```
!git clone https://github.com/Franck-Dernoncourt/pubmed-rct
```

```
Cloning into 'pubmed-rct'...
remote: Enumerating objects: 39, done.
remote: Counting objects: 100% (14/14), done.
remote: Compressing objects: 100% (9/9), done.
remote: Total 39 (delta 8), reused 5 (delta 5), pack-reused 25
Receiving objects: 100% (39/39), 177.08 MiB | 35.46 MiB/s, done.
Resolving deltas: 100% (15/15), done.
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import tensorflow as tf
import tensorflow_hub as hub
from tensorflow.keras import layers
from tensorflow.keras.utils import plot_model

from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

```
def file_data(filepath):
  with open(filepath) as f:
    return f.readlines()
```

```
dataset_directory = "pubmed-rct/PubMed_20k_RCT/"
```

```
import os
os.getcwd()
```

```
'/content'
```

```
# reading data from directory and storing in another directory
training_dir = file_data(dataset_directory + 'train.txt')
```

```
training_dir[13].isspace()
```

```
True
```

```
learning_sample = training_dir[:100]
```

```
learning_sample[:20]
```

```
['###24293578\n',
 'OBJECTIVE\tTo investigate the efficacy of 6 weeks of daily low-dose oral prednisolone in improving pain , mobility , and systemic low-grade inflammation in the short term and whether the effect would be sustained at 12 weeks in older adults with moderate to severe knee osteoarthritis ( OA ) .\n',
 'METHODS\tA total of 125 patients with primary knee OA were randomized 1:1 ; 63 received 7.5 mg/day of prednisolone and 62 received placebo for 6 weeks .\n',
 'METHODS\tOutcome measures included pain reduction and improvement in function scores and systemic inflammation markers .\n',
 'METHODS\tPain was assessed using the visual analog pain scale ( 0-100 mm ) .\n',
 'METHODS\tSecondary outcome measures included the Western Ontario and McMaster Universities Osteoarthritis Index scores , patient global assessment ( PGA ) of the severity of knee OA , and 6-min walk distance ( 6MWD ) .\n',
 'METHODS\tSerum levels of interleukin 1 ( IL-1 ) , IL-6 , tumor necrosis factor ( TNF ) - , and high-sensitivity C-reactive protein ( hsCRP ) were measured .\n',
 'RESULTS\tThere was a clinically relevant reduction in the intervention group compared to the placebo group for knee pain , physical function , PGA , and 6MWD at 6 weeks .\n',
 'RESULTS\tThe mean difference between treatment arms ( 95 % CI ) was 10.9 ( 4.8-18 .0 ) , p < 0.001 ; 9.5 ( 3.7-15 .4 ) , p < 0.05 ; 15.7 ( 5.3-26 .1 ) , p < 0.001 ; and 86.9 ( 29.8-144 .1 ) , p < 0.05 , respectively .\n',
 'RESULTS\tFurther , there was a clinically relevant reduction in the serum levels of IL-1 , IL-6 , TNF - , and hsCRP at 6 weeks in the intervention group when compared to the placebo group .\n',
 'RESULTS\tThese differences remained significant at 12 weeks .\n',
 'RESULTS\tThe Outcome Measures in Rheumatology Clinical Trials-Osteoarthritis Research Society International responder rate was 65 % in the intervention group and 34 % in the placebo group ( p < 0.05 ) .\n',
 'CONCLUSIONS\tLow-dose oral prednisolone had both a short-term and a longer sustained effect resulting in less knee pain , better physical function , and attenuation of systemic inflammation in older patients with knee OA ( ClinicalTrials.gov identifier NCT01619163 ) .\n',
 '\n',
 '###24854809\n',
 'BACKGROUND\tEmotional eating is associated with overeating and the development of obesity .\n',
 'BACKGROUND\tYet , empirical evidence for individual ( trait ) differences in emotional eating and cognitive mechanisms that contribute to eating during sad mood remain equivocal .\n',
 'OBJECTIVE\tThe aim of this study was to test if attention bias for food moderates the effect of self-reported emotional eating during sad mood ( vs neutral mood ) on actual food intake .\n',
 'OBJECTIVE\tIt was expected that emotional eating is predictive of elevated attention for food and higher food intake after an experimentally induced sad mood and that attentional maintenance on food predicts food intake during a sad versus a neutral mood .\n',
```

```
 'METHODS\tParticipants ( N = 85 ) were randomly assigned to one of the two experimental mood induction conditions ( sad/neutral )
.\n']
```

```
def get_data(path):
    raw_data = file_data(path)
    article_data = ''
    data_sample = []
    article_id = 0

    for line in raw_data:
        if line.startswith('###'):
            article_id = int(line.replace('###', '').replace('\n', '')) # getting the ID of the blog
            article_data = ''

        elif line.isspace(): # end of one article
            article_data_split = article_data.splitlines()

            for article_line_number, article_line in enumerate(article_data_split):
                line_data = {} # storing in dictionary
                target_text_split = article_line.split("\t") # split target label from text

                line_data["article_id"] = article_id # storing artice ID
                line_data["line_id"] = f'{article_id}_{article_line_number}_{len(article_data_split)}' # create id for each line fror
                line_data["abstract_text"] = target_text_split[1] # storing target text
                line_data["line_number"] = article_line_number # get line number in the article
                line_data["total_lines"] = len(article_data_split) # total number of lines in article
                line_data['current_line'] = f'{article_line_number}_{len(article_data_split)}' # embedding article lenghth with line
                line_data["target"] = target_text_split[0] # storing the label of the target

                data_sample.append(line_data) # appending the sample data

        else: #line into article line if the condition is not satisfied.
            article_data += line

    return data_sample
```

```
train_samples = get_data(dataset_directory + "train.txt")
val_samples = get_data(dataset_directory + "dev.txt")
test_samples = get_data(dataset_directory + "test.txt")
```

```
train_samples
```

```
  'abstract_text': 'The aim of this study was to test if attention bias for food moderates the effect of self-reported
emotional eating during sad mood ( vs neutral mood ) on actual food intake .',
  'line_number': 2,
  'total_lines': 11,
  'current_line': '2_11',
  'target': 'OBJECTIVE'},
 {'article_id': 24854809,
  'line_id': '24854809_3_11',
  'abstract_text': 'It was expected that emotional eating is predictive of elevated attention for food and higher food intake
after an experimentally induced sad mood and that attentional maintenance on food predicts food intake during a sad versus a
neutral mood .',
  'line_number': 3,
  'total_lines': 11,
  'current_line': '3_11',
  'target': 'OBJECTIVE'},
```


```
# length of the samples
print('1. lenth of the train samples after processing: ',len(train_samples))
print('2. lenth of the test samples after processing: ',len(test_samples))
print('3. lenth of the val samples after processing: ',len(val_samples))
```

```
1. lenth of the train samples after processing:  180040
2. lenth of the test samples after processing:  30135
3. lenth of the val samples after processing:  30212
```

```
train_datafram = pd.DataFrame(train_samples)
val_dataframe = pd.DataFrame(val_samples)
test_dataframe = pd.DataFrame(test_samples)
```

```
train_datafram['target'].value_counts().sort_values()
```

```
OBJECTIVE      13839
BACKGROUND     21727
CONCLUSIONS    27168
RESULTS        57953
METHODS        59353
Name: target, dtype: int64
```

```
train_datafram['target'].value_counts().values
```

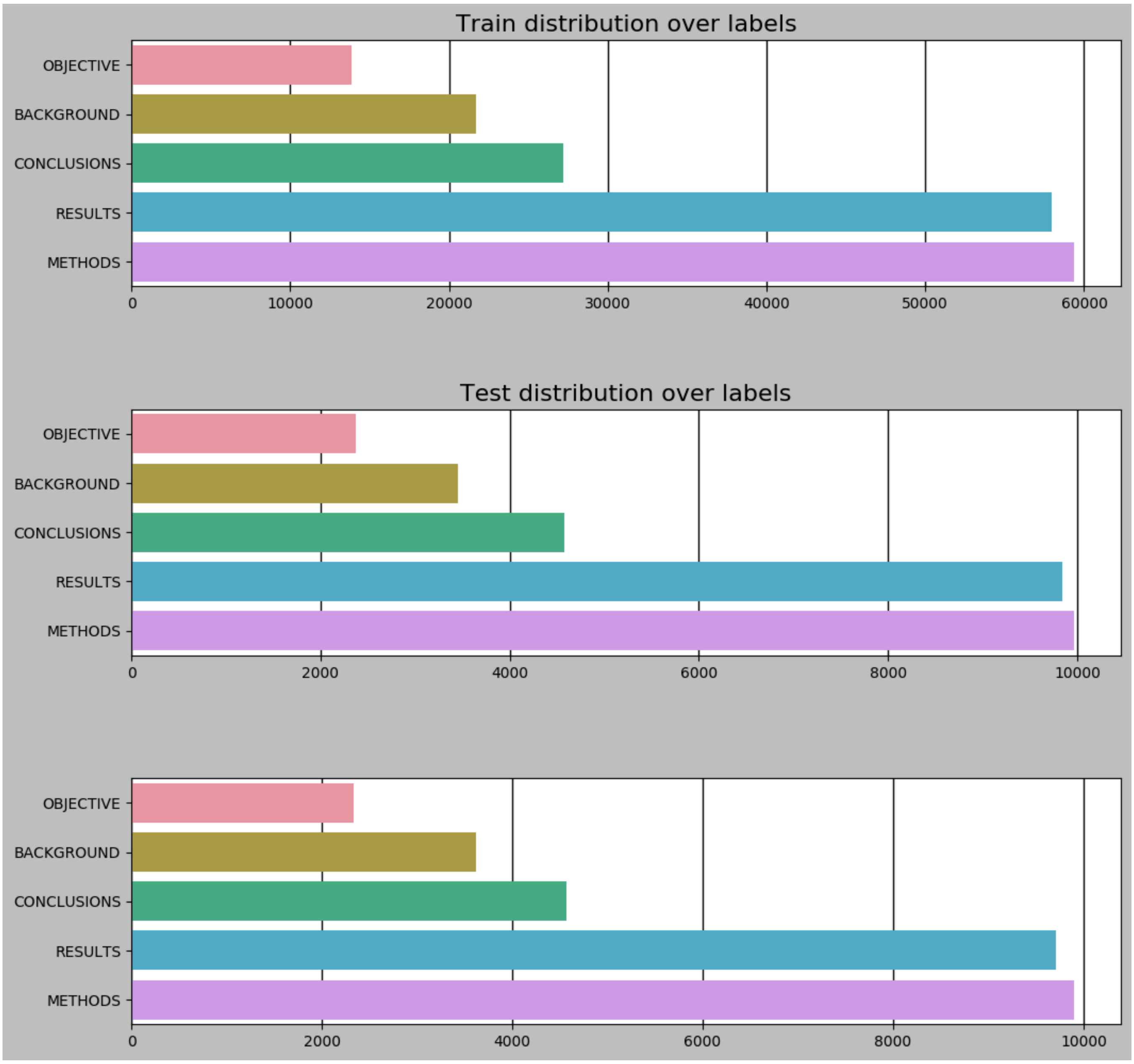
```
array([59353, 57953, 27168, 21727, 13839])
```

```
train_dist = train_datafram['target'].value_counts().sort_values()
val_dist = val_dataframe['target'].value_counts().sort_values()
test_dis = test_dataframe['target'].value_counts().sort_values()
```

```
print(plt.style.available)
```

```
['Solarize_Light2', '_classic_test_patch', '_mpl-gallery', '_mpl-gallery-nogrid', 'bmh', 'classic', 'dark_background', 'fast', 'five
```

```
fig, ax = plt.subplots(3, 1, figsize=(12, 12))
#lt.style.use('grayscale')
sns.barplot(x=train_dist.values, y=list(train_dist.index), ax=ax[0],orient='h')
ax[0].set_title('Train distribution over labels')

sns.barplot(x=val_dist.values, y=list(val_dist.index), ax=ax[1],orient='h')
ax[1].set_title('validation distribution over labels')

sns.barplot(x=test_dis.values, y=list(test_dis.index), ax=ax[2],orient='h')
ax[1].set_title('Test distribution over labels')
plt.subplots_adjust(hspace=0.5)

plt.show()

```




```
ohc = OneHotEncoder(sparse=False)
```

```
train_labels_one_hot_encoded = ohc.fit_transform(train_datafram["target"].to_numpy().reshape(-1, 1))
val_labels_one_hot_encoded = ohc.transform(val_dataframe["target"].to_numpy().reshape(-1, 1))
test_labels_one_hot_encoded = ohc.transform(test_dataframe["target"].to_numpy().reshape(-1, 1))
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868: FutureWarning: `sparse` was renamed to `sparse_outpu
  warnings.warn(
```

```
LE = LabelEncoder()
```

```
train_lables_encoded = LE.fit_transform(train_datafram["target"].to_numpy())
```

```
val_lables_encoded = LE.transform(val_dataframe["target"].to_numpy())
test_lables_encoded = LE.transform(test_dataframe["target"].to_numpy())
```

```
train_lables_encoded
```

```
array([3, 2, 2, ..., 4, 1, 1])
```

```
# number of classes
print('Number of classes: ',len(LE.classes_))
print('All the Classes :', LE.classes_)
```

```
Number of classes:  5
All the Classes : ['BACKGROUND' 'CONCLUSIONS' 'METHODS' 'OBJECTIVE' 'RESULTS']
```

```
ohc_for_lines = OneHotEncoder(sparse=False)
```

```
train_lines_encoded = ohc_for_lines.fit_transform(train_datafram["current_line"].to_numpy().reshape(-1, 1)).astype(np.float32)
val_lines_encoded = ohc_for_lines.transform(val_dataframe["current_line"].to_numpy().reshape(-1, 1)).astype(np.float32)
test_lines_encoded = ohc_for_lines.transform(test_dataframe["current_line"].to_numpy().reshape(-1, 1)).astype(np.float32)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868: FutureWarning: `sparse` was renamed to `sparse_outpu
  warnings.warn(
```

```
def apply_smoothing(line_one_hot, esp=0.01):
    return np.abs(line_one_hot - esp)

def revert_smoothing(line_one_hot_smooth, esp=0.01):
    unsmooth = line_one_hot_smooth

    unsmooth[unsmooth>esp] = 1.0
    unsmooth[unsmooth<=esp] = 0.0

    return unsmooth
```

```
# applying smoothing on train lines
train_lines_encoded = apply_smoothing(train_lines_encoded)
```

```
def create_pipeline(features, labels, batch_size=32, shuffle=False, cache=False, prefetch=False) -> tf.data.Dataset:

    AUTOTUNE = tf.data.AUTOTUNE
    ds = tf.data.Dataset.from_tensor_slices((features, labels))

    # shuffling on the basis of condition
    if shuffle:
        ds = ds.shuffle(buffer_size=1000)
        #batches
    ds = ds.batch(batch_size)

    # Apply caching based on condition
    if cache:
        ds = ds.cache(buffer_size=AUTOTUNE)
    if prefetch:
        ds = ds.prefetch(buffer_size=AUTOTUNE)
    return ds
```

```
train_sentence_list = train_datafram["abstract_text"].tolist()
val_sentence_list = val_dataframe["abstract_text"].tolist()
test_sentence_list = test_dataframe["abstract_text"].tolist()
```

```
BATCH_SIZE = 32

# Create preprocessed training dataset
train_features = (train_sentence_list, train_lines_encoded.astype(np.float32))
train_labels = train_labels_one_hot_encoded.astype(np.float32)

# creating pipeline
train_ds = create_pipeline(
    train_features, train_labels,
    batch_size=BATCH_SIZE, shuffle=True,
    cache=False, prefetch=True)
```

```
# applying the same to val_data
val_features = (val_sentence_list, val_lines_encoded.astype(np.float32))
val_labels = val_labels_one_hot_encoded.astype(np.float32)

val_ds = create_pipeline(val_features, val_labels,
                         batch_size=BATCH_SIZE, shuffle=False,
                         cache=False, prefetch=True)
```

```
# applying to test data
test_features = (test_sentence_list, test_lines_encoded.astype(np.float32))
test_labels = test_labels_one_hot_encoded.astype(np.float32)

test_ds = create_pipeline(test_features, test_labels,
                          batch_size=BATCH_SIZE, shuffle=False,
                          cache=False, prefetch=True)
```

```
# eetting model/processor from hub
def get_tfhub_model(model_link, model_name, model_trainable=False):
    return hub.KerasLayer(model_link,
                          trainable=model_trainable,
                          name=model_name)
```

```
encoder_link = 'https://tfhub.dev/google/universal-sentence-encoder/4'
encoder_name = 'universal_sentence_encoder'
encoder_trainable=False # set trainable to False for inference-only

encoder = get_tfhub_model(encoder_link, encoder_name, model_trainable=encoder_trainable)
```

```
class SelfAttentionBlock(layers.Layer):

    def __init__(self, units: int, activation='gelu', kernel_initializer='GlorotNormal', **kwargs):
        super(SelfAttentionBlock, self).__init__(**kwargs)
        self.units = units
        self.activation = activation
        self.kernel_initializer = tf.keras.initializers.deserialize(kernel_initializer)

        self.query = layers.LSTM(self.units, activation=self.activation,
                                 kernel_initializer=self.kernel_initializer,
                                 return_sequences=True, name=f'block_query_lstm')

        self.value = layers.LSTM(self.units, activation=self.activation,
                                 kernel_initializer=self.kernel_initializer, go_backwards=True,
                                 return_sequences=True, name=f'block_value_lstm')

        self.attention = layers.AdditiveAttention(name='block_attention')
        self.average_pooler = layers.GlobalAveragePooling1D(name='block_average_pooler')
        self.query_batch_norm = layers.BatchNormalization(name='block_query_batch_norm')
        self.attention_batch_norm = layers.BatchNormalization(name='block_attention_batch_norm')
        self.residual = layers.Add(name='block_residual')


    def __call__(self, x):
        dim_expand_layer = layers.Lambda(lambda embedding: tf.expand_dims(embedding, axis=1), name='block_dim_expand')
        x_expanded = dim_expand_layer(x)

        #LSTM sequences
        block_query = self.query(x_expanded)
        block_value = self.value(x_expanded)

        #self-attention to LSTM
        block_attention = self.attention([block_query, block_value])

        # Apply GlobalAvgPooling and BatchNorm to ensure output shape is 1D
        block_query_pooling = self.average_pooler(block_query)
        block_query_batch_norm = self.query_batch_norm(block_query_pooling)

        block_attention_pooling = self.average_pooler(block_attention)
        block_attention_batch_norm = self.attention_batch_norm(block_attention_pooling)

        # Generate addition residual with processed query and attention
        block_residual = self.residual([block_query_batch_norm, block_attention_batch_norm])

        return block_residual
```

```
def build_model():
  abstract_input = layers.Input(shape=[], dtype=tf.string, name='abstract_text_input')
  abstract_current_line = layers.Input(shape=(460), dtype=tf.float32, name='abstract_current_line')

  initializer = tf.keras.initializers.GlorotNormal()

  abstract_embedding = encoder(abstract_input)
  add_attention_block = SelfAttentionBlock(64)(abstract_embedding)
  abstract_dense = layers.Dense(64, activation='gelu', kernel_initializer=initializer)(abstract_embedding)
  attention_residual = layers.Multiply(name='mul_residual')([add_attention_block, abstract_dense])
  current_line_dense = layers.Dense(32, activation='gelu', kernel_initializer=initializer)(abstract_current_line)
  current_line_dense = layers.Dropout(0.2)(current_line_dense)


  streams_concat = layers.Concatenate()([
      attention_residual,
      current_line_dense
  ])

  output_layer = layers.Dense(64, activation='gelu', kernel_initializer=initializer)(streams_concat)
  output_layer = layers.Dense(5, activation='softmax', kernel_initializer=initializer)(output_layer)

  return tf.keras.Model(inputs=[abstract_input,
                                abstract_current_line],
                        outputs=[output_layer], name="use_attention_model")
```

```
model = build_model()
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/initializers/initializers.py:120: UserWarning: The initializer GlorotNormal is uns
  warnings.warn(
```

```
model.summary()
```

```
Model: "use_attention_model"
__________________________________________________________________________________________________
 Layer (type)                Output Shape                 Param #   Connected to
==================================================================================================
 abstract_text_input (Input  [(None,)]                    0         []
 Layer)

 universal_sentence_encoder  (None, 512)                  2567978   ['abstract_text_input[0][0]']
  (KerasLayer)                                            24

 block_dim_expand (Lambda)   (None, 1, 512)               0         ['universal_sentence_encoder[0
                                                                    ][0]']

 block_query_lstm (LSTM)     (None, 1, 64)                147712    ['block_dim_expand[0][0]']

 block_value_lstm (LSTM)     (None, 1, 64)                147712    ['block_dim_expand[0][0]']

 block_attention (AdditiveA  (None, 1, 64)                64        ['block_query_lstm[0][0]',
 ttention)                                                           'block_value_lstm[0][0]']

 block_average_pooler (Glob  (None, 64)                   0         ['block_query_lstm[0][0]',
 alAveragePooling1D)                                                 'block_attention[0][0]']

 block_query_batch_norm (Ba  (None, 64)                   256       ['block_average_pooler[0][0]']
 tchNormalization)

 block_attention_batch_norm  (None, 64)                   256       ['block_average_pooler[1][0]']
  (BatchNormalization)

 abstract_current_line (Inp  [(None, 460)]                0         []
 utLayer)

 block_residual (Add)        (None, 64)                   0         ['block_query_batch_norm[0][0]
                                                                    ',
                                                                     'block_attention_batch_norm[0
                                                                    ][0]']

 dense (Dense)               (None, 64)                   32832     ['universal_sentence_encoder[0
                                                                    ][0]']

 dense_1 (Dense)             (None, 32)                   14752     ['abstract_current_line[0][0]'
                                                                    ]

 mul_residual (Multiply)     (None, 64)                   0         ['block_residual[0][0]',
                                                                     'dense[0][0]']

 dropout (Dropout)           (None, 32)                   0         ['dense_1[0][0]']

 concatenate (Concatenate)   (None, 96)                   0         ['mul_residual[0][0]',
                                                                     'dropout[0][0]']
```

```
 dense_2 (Dense)             (None, 64)                6208      ['concatenate[0][0]']

 dense_3 (Dense)             (None, 5)                 325       ['dense_2[0][0]']

==================================================================================================
Total params: 257147941 (980.94 MB)
Trainable params: 349861 (1.33 MB)
```

```python
def train_model(model, num_epochs, callbacks_list, tf_train_data,
                tf_valid_data=None, shuffling=False):

    model_history = {}

    if tf_valid_data != None:
        model_history = model.fit(tf_train_data,
                                  epochs=num_epochs,
                                  validation_data=tf_valid_data,
                                  validation_steps=int(len(tf_valid_data)),
                                  callbacks=callbacks_list,
                                  shuffle=shuffling)

    if tf_valid_data == None:
        model_history = model.fit(tf_train_data,
                                  epochs=num_epochs,
                                  callbacks=callbacks_list,
                                  shuffle=shuffling)
    return model_history
```

```python
early_stopping_callback = tf.keras.callbacks.EarlyStopping(
    monitor='val_loss',
    patience=4,
    restore_best_weights=True)

reduce_lr_callback = tf.keras.callbacks.ReduceLROnPlateau(
    monitor='val_loss',
    patience=2,
    factor=0.1,
    verbose=1)

EPOCHS = 10
CALLBACKS = [early_stopping_callback, reduce_lr_callback]
```

```python
train_sentences_count = len(train_sentence_list)
val_sentences_count = len(val_sentence_list)
test_sentences_count = len(test_sentence_list)
total_sentences_count = train_sentences_count + val_sentences_count + test_sentences_count
```

```python
tf.random.set_seed(42)

model.compile(
    loss=tf.keras.losses.CategoricalCrossentropy(label_smoothing=0.1),
    optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
    metrics=['accuracy']
)

print(f'Training {model.name}.')
print(f'Train on {train_sentences_count} samples, validate on {val_sentences_count} samples.')
print('----------------------------------')

model_history = train_model(
    model, EPOCHS, CALLBACKS,
    train_ds, val_ds,
    shuffling=False
)
```

```
Training use_attention_model.
Train on 180040 samples, validate on 30212 samples.
----------------------------------
Epoch 1/10
5627/5627 [==============================] - 145s 24ms/step - loss: 0.6963 - accuracy: 0.8476 - val_loss: 0.6421 - val_accuracy: 0.8
Epoch 2/10
5627/5627 [==============================] - 129s 23ms/step - loss: 0.6315 - accuracy: 0.8794 - val_loss: 0.6390 - val_accuracy: 0.8
Epoch 3/10
5627/5627 [==============================] - 142s 25ms/step - loss: 0.6140 - accuracy: 0.8878 - val_loss: 0.6339 - val_accuracy: 0.8
Epoch 4/10
5627/5627 [==============================] - 131s 23ms/step - loss: 0.6014 - accuracy: 0.8938 - val_loss: 0.6358 - val_accuracy: 0.8
Epoch 5/10
5626/5627 [============================>.] - ETA: 0s - loss: 0.5909 - accuracy: 0.8999
Epoch 5: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
5627/5627 [==============================] - 139s 25ms/step - loss: 0.5909 - accuracy: 0.8999 - val_loss: 0.6388 - val_accuracy: 0.8
Epoch 6/10
5627/5627 [==============================] - 139s 25ms/step - loss: 0.5686 - accuracy: 0.9124 - val_loss: 0.6413 - val_accuracy: 0.8
Epoch 7/10
```

```
5626/5627 [============================>.] - ETA: 0s - loss: 0.5635 - accuracy: 0.9155
Epoch 7: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
5627/5627 [==============================] - 142s 25ms/step - loss: 0.5635 - accuracy: 0.9155 - val_loss: 0.6424 - val_accuracy: 0.8
```

```
model.evaluate(test_ds)
```

```
942/942 [==============================] - 16s 16ms/step - loss: 0.6438 - accuracy: 0.8715
[0.6438229084014893, 0.8715115189552307]
```

```
val_prob = model.predict(val_ds, verbose=1)
val_predictions = tf.argmax(val_prob, axis=1)
```

```
945/945 [==============================] - 14s 14ms/step
```

```
test_prob = model.predict(test_ds, verbose=1)
test_predict = tf.argmax(test_prob, axis=1)
```

```
942/942 [==============================] - 18s 19ms/step
```

```
print(val_predictions)
print(test_predict)
```

```
tf.Tensor([0 0 3 ... 4 1 1], shape=(30212,), dtype=int64)
tf.Tensor([0 2 2 ... 4 4 1], shape=(30135,), dtype=int64)
```

```
LE.classes_
```

```
array(['BACKGROUND', 'CONCLUSIONS', 'METHODS', 'OBJECTIVE', 'RESULTS'],
      dtype=object)
```

```
class_labels = LE.classes_
```

```
# Generate validation classification report
print(classification_report(val_lables_encoded, val_predictions, target_names=class_labels))
```

```
              precision    recall  f1-score   support

  BACKGROUND       0.71      0.82      0.76      3449
 CONCLUSIONS       0.89      0.93      0.91      4582
     METHODS       0.92      0.91      0.92      9964
   OBJECTIVE       0.71      0.58      0.64      2376
     RESULTS       0.92      0.90      0.91      9841

    accuracy                           0.87     30212
   macro avg       0.83      0.83      0.83     30212
weighted avg       0.88      0.87      0.87     30212
```

```
# Generate test classification report
print(classification_report(test_lables_encoded, test_predict, target_names=class_labels))
```

```
              precision    recall  f1-score   support

  BACKGROUND       0.72      0.81      0.76      3621
 CONCLUSIONS       0.89      0.93      0.91      4571
     METHODS       0.91      0.92      0.92      9897
   OBJECTIVE       0.69      0.59      0.63      2333
     RESULTS       0.92      0.89      0.90      9713

    accuracy                           0.87     30135
   macro avg       0.83      0.83      0.83     30135
weighted avg       0.87      0.87      0.87     30135
```

```
from sklearn.metrics import accuracy_score,top_k_accuracy_score, precision_recall_fscore_support,matthews_corrcoef
def performance_metrics(y_actual, y_predicted, y_probabilities):

    model_accuracy = round(accuracy_score(y_actual, y_predicted), 5)
    top_3_accuracy = round(top_k_accuracy_score(y_actual, y_probabilities, k=3), 5)
    model_precision, model_recall, model_f1, _ = precision_recall_fscore_support(test_lables_encoded,
                                                                                  test_predict,
                                                                                  average="weighted")
    model_precision, model_recall, model_f1 = round(model_precision, 5), round(model_recall, 5), round(model_f1, 5)
    model_matthews_corrcoef = round(matthews_corrcoef(y_actual, y_predicted), 5)

    print(f'\nPerformance Metrics:\n')
    print('----------------**-------------------')
    print(f'accuracy_score:\t\t{model_accuracy}\n')
    print('*********************************')
    print(f'top_3_accuracy_score:\t{top_3_accuracy}\n')
    print('*********************************')
    print(f'precision_score:\t{model_precision}\n')
    print('*********************************')
    print(f'recall_score:\t\t{model_recall}\n')
    print('*********************************')
    print(f'f1_score:\t\t{model_f1}\n')
    print('*********************************')
    print(f'matthews_corrcoef:\t{model_matthews_corrcoef}\n')

    return
```

```
performance_metrics(val_lables_encoded,val_predictions,val_prob)
```

```
Performance Metrics:

----------------**-------------------
accuracy_score:         0.87452

*********************************
top_3_accuracy_score:   0.99533

*********************************
precision_score:        0.87183

*********************************
recall_score:           0.87151

*********************************
f1_score:               0.87094

*********************************
matthews_corrcoef:      0.83177
```

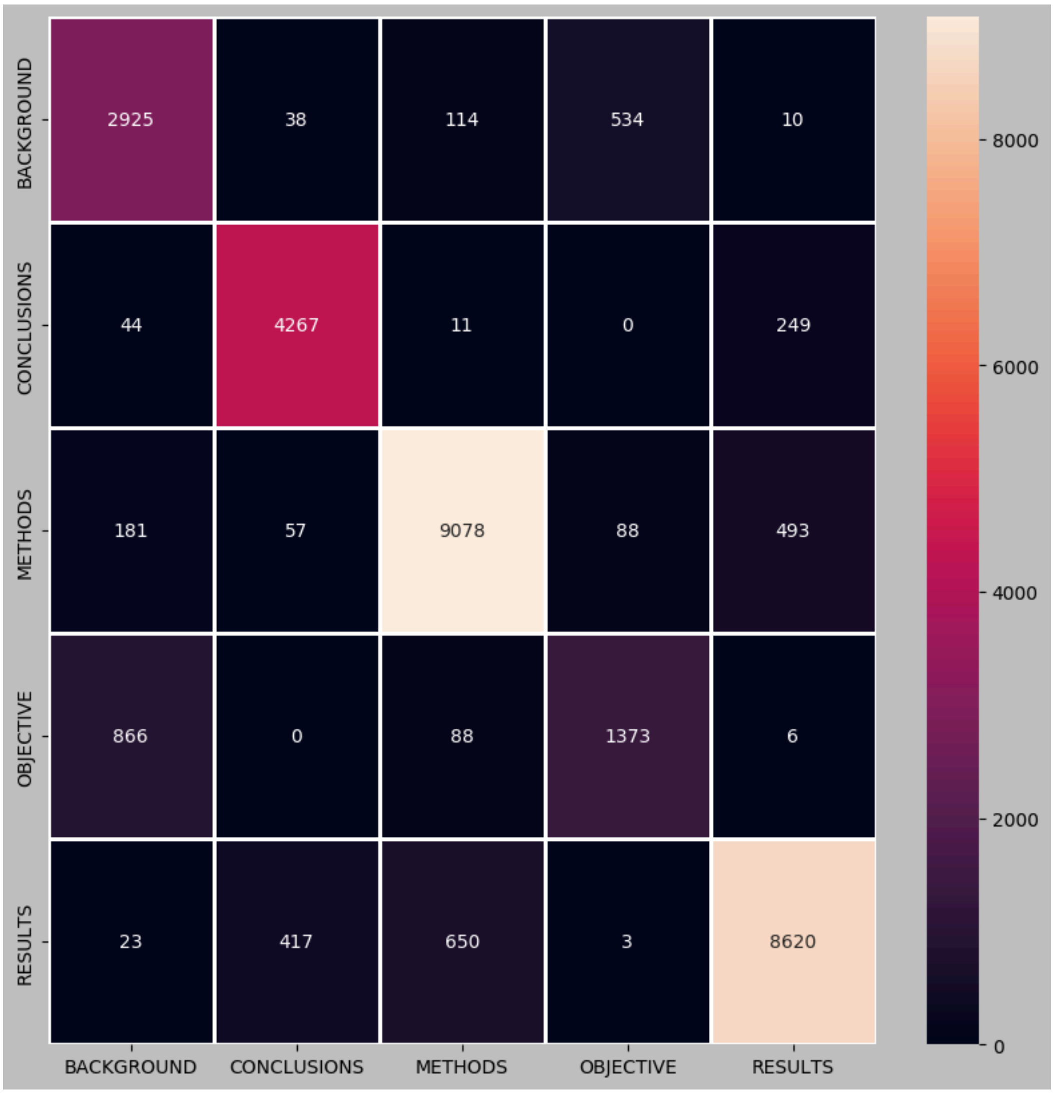
```
performance_metrics(test_lables_encoded,test_predict,test_prob)
```

```
Performance Metrics:

----------------**-------------------
accuracy_score:         0.87151

*********************************
top_3_accuracy_score:   0.99363

*********************************
precision_score:        0.87183

*********************************
recall_score:           0.87151

*********************************
f1_score:               0.87094

*********************************
matthews_corrcoef:      0.82805
```

```
cm = confusion_matrix(test_lables_encoded,test_predict)
```

```
plt.figure(figsize=(10,10))
sns.heatmap(cm,annot=True,linewidths=1,xticklabels=class_labels,yticklabels=class_labels,fmt='d')
```

```
<Axes: >
```




```
# importing required libraries
import numpy as np
import pandas as pd
import os
import librosa
import librosa.display
import IPython as ipd
import glob

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation, Flatten
from tensorflow.keras.layers import Convolution2D, Conv2D, MaxPooling2D, GlobalAveragePooling2D
from tensorflow.keras.optimizers import Adam
from sklearn import metrics
from tensorflow.keras.layers import Conv2D, Flatten, Dense, MaxPool2D, Dropout
```

```
# directory path of mounted gdrive
bas_dir_path = r'/content/drive/MyDrive/edge-collected-gunshot-audio.zip'
```

```
#creating directory for the extracted data
os.makedirs(os.path.join(os.getcwd(),'extracted_data'))
```

```
# unzipping all the files into to extracted_data created directory
import zipfile
with zipfile.ZipFile(bas_dir_path,'r') as zip_ref:
  zip_ref.extractall(os.path.join(bas_dir_path,'/content/extracted_data'))
```

```
!pip install split-folders
```

```
Collecting split-folders
  Downloading split_folders-0.5.1-py3-none-any.whl (8.4 kB)
Installing collected packages: split-folders
Successfully installed split-folders-0.5.1
```

```
os.makedirs(os.path.join(os.getcwd(),'my_split_data')) # directory for storing the splitted data
```

```
# splitting the data into 80:20 ratio
import splitfolders
splitfolders.ratio('/content/extracted_data/edge-collected-gunshot-audio','/content/my_split_data',seed=42,ratio=(0.8,0.2))
```

```
Copying files: 2148 files [00:11, 180.55 files/s]
```

```
train_dir_path = r'/content/my_split_data/train' # newly created train directory which contains 80% of the files
val_dir_path = r'/content/my_split_data/val' # newly created validation directory which contains 20% of tha files
```

```
# creating function for extracting features of the given .wav files
def extract_features(filename):
  audio, sr = librosa.load(filename,sr = None,res_type='kaiser_fast')
  mfccs = librosa.feature.mfcc(y=audio,sr=sr,n_mfcc=40)
  mfcc_scaled = np.mean(mfccs.T,axis=0)
  return mfcc_scaled
```

```
# checking for sample_rate
ex_data, sampling_rate = librosa.load('/content/extracted_data/edge-collected-gunshot-audio/38s&ws_dot38_caliber/03fc4685-909e-42c5-
print(sampling_rate)
```

```
44100
```

```
!pip install resampy # internally res_type='kaiser_fast' calling resampy
```

```
Collecting resampy
  Downloading resampy-0.4.2-py3-none-any.whl (3.1 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 3.1/3.1 MB 28.1 MB/s eta 0:00:00
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-packages (from resampy) (1.23.5)
Requirement already satisfied: numba>=0.53 in /usr/local/lib/python3.10/dist-packages (from resampy) (0.58.1)
Requirement already satisfied: llvmlite<0.42,>=0.41.0dev0 in /usr/local/lib/python3.10/dist-packages (from numba>=0.53->resampy) (0
Installing collected packages: resampy
Successfully installed resampy-0.4.2
```

```
features=[] # collecting the features and labels for the .wav files
firearm = ''
for folder in os.listdir('/content/my_split_data/train'):
  gen = glob.iglob('**/*.wav',root_dir=os.path.join('/content/my_split_data/train',folder),recursive=True) # using iglob generator fo
  for files in gen:
    path = os.path.join(os.path.join('/content/my_split_data/train',folder),files) # path to provide for extract_features fucntion.
    data = extract_features(path) # calling extract_features functions for loading features
    firearm = folder # assigning the name of the firearm as label
    features.append([data,firearm]) # appending the extracted features and labels
```

```
#df = pd.DataFrame()
df = pd.DataFrame(features,columns=['feature','class']) # converting into dataframe for the extracted features and labels
df.head()
```

	feature	class
0	[-479.21558, 115.43387, 4.464393, -2.232155, 0...	remington_870_12_gauge
1	[-622.7922, 160.48073, -31.198713, -13.155003,...	remington_870_12_gauge
2	[-685.34485, 205.09016, -12.939822, -16.207764...	remington_870_12_gauge
3	[-244.56116, 180.25233, -31.406918, 10.96077, ...	remington_870_12_gauge
4	[-683.1073, 138.53195, 10.358094, -3.0826027, ...	remington_870_12_gauge

```
X_copy = df['feature'].copy()  # copying the data from the above dataframe for nor editing the original data.
y_copy = df['class'].copy() # copying the labels correpondingly.
```

```
X = np.array(X_copy.to_list()) # into list
y = np.array(y_copy.to_list())
```

```
X = np.array(X_copy.to_list()) # converting into array
y = np.array(y_copy.to_list())
from sklearn.preprocessing import LabelEncoder
from keras.utils import to_categorical
LE = LabelEncoder()
yy = to_categorical(LE.fit_transform(y)) # fitting and transforming on training data of labels and converting into to_categorical
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,yy, test_size=0.2, random_state=42) # splitting into train and test
```

```
#validation data
val_features=[] # applying fucntion on validation data and storing in list.
val_labels = ''
for folder in os.listdir('/content/my_split_data/val'):
  gen = glob.iglob('**/*.wav',root_dir=os.path.join('/content/my_split_data/val',folder),recursive=True)
  for files in gen:
    path = os.path.join(os.path.join('/content/my_split_data/val',folder),files)
    value = extract_features(path)
    val_labels = folder
    val_features.append([value,val_labels])
```

```
# total number of files in validation data
len(os.listdir('/content/my_split_data/val/38s&ws_dot38_caliber')) + len(os.listdir('/content/my_split_data/val/glock_17_9mm_caliber
```

```
431
```

```
val_df = pd.DataFrame(val_features,columns=['val_features','val_labels']) # into DataFrame
```

```
val_df.shape # verifying the shape of the data
```

```
(431, 2)
```

```
x_val_copy = val_df['val_features'].copy() # creating copies of original data
y_val_copy = val_df['val_labels'].copy()
x_val_array = np.array(x_val_copy.to_list()) # into list
y_val_array = np.array(y_val_copy.to_list())
```

```
y_val_array_encoded = to_categorical(LE.fit_transform(y_val_array)) # transforming with the help of 'LE' and convering into to_catego
```

```
num_rows = 4
num_columns = 10
num_channels = 1
num_labels = yy.shape[1]
filter_size = 2
x_train = X_train.reshape(X_train.shape[0], num_rows, num_columns, num_channels) # reshaping the training and validation data for fee
x_val = x_val_array.reshape(x_val_array.shape[0], num_rows, num_columns, num_channels)
```

```
# Construct model
model = Sequential()
model.add(Conv2D(filters=16, kernel_size=2, padding="same", input_shape=(num_rows, num_columns, num_channels), activation='relu'))
model.add(MaxPooling2D(pool_size=1))
model.add(Dropout(0.2))

model.add(Conv2D(filters=32, kernel_size=2, padding="same", activation='relu'))
model.add(MaxPooling2D(pool_size=1))
model.add(Dropout(0.2))

model.add(Conv2D(filters=64, kernel_size=2, padding="same", activation='relu'))
model.add(MaxPooling2D(pool_size=1))
model.add(Dropout(0.2))

model.add(Conv2D(filters=128, kernel_size=2, padding="same", activation='relu'))
model.add(MaxPooling2D(pool_size=1))
model.add(Dropout(0.2))
model.add(GlobalAveragePooling2D())

model.add(Dense(num_labels, activation='softmax'))
```

```
# Compile the model
model.compile(loss='binary_crossentropy', metrics=['accuracy'], optimizer='adam')

# Display model architecture summary
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_4 (Conv2D)           (None, 4, 10, 16)         80

 max_pooling2d_4 (MaxPoolin  (None, 4, 10, 16)         0
 g2D)

 dropout_4 (Dropout)         (None, 4, 10, 16)         0

 conv2d_5 (Conv2D)           (None, 4, 10, 32)         2080
```

```
 max_pooling2d_5 (MaxPoolin  (None, 4, 10, 32)         0
 g2D)

 dropout_5 (Dropout)         (None, 4, 10, 32)         0

 conv2d_6 (Conv2D)           (None, 4, 10, 64)         8256

 max_pooling2d_6 (MaxPoolin  (None, 4, 10, 64)         0
 g2D)

 dropout_6 (Dropout)         (None, 4, 10, 64)         0

 conv2d_7 (Conv2D)           (None, 4, 10, 128)        32896

 max_pooling2d_7 (MaxPoolin  (None, 4, 10, 128)        0
 g2D)

 dropout_7 (Dropout)         (None, 4, 10, 128)        0

 global_average_pooling2d_1  (None, 128)               0
  (GlobalAveragePooling2D)

 dense_1 (Dense)             (None, 4)                 516

=================================================================
Total params: 43828 (171.20 KB)
Trainable params: 43828 (171.20 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
num_epochs = 50
num_batch_size = 50
# fitting the model
model.fit(x_train, y_train, batch_size=num_batch_size, epochs=num_epochs, validation_data=(x_val, y_val_array_encoded), verbose=1)
```

```
Epoch 1/50
28/28 [==============================] - 4s 68ms/step - loss: 0.5877 - accuracy: 0.2935 - val_loss: 0.5705 - val_accuracy: 0.310
Epoch 2/50
28/28 [==============================] - 2s 54ms/step - loss: 0.5601 - accuracy: 0.3081 - val_loss: 0.5588 - val_accuracy: 0.324
Epoch 3/50
28/28 [==============================] - 1s 35ms/step - loss: 0.5561 - accuracy: 0.3248 - val_loss: 0.5538 - val_accuracy: 0.368
Epoch 4/50
28/28 [==============================] - 1s 34ms/step - loss: 0.5531 - accuracy: 0.3372 - val_loss: 0.5491 - val_accuracy: 0.350
Epoch 5/50
28/28 [==============================] - 1s 33ms/step - loss: 0.5478 - accuracy: 0.3540 - val_loss: 0.5449 - val_accuracy: 0.385
Epoch 6/50
28/28 [==============================] - 1s 33ms/step - loss: 0.5407 - accuracy: 0.4020 - val_loss: 0.5401 - val_accuracy: 0.452
Epoch 7/50
28/28 [==============================] - 1s 33ms/step - loss: 0.5420 - accuracy: 0.3889 - val_loss: 0.5352 - val_accuracy: 0.431
Epoch 8/50
28/28 [==============================] - 1s 33ms/step - loss: 0.5355 - accuracy: 0.4086 - val_loss: 0.5297 - val_accuracy: 0.457
Epoch 9/50
28/28 [==============================] - 1s 33ms/step - loss: 0.5259 - accuracy: 0.4428 - val_loss: 0.5193 - val_accuracy: 0.457
Epoch 10/50
28/28 [==============================] - 1s 36ms/step - loss: 0.5183 - accuracy: 0.4363 - val_loss: 0.5173 - val_accuracy: 0.422
Epoch 11/50
28/28 [==============================] - 1s 34ms/step - loss: 0.5165 - accuracy: 0.4319 - val_loss: 0.5087 - val_accuracy: 0.443
Epoch 12/50
28/28 [==============================] - 1s 43ms/step - loss: 0.5121 - accuracy: 0.4443 - val_loss: 0.5049 - val_accuracy: 0.475
Epoch 13/50
28/28 [==============================] - 1s 44ms/step - loss: 0.5094 - accuracy: 0.4545 - val_loss: 0.4965 - val_accuracy: 0.489
Epoch 14/50
28/28 [==============================] - 2s 55ms/step - loss: 0.5003 - accuracy: 0.4705 - val_loss: 0.4967 - val_accuracy: 0.466
Epoch 15/50
28/28 [==============================] - 1s 51ms/step - loss: 0.4991 - accuracy: 0.4727 - val_loss: 0.4868 - val_accuracy: 0.508
Epoch 16/50
28/28 [==============================] - 2s 54ms/step - loss: 0.4996 - accuracy: 0.4639 - val_loss: 0.5043 - val_accuracy: 0.433
Epoch 17/50
28/28 [==============================] - 2s 54ms/step - loss: 0.4952 - accuracy: 0.4843 - val_loss: 0.4940 - val_accuracy: 0.482
Epoch 18/50
28/28 [==============================] - 1s 46ms/step - loss: 0.4932 - accuracy: 0.4727 - val_loss: 0.4835 - val_accuracy: 0.487
Epoch 19/50
28/28 [==============================] - 1s 37ms/step - loss: 0.4879 - accuracy: 0.4953 - val_loss: 0.4790 - val_accuracy: 0.508
Epoch 20/50
28/28 [==============================] - 1s 33ms/step - loss: 0.4835 - accuracy: 0.4982 - val_loss: 0.4718 - val_accuracy: 0.524
Epoch 21/50
28/28 [==============================] - 1s 33ms/step - loss: 0.4885 - accuracy: 0.5011 - val_loss: 0.4758 - val_accuracy: 0.512
Epoch 22/50
28/28 [==============================] - 1s 33ms/step - loss: 0.4764 - accuracy: 0.5157 - val_loss: 0.4851 - val_accuracy: 0.489
Epoch 23/50
28/28 [==============================] - 1s 33ms/step - loss: 0.4775 - accuracy: 0.5025 - val_loss: 0.4679 - val_accuracy: 0.515
Epoch 24/50
28/28 [==============================] - 1s 33ms/step - loss: 0.4703 - accuracy: 0.5178 - val_loss: 0.4595 - val_accuracy: 0.549
Epoch 25/50
28/28 [==============================] - 1s 32ms/step - loss: 0.4704 - accuracy: 0.5310 - val_loss: 0.4723 - val_accuracy: 0.536
Epoch 26/50
28/28 [==============================] - 1s 35ms/step - loss: 0.4677 - accuracy: 0.5302 - val_loss: 0.4570 - val_accuracy: 0.584
Epoch 27/50
28/28 [==============================] - 1s 34ms/step - loss: 0.4648 - accuracy: 0.5302 - val_loss: 0.4628 - val_accuracy: 0.568
```

```
Epoch 28/50
28/28 [==============================] - 1s 32ms/step - loss: 0.4615 - accuracy: 0.5310 - val_loss: 0.4684 - val_accuracy: 0.538
Epoch 29/50
```

```
X_test = X_test.reshape(X_test.shape[0], num_rows, num_columns, num_channels) # converting test_data for predictions
```

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from tensorflow.math import confusion_matrix
# Evaluate the model
y_pred = model.predict(X_test)
y_pred_classes = np.argmax(y_pred, axis=1)
y_test_classes = np.argmax(y_test, axis=1)

# Calculate evaluation metrics
accuracy = accuracy_score(y_test_classes, y_pred_classes)
precision = precision_score(y_test_classes, y_pred_classes, average='weighted')
recall = recall_score(y_test_classes, y_pred_classes, average='weighted')
f1 = f1_score(y_test_classes, y_pred_classes, average='weighted')

# Print the evaluation metrics
print(f'Accuracy - CNN: {accuracy}')
print(f'Precision - CNN: {precision}')
print(f'Recall - CNN: {recall}')
print(f'F1 Score - CNN: {f1}')

print('Confusion_matrix - CNN: ',confusion_matrix(y_test_classes, y_pred_classes))
```

```
11/11 [==============================] - 0s 22ms/step
Accuracy - CNN: 0.6133720930232558
Precision - CNN: 0.6331407042803696
Recall - CNN: 0.6133720930232558
F1 Score - CNN: 0.5888214198046698
Confusion_matrix - CNN:  tf.Tensor(
[[35 12  3 22]
 [14 73  1 24]
 [10 18 14 19]
 [ 2  7  1 89]], shape=(4, 4), dtype=int32)
```

```
from tensorflow.keras.layers import LSTM, Dense,Dropout,Flatten
from tensorflow import keras
# Build a simple LSTM model
model_LSTM = Sequential()
model_LSTM.add(LSTM(128, input_shape=(X_train.shape[1], 1)))
model_LSTM.add(Dropout(0.5))
model_LSTM.add(Dense(len(LE.classes_), activation='softmax'))

# Compile the model
model_LSTM.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

# Reshape features for LSTM input
x_train = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
x_val = x_val_array.reshape((x_val_array.shape[0], x_val_array.shape[1], 1))
x_test = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Train the model
model_LSTM.fit(x_train, y_train, epochs=50, batch_size=32, validation_data=(x_val, y_val_array_encoded), verbose=1)

# Evaluate the model
loss, accuracy = model_LSTM.evaluate(x_test, y_test)
print(f'Test Loss: {loss}, Test Accuracy: {accuracy}')

```

```
Epoch 1/50
43/43 [==============================] - 8s 74ms/step - loss: 1.3604 - accuracy: 0.3132 - val_loss: 1.3335 - val_accuracy: 0.348
Epoch 2/50
43/43 [==============================] - 4s 85ms/step - loss: 1.3104 - accuracy: 0.3846 - val_loss: 1.2868 - val_accuracy: 0.375
Epoch 3/50
43/43 [==============================] - 4s 102ms/step - loss: 1.2635 - accuracy: 0.4246 - val_loss: 1.2519 - val_accuracy: 0.43
Epoch 4/50
43/43 [==============================] - 3s 62ms/step - loss: 1.2567 - accuracy: 0.4275 - val_loss: 1.2413 - val_accuracy: 0.436
Epoch 5/50
43/43 [==============================] - 2s 56ms/step - loss: 1.2228 - accuracy: 0.4545 - val_loss: 1.2253 - val_accuracy: 0.431
Epoch 6/50
43/43 [==============================] - 2s 55ms/step - loss: 1.2218 - accuracy: 0.4712 - val_loss: 1.2191 - val_accuracy: 0.468
Epoch 7/50
43/43 [==============================] - 4s 97ms/step - loss: 1.1966 - accuracy: 0.4669 - val_loss: 1.1939 - val_accuracy: 0.466
Epoch 8/50
43/43 [==============================] - 4s 103ms/step - loss: 1.1774 - accuracy: 0.4894 - val_loss: 1.2091 - val_accuracy: 0.43
Epoch 9/50
43/43 [==============================] - 3s 76ms/step - loss: 1.1400 - accuracy: 0.5040 - val_loss: 1.1334 - val_accuracy: 0.505
Epoch 10/50
43/43 [==============================] - 2s 56ms/step - loss: 1.1336 - accuracy: 0.5127 - val_loss: 1.1332 - val_accuracy: 0.522
Epoch 11/50
```

```
43/43 [==============================] - 2s 57ms/step - loss: 1.1263 - accuracy: 0.5222 - val_loss: 1.1022 - val_accuracy: 0.522
Epoch 12/50
43/43 [==============================] - 2s 56ms/step - loss: 1.0958 - accuracy: 0.5317 - val_loss: 1.0851 - val_accuracy: 0.561
Epoch 13/50
43/43 [==============================] - 3s 76ms/step - loss: 1.0777 - accuracy: 0.5317 - val_loss: 1.0578 - val_accuracy: 0.540
Epoch 14/50
43/43 [==============================] - 4s 96ms/step - loss: 1.0772 - accuracy: 0.5433 - val_loss: 1.0943 - val_accuracy: 0.517
Epoch 15/50
43/43 [==============================] - 3s 71ms/step - loss: 1.0912 - accuracy: 0.5193 - val_loss: 1.0740 - val_accuracy: 0.540
Epoch 16/50
43/43 [==============================] - 2s 54ms/step - loss: 1.0460 - accuracy: 0.5564 - val_loss: 1.0626 - val_accuracy: 0.554
Epoch 17/50
43/43 [==============================] - 2s 54ms/step - loss: 1.0217 - accuracy: 0.5717 - val_loss: 1.0229 - val_accuracy: 0.554
Epoch 18/50
43/43 [==============================] - 2s 55ms/step - loss: 0.9757 - accuracy: 0.5870 - val_loss: 0.9769 - val_accuracy: 0.589
Epoch 19/50
43/43 [==============================] - 3s 68ms/step - loss: 0.9680 - accuracy: 0.5972 - val_loss: 1.0552 - val_accuracy: 0.536
Epoch 20/50
43/43 [==============================] - 4s 102ms/step - loss: 0.9286 - accuracy: 0.6111 - val_loss: 0.9865 - val_accuracy: 0.58
Epoch 21/50
43/43 [==============================] - 5s 112ms/step - loss: 0.9033 - accuracy: 0.6242 - val_loss: 0.9597 - val_accuracy: 0.60
Epoch 22/50
43/43 [==============================] - 2s 55ms/step - loss: 0.9037 - accuracy: 0.6373 - val_loss: 0.9576 - val_accuracy: 0.596
Epoch 23/50
43/43 [==============================] - 2s 53ms/step - loss: 0.8743 - accuracy: 0.6431 - val_loss: 0.9737 - val_accuracy: 0.589
Epoch 24/50
43/43 [==============================] - 2s 55ms/step - loss: 0.8083 - accuracy: 0.6686 - val_loss: 0.8655 - val_accuracy: 0.619
Epoch 25/50
43/43 [==============================] - 4s 96ms/step - loss: 0.8155 - accuracy: 0.6715 - val_loss: 0.9576 - val_accuracy: 0.573
Epoch 26/50
43/43 [==============================] - 4s 101ms/step - loss: 0.7919 - accuracy: 0.6934 - val_loss: 0.9172 - val_accuracy: 0.62
Epoch 27/50
43/43 [==============================] - 2s 57ms/step - loss: 0.7621 - accuracy: 0.7087 - val_loss: 0.9094 - val_accuracy: 0.638
Epoch 28/50
43/43 [==============================] - 2s 55ms/step - loss: 0.7228 - accuracy: 0.7109 - val_loss: 0.8931 - val_accuracy: 0.628
```

```python
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

# Evaluate the model
y_pred = model_LSTM.predict(x_test)
y_pred_classes = np.argmax(y_pred, axis=1)
y_test_classes = np.argmax(y_test, axis=1)

# Calculate evaluation metrics
accuracy = accuracy_score(y_test_classes, y_pred_classes)
precision = precision_score(y_test_classes, y_pred_classes, average='weighted')
recall = recall_score(y_test_classes, y_pred_classes, average='weighted')
f1 = f1_score(y_test_classes, y_pred_classes, average='weighted')

# Print the evaluation metrics
print(f'Accuracy - LSTM: {accuracy}')
print(f'Precision - LSTM: {precision}')
```