoch.
    total_loss = 0

    # Put the model into training mode. Don't be mislead--the call to
```

```
    # `train` just changes the *mode*, it doesn't *perform* the training.
    # `dropout` and `batchnorm` layers behave differently during training
    # vs. test (source: https://stackoverflow.com/questions/51433378/what-does-mode
    model.train()

    # For each batch of training data...
    for step, batch in enumerate(train_dataloader):

        # Progress update every 40 batches.
        if step % 40 == 0 and not step == 0:
            # Calculate elapsed time in minutes.
            elapsed = format_time(time.time() - t0)

            # Report progress.
            print('  Batch {:>5,}  of  {:>5,}.    Elapsed: {:}.'.format(step, len(t

        # Unpack this training batch from our dataloader.
        b_input_ids = batch[0]
        b_input_mask = batch[1]
        b_labels = batch[2]

        # Always clear any previously calculated gradients before performing a
        # backward pass. PyTorch doesn't do this automatically because
        # accumulating the gradients is "convenient while training RNNs".
        # (source: https://stackoverflow.com/questions/48001598/why-do-we-need-to-c
        model.zero_grad()

        # Perform a forward pass (evaluate the model on this training batch).
        outputs = model(b_input_ids,
                        token_type_ids=None,
                        attention_mask=b_input_mask,
                        labels=b_labels)

        # The call to `model` always returns a tuple, so we need to pull the
        # loss value out of the tuple.
        loss = outputs.loss

        # Accumulate the training loss over all of the batches so that we can
        # calculate the average loss at the end.
        total_loss += loss.item()

        # Perform a backward pass to calculate the gradients.
        loss.backward()

        # Clip the norm of the gradients to 1.0.
        # This is to help prevent the "exploding gradients" problem.
        torch.nn.utils.clip_grad_norm_(model.parameters(), 1.0)

        # Update parameters and take a step using the computed gradient.
        # The optimizer dictates the "update rule"--how the parameters are
        # modified based on their gradients, the learning rate, etc.
        optimizer.step()

        # Update the learning rate.
        scheduler.step()

    # Calculate the average loss over the training data.
    avg_train_loss = total_loss / len(train_dataloader)

    # Store the loss value for plotting the learning curve.
    loss_values.append(avg_train_loss)

    print("")
    print("  Average training loss: {0:.2f}".format(avg_train_loss))
```

```
    print("  Training epoch took: {:}".format(format_time(time.time() - t0)))

    # ========================================
    #               Validation
    # ========================================
    # After the completion of each training epoch, measure our performance on
    # our validation set.

    print("")
    print("Running Validation...")

    t0 = time.time()

    # Put the model in evaluation mode--the dropout layers behave differently
    # during evaluation.
    model.eval()

    # Tracking variables
    eval_loss, eval_accuracy = 0, 0
    nb_eval_steps, nb_eval_examples = 0, 0

    # Evaluate data for one epoch
    for batch in validation_dataloader:

        # Add batch to GPU (if available)
        b_input_ids = batch[0]
        b_input_mask = batch[1]
        b_labels = batch[2]

        # Telling the model not to compute or store gradients, saving memory and
        # speeding up validation
        with torch.no_grad():

            # Forward pass, calculate logit predictions.
            outputs = model(b_input_ids,
                            token_type_ids=None,
                            attention_mask=b_input_mask)

        # Get the "logits" output by the model. The "logits" are the output
        # values prior to applying an activation function like the softmax.
        logits = outputs.logits

        # Move


        # Move logits and labels to CPU
        logits = logits.detach().cpu().numpy()
        label_ids = b_labels.to('cpu').numpy()

        # Calculate the accuracy for this batch of test sentences.
        tmp_eval_accuracy = flat_accuracy(logits, label_ids)

        # Accumulate the total accuracy.
        eval_accuracy += tmp_eval_accuracy

        # Track the number of batches
        nb_eval_steps += 1

    # Report the final accuracy for this validation run.
    print("  Accuracy: {0:.2f}".format(eval_accuracy/nb_eval_steps))
    print("  Validation took: {:}".format(format_time(time.time() - t0)))

print("")
print("Training complete!")
```

```
======== Epoch 1 / 5 ========
Training...

  Average training loss: 0.70
  Training epoch took: 0:02:15

Running Validation...
  Accuracy: 0.60
  Validation took: 0:00:06

======== Epoch 2 / 5 ========
Training...

  Average training loss: 0.57
  Training epoch took: 0:02:12

Running Validation...
  Accuracy: 0.67
  Validation took: 0:00:06

======== Epoch 3 / 5 ========
Training...

  Average training loss: 0.41
  Training epoch took: 0:02:12

Running Validation...
  Accuracy: 0.73
  Validation took: 0:00:06

======== Epoch 4 / 5 ========
Training...

  Average training loss: 0.25
  Training epoch took: 0:02:15

Running Validation...
  Accuracy: 0.73
  Validation took: 0:00:06

======== Epoch 5 / 5 ========
Training...

  Average training loss: 0.18
  Training epoch took: 0:02:09

Running Validation...
  Accuracy: 0.87
  Validation took: 0:00:06

Training complete!
```

In [27]:

```
print(loss_values) #Having a view of stored loss values in the list
```

```
[0.7038919553160667, 0.5734166726469994, 0.4106128290295601, 0.24524438008666039,
0.17698074504733086]
```

In [28]:

```
#Loading the test data and applying the same preprocessing techniques which we perf

# Report the number of sentences.
print('Number of test sentences: {:,}\n'.format(df.shape[0]))

# Create sentence and label lists
sentences = df.Sentences.values
```

```
labels = df.Label.values

# Tokenize all of the sentences and map the tokens to thier word IDs.
input_ids = []

# For every sentence...
for sent in sentences:
    # `encode` will:
    #   (1) Tokenize the sentence.
    #   (2) Prepend the `[CLS]` token to the start.
    #   (3) Append the `[SEP]` token to the end.
    #   (4) Map tokens to their IDs.
    encoded_sent = tokenizer.encode(
                        sent,                      # Sentence to encode.
                        add_special_tokens = True, # Add '[CLS]' and '[SEP]'
                   )

    input_ids.append(encoded_sent)

# Pad our input tokens
input_ids = pad_sequences(input_ids, maxlen=MAX_LEN,
                          dtype="long", truncating="post", padding="post")

# Create attention masks
attention_masks = []

# Create a mask of 1s for each token followed by 0s for padding
for seq in input_ids:
    seq_mask = [float(i>0) for i in seq]
    attention_masks.append(seq_mask)

# Convert to tensors.
prediction_inputs = torch.tensor(input_ids)
prediction_masks = torch.tensor(attention_masks)
prediction_labels = torch.tensor(labels)

# Set the batch size.
batch_size = 32

# Create the DataLoader.
prediction_data = TensorDataset(prediction_inputs, prediction_masks, prediction_lab
prediction_sampler = SequentialSampler(prediction_data)
prediction_dataloader = DataLoader(prediction_data, sampler=prediction_sampler, bat
```

```
Number of test sentences: 300
```

In [29]:

```
# Report the number of sentences.
print('Number of test sentences: {:,}\n'.format(test_inputs.shape[0]))

# Convert to tensors.
prediction_inputs = torch.tensor(test_inputs)
prediction_masks = torch.tensor(test_masks)
prediction_labels = torch.tensor(test_labels)

# Set the batch size.
batch_size = 32

# Create the DataLoader.
prediction_data = TensorDataset(prediction_inputs, prediction_masks, prediction_lab
prediction_sampler = SequentialSampler(prediction_data)
prediction_dataloader = DataLoader(prediction_data, sampler=prediction_sampler, bat
```

```
Number of test sentences: 30
```

In [30]:

```python
# Report the number of sentences.
print('Predicting labels for {:,} test sentences...'.format(len(test_inputs)))


# Put model in evaluation mode
model.eval()

# Tracking variables
predictions, true_labels = [], []

# Create the DataLoader.
test_data = TensorDataset(torch.tensor(test_inputs), torch.tensor(test_masks), torc
test_sampler = SequentialSampler(test_data)
test_dataloader = DataLoader(test_data, sampler=test_sampler, batch_size=batch_size

# Predict
for batch in test_dataloader:
    # Unpack the inputs from our dataloader
    b_input_ids, b_input_mask, b_labels = batch

    # Telling the model not to compute or store gradients, saving memory and
    # speeding up prediction
    with torch.no_grad():
        # Forward pass, calculate logit predictions
        outputs = model(b_input_ids, token_type_ids=None, attention_mask=b_input_ma

    logits = outputs.logits.detach().numpy()

    # Move labels to CPU
    label_ids = b_labels.numpy()

    # Store predictions and true labels
    predictions.append(logits)
    true_labels.append(label_ids)
```

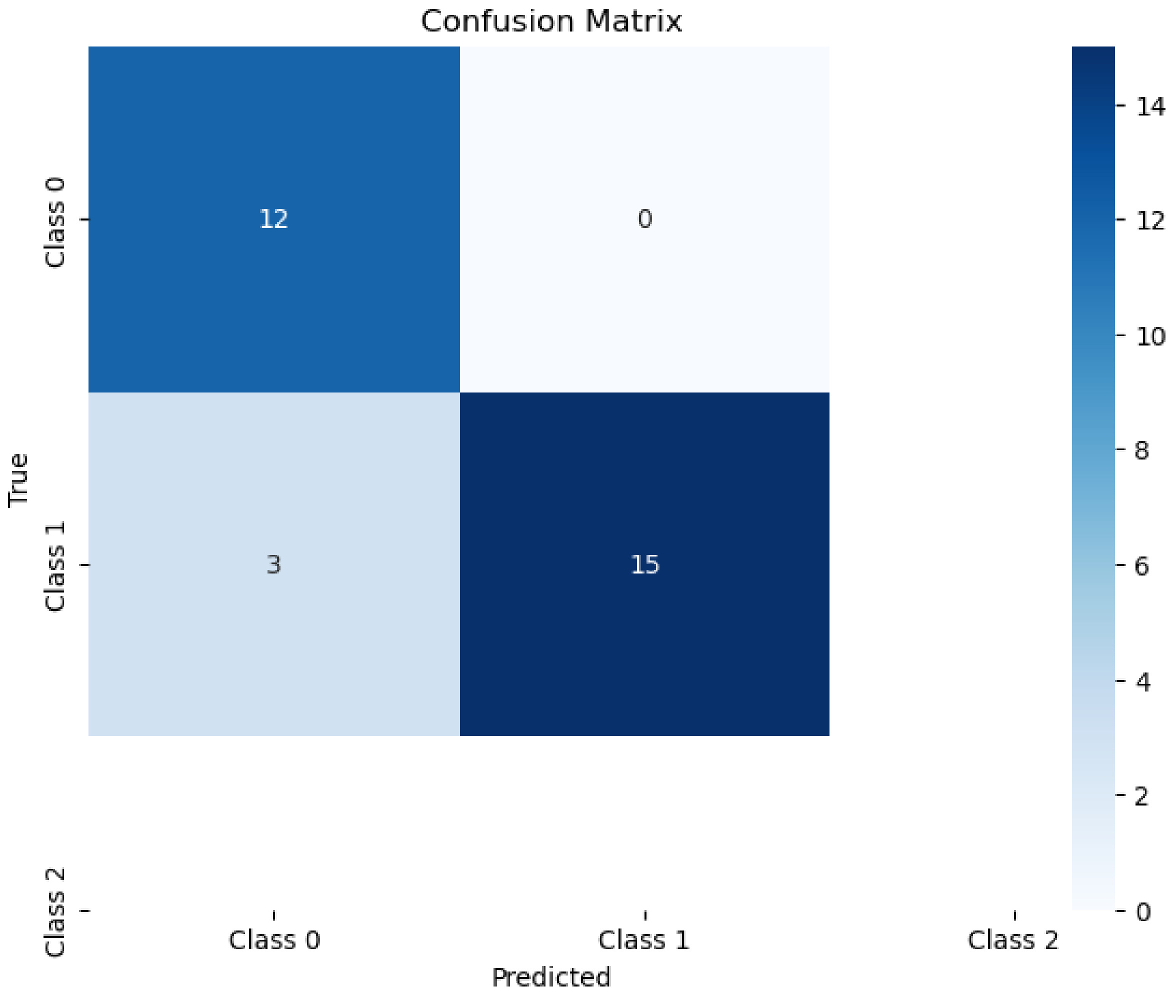
```
Predicting labels for 30 test sentences...
```

In [31]:

```python
# Flatten the nested lists of predictions and true labels
flat_predictions = np.concatenate(predictions, axis=0)
flat_true_labels = np.concatenate(true_labels, axis=0)

# Convert logits to predicted labels
predicted_labels = np.argmax(flat_predictions, axis=1)

# Generate confusion matrix
conf_matrix = confusion_matrix(flat_true_labels, predicted_labels)

# Calculate metrics
accuracy = accuracy_score(flat_true_labels, predicted_labels)
precision = precision_score(flat_true_labels, predicted_labels, average='weighted',
recall = recall_score(flat_true_labels, predicted_labels, average='weighted')
f1 = f1_score(flat_true_labels, predicted_labels, average='weighted')

# Print metrics
print(f'Accuracy: {accuracy:.4f}')
print(f'Precision: {precision:.4f}')
print(f'Recall: {recall:.4f}')
print(f'F1 Score: {f1:.4f}')

# Plot the confusion matrix with seaborn
plt.figure(figsize=(8, 6))
```

```
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Class 0',
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Accuracy: 0.9000
Precision: 0.9200
Recall: 0.9000
F1 Score: 0.9010
```



In [32]:
```
import pandas as pd
import numpy as np

# Flatten the nested lists of predictions and true labels
flat_predictions = np.concatenate(predictions, axis=0)
flat_true_labels = np.concatenate(true_labels, axis=0)

# Convert logits to predicted labels
predicted_labels = np.argmax(flat_predictions, axis=1)

# Ensure that the lengths match
min_length = min(len(flat_true_labels), len(predicted_labels), len(sentences))
flat_true_labels = flat_true_labels[:min_length]
predicted_labels = predicted_labels[:min_length]
sentences = sentences[:min_length]

# Create a DataFrame for misclassified sentences
misclassified_df = pd.DataFrame({
    'True Label': flat_true_labels,
    'Predicted Label': predicted_labels,
    'Sentence': sentences
})
```

```
# Filter the DataFrame to include only misclassified sentences
misclassified_df = misclassified_df[misclassified_df['True Label'] != misclassifiec

# Set pandas options for better display
pd.set_option('display.max_rows', None)
pd.set_option('display.max_colwidth', None)

# Assuming you have the misclassified DataFrame named misclassified_df

# Change labels for better readability
misclassified_df['True Label'] = np.where(misclassified_df['True Label'] == 1, 'Cor
misclassified_df['Predicted Label'] = np.where(misclassified_df['Predicted Label']

# Save the misclassified DataFrame to an Excel file
misclassified_df.to_excel("misclassified_sentences2.xlsx", index=False)

# Now, read the Excel file into a new DataFrame
misclassified_df_from_excel = pd.read_excel("misclassified_sentences2.xlsx")

misclassified_df_from_excel
```

Out[32]:

	True Label	Predicted Label	Sentence
0	Correct	Incorrect	There were no significant differences between the trials for the TTF at 110% V ̇O2max (F 5156.1635.5, S5223.7 642.9, W 5161.1621.4 seconds, p50.18; ES, 20.54; 95% CI, 139.4 –221.2).
1	Correct	Incorrect	Given the working-set MCVs in both conditions did not differ greatly, it is possible the current subjects were not strong enough to exhibit a PAP response during the down sets or a longer rest interval was needed after the working sets to dissipate fatigue before performing the down set.
2	Correct	Incorrect	This hypothesis, however, was not supported when investigating ingame performance.

In [33]:
```
import os
# Specify the directory where you want to save the model
output_dir = './trained_model2/'

# Create the directory if it doesn't exist
if not os.path.exists(output_dir):
    os.makedirs(output_dir)

# Save model to directory
model.save_pretrained(output_dir)

# Save tokenizer to directory
tokenizer.save_pretrained(output_dir)

# Save configuration to directory
model.config.save_pretrained(output_dir)
```

In [34]:
```
from transformers import BertForSequenceClassification, BertTokenizer

# Load the saved model and tokenizer
model = BertForSequenceClassification.from_pretrained(output_dir)
tokenizer = BertTokenizer.from_pretrained(output_dir)
```

In [35]:
```
from transformers import BertTokenizer, BertForSequenceClassification
import torch
```

```
# Load the saved model and tokenizer
output_dir = './trained_model2/'
model = BertForSequenceClassification.from_pretrained(output_dir)
tokenizer = BertTokenizer.from_pretrained(output_dir)

# Input sentences for classification
sentences = [
  "Given the working-set MCVs in both conditions did not differ greatly, it is poss
  "The results for the plankhold followed a similar pattern but were not statistica
  "Rows that share the same subscript letter, do not differ significantly.",
  "Aerobic fitness groups did not differ significantly by  ethnicity, race, sex, es
  "Repeatedmeasures ANOVA results indicated a significant effect between each 5 s i
  "LT assessedby VO 2(Figure 2 (E)) did also not differ significantly between BC su
  "Although we did note a trend toward increased D’ and time to exhaustion in a coh
  "In this respect, recent reviews have suggested that the use of compression garme
  "Similarly, there was a decrease in PLB (2.16±0.34  m.s1) and MC (2.17±0.33 m.s1)
  "Nonetheless, they were significantly higher in DELAY  (+ 3.6 ± 3.5 mU · L1; p = 
  "5.2 ± 0.6 mmol · L1) as compared to PLA (4.2 ± 0.6  and 3.3 ± 0.6 mmol ·  L1) at
  "AUC for glucose was significantly higher in CHO as compared with PLA (p =  0.006
  "AUC for lactate was significantly higher in CHO as compared with PLA (p = 0.029 
  "However, in their study, the preservation of muscular force could  not be attrib
  "There were no differences in T lim between conditions (BR = 22.8 ± 8.1 min;  Pla
  "Dietary NO 3 supplementation had no effect on exercise tolerance or thermoregula
  "There were no differences ( t(10)= 1.4, P = 0.184) in T lim between the BR and P
  "There were no differences between  PLA and BR for H prod (t(10) = 0.103, P = 0.9
]

# Tokenize input sentences
tokenized_input = tokenizer(sentences, padding=True, truncation=True, return_tensor

# Ensure the model is in evaluation mode
model.eval()

# Make predictions
with torch.no_grad():
    # Forward pass
    outputs = model(**tokenized_input)

# Get the predicted probabilities
probs = torch.nn.functional.softmax(outputs.logits, dim=-1)

# Get the predicted class (0 or 1 in binary classification)
predicted_class = torch.argmax(probs, dim=1).tolist()

# Display results
for sentence, label in zip(sentences, predicted_class):
    print(f"Sentence: {sentence}")
    print(f"Predicted Label: {label}")
    print()


#1 is correct 0 is incorrect
```

```
Asking to truncate to max_length but no maximum length is provided and the model h
as no predefined maximum length. Default to no truncation.
```

```
Sentence: Given the working-set MCVs in both conditions did not differ greatly, it
is possible the current subjects were not strong enough to exhibit a PAP response
during the down sets or a longer rest interval was needed after the working sets t
o dissipate fatigue before performing the down set.
Predicted Label: 1

Sentence: The results for the plankhold followed a similar pattern but were not st
atistically significant.
Predicted Label: 0

Sentence: Rows that share the same subscript letter, do not differ significantly.
Predicted Label: 1

Sentence: Aerobic fitness groups did not differ significantly by  ethnicity, race,
sex, estimated IQ, education, pastyear cannabis use,  pastyear alcohol use, recent
nicotine exposure (cotinine level), or amount of sedentary behavior (see Table 1).
Predicted Label: 0

Sentence: Repeatedmeasures ANOVA results indicated a significant effect between ea
ch 5 s interval (p < 0.001), but no differences  were observed between trials ( p
> 0.05).
Predicted Label: 1

Sentence: LT assessedby VO 2(Figure 2 (E)) did also not differ significantly betwe
en BC supplementation and placebo ( p>.
Predicted Label: 0

Sentence: Although we did note a trend toward increased D’ and time to exhaustion
in a cohort of our subjects, but these were weak trends that did not reach statist
ical significance and the effect sizes were small to medium, but variable.
Predicted Label: 1

Sentence: In this respect, recent reviews have suggested that the use of compressi
on garments after running  has little or no effect on muscle damage and inflammato
ry markers (Brown et al., 2017; Engel et  al., 2016).
Predicted Label: 0

Sentence: Similarly, there was a decrease in PLB (2.16±0.34  m.s1) and MC (2.17±0.
33 m.s1) drop jump performance from 24h prematch to 48h postmatch  (PLB: 2.05±0.40
m.s1 and MC: 2.06±0.41 m.s1) although this was not statistically significant  (P=
0.228 and P =0.893, respectively).
Predicted Label: 0

Sentence: Nonetheless, they were significantly higher in DELAY  (+ 3.6 ± 3.5 mU ·
L1; p = 0.003) and CHO (+ 4.7 ± 3.0; mU · L1 p < 0.001) as compared with PLA , whe
reas there was no difference between DELAY and CHO (p > 0.999) at 60min.
Predicted Label: 0

Sentence: 5.2 ± 0.6 mmol · L1) as compared to PLA (4.2 ± 0.6  and 3.3 ± 0.6 mmol ·
L1) at 60min and post TT time points (p < 0.05) with no difference between CHO and
DELAY (p >  0.999) conditions.
Predicted Label: 0

Sentence: AUC for glucose was significantly higher in CHO as compared with PLA (p
=  0.006), whereas there was no difference between CHO and DELAY (p = 0.189) or PL
A and  DELAY (p = 0.228 ).
Predicted Label: 0

Sentence: AUC for lactate was significantly higher in CHO as compared with PLA (p
= 0.029 ) and  DELAY (p = 0.019), whereas there was no difference between PLA and
DELAY (p = 0.974).
Predicted Label: 0

Sentence: However, in their study, the preservation of muscular force could  not b
```

```
e attributed to changes in the central factor because voluntary activation (VA) d
oes not differ  between the maltodextrin and placebo mouth rinse groups.
Predicted Label: 0

Sentence: There were no differences in T lim between conditions (BR = 22.8 ± 8.1 m
in;  Placebo = 20.7 ± 7.9 min) ( P = 0.184), despite increases in plasma
Predicted Label: 0

Sentence: Dietary NO 3 supplementation had no effect on exercise tolerance or ther
moregulation in hot, dry  conditions, despite reductions in resting MAP and increa
ses in plasma
Predicted Label: 0

Sentence: There were no differences ( t(10)= 1.4, P = 0.184) in T lim between the
BR and PLA  conditions, despite seven out of the eleven participants extending the
ir performance  after BR supplementation (BR = 22.8 ± 8 .1min; Placebo = 20.7 ± 7.
9min).
Predicted Label: 0

Sentence: There were no differences between  PLA and BR for H prod (t(10) = 0.103,
P = 0.920), H dry (t(10) = 1.913, P = 0.085), E req (t(10)  = 0.789, P = 0.448), h
eat storage ( t(10) = 0.941, P = 0.369), E max (t(10) = 1.919, P =  0.084) or W (
t(10) = 0.101, P = 0.337)
Predicted Label: 1
```

In [ ]:

In [ ]:

In [ ]: