

# CNN-SeqSelfAttention

This notebook was inspired to Tonmoy with some attempts to tune by us

## (i) Importing the necessary packages

```
In [ ]: import numpy as np
import pandas as pd
import tensorflow as tf
import keras
from keras_self_attention import SeqSelfAttention

from keras import layers
from keras.models import Sequential, Model
from keras.layers import Dense, Activation, Flatten, Dropout, MultiHeadAttention
from keras.layers import Conv2D, LSTM, BatchNormalization, MaxPooling2D, Reshape
from keras.utils import to_categorical
import matplotlib.pyplot as plt

tf.compat.v1.random.set_random_seed(0)
```

## (ii) Preprocessing the dataset and preparing the training, validation, and test datasets

```

In [ ]: def data_prep(X,y,sub_sample,average,noise):

    total_X = None
    total_y = None

    # Trimming the data (sample,22,1000) -> (sample,22,500)
    X = X[:, :, 0:500]
    print('Shape of X after trimming:', X.shape)

    # Maxpooling the data (sample,22,1000) -> (sample,22,500/sub_sample)
    X_max = np.max(X.reshape(X.shape[0], X.shape[1], -1, sub_sample), axis=3)

    total_X = X_max
    total_y = y
    print('Shape of X after maxpooling:', total_X.shape)

    # Averaging + noise
    X_average = np.mean(X.reshape(X.shape[0], X.shape[1], -1, average), axis=3)
    X_average = X_average + np.random.normal(0.0, 0.5, X_average.shape)

    total_X = np.vstack((total_X, X_average))
    total_y = np.hstack((total_y, y))
    print('Shape of X after averaging+noise and concatenating:', total_X.shape)

    # Subsampling
    for i in range(sub_sample):

        X_subsample = X[:, :, i::sub_sample] + \
            (np.random.normal(0.0, 0.5, X[:, :, i::sub_sample].shape))

        total_X = np.vstack((total_X, X_subsample))
        total_y = np.hstack((total_y, y))

    print('Shape of X after subsampling and concatenating:', total_X.shape)
    return total_X, total_y

```

```

In [ ]: ## Loading the dataset

X_test = np.load("X_test.npy")
y_test = np.load("y_test.npy")
person_train_valid = np.load("person_train_valid.npy")
X_train_valid = np.load("X_train_valid.npy")
y_train_valid = np.load("y_train_valid.npy")
person_test = np.load("person_test.npy")

## Adjusting the labels so that

# Cue onset left - 0
# Cue onset right - 1
# Cue onset foot - 2
# Cue onset tongue - 3

y_train_valid -= 769
y_test -= 769

## Random splitting and reshaping the data
# First generating the training and validation indices using random splitting

ind_valid = np.random.choice(2115, 375, replace=False)
ind_train = np.array(list(set(range(2115)).difference(set(ind_valid))))

# Creating the training and validation sets using the generated indices
(X_train, X_valid) = X_train_valid[ind_train], X_train_valid[ind_valid]
(y_train, y_valid) = y_train_valid[ind_train], y_train_valid[ind_valid]

## Preprocessing the dataset
x_train, y_train = data_prep(X_train, y_train, 2, 2, True)
x_valid, y_valid = data_prep(X_valid, y_valid, 2, 2, True)
X_test_prep, y_test_prep = data_prep(X_test, y_test, 2, 2, True)

print('Shape of training set:', x_train.shape)
print('Shape of validation set:', x_valid.shape)
print('Shape of training labels:', y_train.shape)
print('Shape of validation labels:', y_valid.shape)
print('Shape of testing set:', X_test_prep.shape)
print('Shape of testing labels:', y_test_prep.shape)

# Converting the labels to categorical variables for multiclass classification
y_train = to_categorical(y_train, 4)
y_valid = to_categorical(y_valid, 4)
y_test = to_categorical(y_test_prep, 4)
print('Shape of training labels after categorical conversion:', y_train.shape)
print('Shape of validation labels after categorical conversion:', y_valid.shape)
print('Shape of test labels after categorical conversion:', y_test.shape)

# Adding width of the segment to be 1
x_train = x_train.reshape(x_train.shape[0], x_train.shape[1], x_train.shape[2], 1)

```

```

x_valid = x_valid.reshape(x_valid.shape[0], x_valid.shape[1], x_train.shape[1])
x_test = X_test_prep.reshape(X_test_prep.shape[0], X_test_prep.shape[1], X_train.shape[1])
print('Shape of training set after adding width info:',x_train.shape)
print('Shape of validation set after adding width info:',x_valid.shape)
print('Shape of test set after adding width info:',x_test.shape)

# Reshaping the training and validation dataset
x_train = np.swapaxes(x_train, 1,3)
x_train = np.swapaxes(x_train, 1,2)
x_valid = np.swapaxes(x_valid, 1,3)
x_valid = np.swapaxes(x_valid, 1,2)
x_test = np.swapaxes(x_test, 1,3)
x_test = np.swapaxes(x_test, 1,2)
print('Shape of training set after dimension reshaping:',x_train.shape)
print('Shape of validation set after dimension reshaping:',x_valid.shape)
print('Shape of test set after dimension reshaping:',x_test.shape)

keras.backend.clear_session()

Shape of X after trimming: (1740, 22, 500)
Shape of X after maxpooling: (1740, 22, 250)
Shape of X after averaging+noise and concatenating: (3480, 22, 250)
Shape of X after subsampling and concatenating: (6960, 22, 250)
Shape of X after trimming: (375, 22, 500)
Shape of X after maxpooling: (375, 22, 250)
Shape of X after averaging+noise and concatenating: (750, 22, 250)
Shape of X after subsampling and concatenating: (1500, 22, 250)
Shape of X after trimming: (443, 22, 500)
Shape of X after maxpooling: (443, 22, 250)
Shape of X after averaging+noise and concatenating: (886, 22, 250)
Shape of X after subsampling and concatenating: (1772, 22, 250)
Shape of training set: (6960, 22, 250)
Shape of validation set: (1500, 22, 250)
Shape of training labels: (6960,)
Shape of validation labels: (1500,)
Shape of testing set: (1772, 22, 250)
Shape of testing labels: (1772,)
Shape of training labels after categorical conversion: (6960, 4)
Shape of validation labels after categorical conversion: (1500, 4)
Shape of test labels after categorical conversion: (1772, 4)
Shape of training set after adding width info: (6960, 22, 250, 1)
Shape of validation set after adding width info: (1500, 22, 250, 1)
Shape of test set after adding width info: (1772, 22, 250, 1)
Shape of training set after dimension reshaping: (6960, 250, 1, 22)
Shape of validation set after dimension reshaping: (1500, 250, 1, 22)
Shape of test set after dimension reshaping: (1772, 250, 1, 22)

```

### (iii)(CNN-Self-Attention) Defining the architecture of the hybrid CNN-LSTM model

```

In [ ]: # Building the CNN model using functional class
def build_model():
    # models = []

    n_frames = 250
    n_channels = 22
    # Conv. block 1
    In1 = keras.Input(shape=(250,1,22) )
    c1 = Conv2D(filters=30, kernel_size=(11,1), padding='same', activation='s
    p1 = MaxPooling2D(pool_size=(4,1), padding='same')(c1) # Read the keras
    b1 = BatchNormalization()(p1)
    d1 = Dropout(0.8)(b1)

    # Conv. block 2
    c2 = Conv2D(filters=60, kernel_size=(9,1), padding='same', activation='s
    p2 = MaxPooling2D(pool_size=(4,1), padding='same')(c2) # Read the keras
    b2 = BatchNormalization()(p2)
    d2 = Dropout(0.7)(b2)

    # Conv. block 3
    c3 = Conv2D(filters=120, kernel_size=(5,1), padding='same', activation='
    p3 = MaxPooling2D(pool_size=(4,1), padding='same')(c3) # Read the keras
    b3 = BatchNormalization()(p3)
    d3 = Dropout(0.6)(b3)

    c4 = Conv2D(filters=240, kernel_size=(3,1), padding='same', activation='
    p4 = MaxPooling2D(pool_size=(4,1), padding='same')(c4) # Read the keras
    b4 = BatchNormalization()(p4)
    d4 = Dropout(0.5)(b4)

    # self attention block
    selfatt = tf.squeeze(d4, axis=2)
    selfatt = SeqSelfAttention(attention_activation='gelu')(selfatt)
    selfatt = GlobalAveragePooling1D()(selfatt)

    # Add fully connected layers
    fc1 = Dense(64, activation='relu')(selfatt)
    fc1_dropout = Dropout(rate=0.5)(fc1)
    fc2 = Dense(4, activation='softmax')(fc1_dropout)

    # Define the final model
    final_model = Model(inputs=In1, outputs=[fc2])

    # # Printing the model summary
    final_model.compile(loss='categorical_crossentropy',
                        optimizer='adam',
                        metrics=['accuracy'])
    final_model.summary()
    return final_model

```

(iv)(CNN-LSTM) Defining the hyperparameters of the hybrid CNN-LSTM model

```
In [ ]: # Model parameters
epochs = 300
initial_learning_rate = 1e-3
decay_steps = 1000
decay_rate = 0.99

lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate,
    decay_steps=decay_steps,
    decay_rate=decay_rate
)

optimizer = keras.optimizers.Adam(learning_rate=lr_schedule)
```

## (v)Attention at the end

```
In [ ]: # Compiling the model
keras.backend.clear_session()

# Training and validating the model

batch_sizes = [32,64,128]
import matplotlib.pyplot as plt

hybrid_cnn_lstm_model = build_model()
# Compiling the model
hybrid_cnn_lstm_model.compile(loss='categorical_crossentropy',
                              optimizer=optimizer,
                              metrics=['accuracy'])

# Training and validating the model
acc = 0.73
class myCallback(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs={}):
        if((logs.get('val_accuracy') > acc)):
            print("\nval accuracy high enough and difference bet
                self.model.stop_training = True

# Instantiate a callback object
callback = myCallback()
# callback = keras.callbacks.EarlyStopping(monitor='val_loss', patience=10)
hybrid_cnn_lstm_model_results = hybrid_cnn_lstm_model.fit(x_train,
    y_train,
    batch_size=32,
    epochs=epochs,
    validation_data=(x_valid, y_valid),
    verbose=True,
    callbacks = [callback]
)
```

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 250, 1, 22)]	0
conv2d (Conv2D)	(None, 250, 1, 30)	7290
max_pooling2d (MaxPooling2D)	(None, 63, 1, 30)	0
batch_normalization (Batch Normalization)	(None, 63, 1, 30)	120
dropout (Dropout)	(None, 63, 1, 30)	0
conv2d_1 (Conv2D)	(None, 63, 1, 60)	16260
max_pooling2d_1 (MaxPooling2D)	(None, 16, 1, 60)	0
batch_normalization_1 (Batch Normalization)	(None, 16, 1, 60)	240
dropout_1 (Dropout)	(None, 16, 1, 60)	0
conv2d_2 (Conv2D)	(None, 16, 1, 120)	36120
max_pooling2d_2 (MaxPooling2D)	(None, 4, 1, 120)	0
batch_normalization_2 (Batch Normalization)	(None, 4, 1, 120)	480
dropout_2 (Dropout)	(None, 4, 1, 120)	0
conv2d_3 (Conv2D)	(None, 4, 1, 240)	86640
max_pooling2d_3 (MaxPooling2D)	(None, 1, 1, 240)	0
batch_normalization_3 (Batch Normalization)	(None, 1, 1, 240)	960
dropout_3 (Dropout)	(None, 1, 1, 240)	0
tf.compat.v1.squeeze (TFOPLambda)	(None, 1, 240)	0
seq_self_attention (SeqSelf Attention)	(None, 1, 240)	15425
global_average_pooling1d (GlobalAveragePooling1D)	(None, 240)	0
dense (Dense)	(None, 64)	15424

dropout_4 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 4)	260

```

=====
Total params: 179,219
Trainable params: 178,319
Non-trainable params: 900

```

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```

Epoch 1/300
218/218 [=====] - 4s 14ms/step - loss: 2.0168 - ac
curacy: 0.2511 - val_loss: 1.4256 - val_accuracy: 0.2720
Epoch 2/300
218/218 [=====] - 3s 15ms/step - loss: 1.5723 - ac
curacy: 0.2645 - val_loss: 1.3932 - val_accuracy: 0.2720
Epoch 3/300
218/218 [=====] - 3s 14ms/step - loss: 1.4544 - ac
curacy: 0.2670 - val_loss: 1.3795 - val_accuracy: 0.2667
Epoch 4/300
218/218 [=====] - 4s 18ms/step - loss: 1.4107 - ac
curacy: 0.2707 - val_loss: 1.3814 - val_accuracy: 0.2680
Epoch 5/300
218/218 [=====] - 3s 15ms/step - loss: 1.4007 - ac
curacy: 0.2740 - val_loss: 1.3816 - val_accuracy: 0.2740
Epoch 6/300
218/218 [=====] - 3s 15ms/step - loss: 1.3872 - ac
curacy: 0.2763 - val_loss: 1.3782 - val_accuracy: 0.2807
Epoch 7/300
218/218 [=====] - 4s 17ms/step - loss: 1.3792 - ac
curacy: 0.2865 - val_loss: 1.3789 - val_accuracy: 0.2767
Epoch 8/300
218/218 [=====] - 3s 15ms/step - loss: 1.3788 - ac
curacy: 0.2772 - val_loss: 1.3762 - val_accuracy: 0.2867
Epoch 9/300
218/218 [=====] - 3s 14ms/step - loss: 1.3747 - ac
curacy: 0.2912 - val_loss: 1.3781 - val_accuracy: 0.2773
Epoch 10/300
218/218 [=====] - 3s 14ms/step - loss: 1.3723 - ac
curacy: 0.2920 - val_loss: 1.3802 - val_accuracy: 0.2993
Epoch 11/300
218/218 [=====] - 3s 14ms/step - loss: 1.3601 - ac
curacy: 0.3195 - val_loss: 1.3610 - val_accuracy: 0.2960
Epoch 12/300
218/218 [=====] - 3s 14ms/step - loss: 1.3547 - ac
curacy: 0.3236 - val_loss: 1.3573 - val_accuracy: 0.3060
Epoch 13/300
218/218 [=====] - 3s 14ms/step - loss: 1.3361 - ac
curacy: 0.3437 - val_loss: 1.3372 - val_accuracy: 0.3127
Epoch 14/300
218/218 [=====] - 3s 14ms/step - loss: 1.3325 - ac
curacy: 0.3458 - val_loss: 1.3455 - val_accuracy: 0.3107
Epoch 15/300
218/218 [=====] - 3s 14ms/step - loss: 1.3198 - ac
curacy: 0.3612 - val_loss: 1.3095 - val_accuracy: 0.3840
Epoch 16/300

```



218/218 [=====] - 3s 14ms/step - loss: 1.3052 - accuracy: 0.3761 - val\_loss: 1.3052 - val\_accuracy: 0.3700  
Epoch 17/300  
218/218 [=====] - 3s 14ms/step - loss: 1.2919 - accuracy: 0.3787 - val\_loss: 1.3137 - val\_accuracy: 0.3400  
Epoch 18/300  
218/218 [=====] - 3s 14ms/step - loss: 1.2799 - accuracy: 0.4009 - val\_loss: 1.2754 - val\_accuracy: 0.3900  
Epoch 19/300  
218/218 [=====] - 3s 14ms/step - loss: 1.2698 - accuracy: 0.4046 - val\_loss: 1.3078 - val\_accuracy: 0.3700  
Epoch 20/300  
218/218 [=====] - 3s 14ms/step - loss: 1.2562 - accuracy: 0.4109 - val\_loss: 1.2546 - val\_accuracy: 0.3913  
Epoch 21/300  
218/218 [=====] - 3s 14ms/step - loss: 1.2535 - accuracy: 0.4190 - val\_loss: 1.2611 - val\_accuracy: 0.3773  
Epoch 22/300  
218/218 [=====] - 3s 14ms/step - loss: 1.2408 - accuracy: 0.4249 - val\_loss: 1.2488 - val\_accuracy: 0.4073  
Epoch 23/300  
218/218 [=====] - 3s 14ms/step - loss: 1.2230 - accuracy: 0.4425 - val\_loss: 1.2628 - val\_accuracy: 0.3727  
Epoch 24/300  
218/218 [=====] - 3s 14ms/step - loss: 1.2225 - accuracy: 0.4476 - val\_loss: 1.2547 - val\_accuracy: 0.3733  
Epoch 25/300  
218/218 [=====] - 3s 15ms/step - loss: 1.2171 - accuracy: 0.4441 - val\_loss: 1.2371 - val\_accuracy: 0.4087  
Epoch 26/300  
218/218 [=====] - 3s 14ms/step - loss: 1.2101 - accuracy: 0.4474 - val\_loss: 1.2268 - val\_accuracy: 0.4227  
Epoch 27/300  
218/218 [=====] - 3s 15ms/step - loss: 1.2093 - accuracy: 0.4460 - val\_loss: 1.2175 - val\_accuracy: 0.4333  
Epoch 28/300  
218/218 [=====] - 3s 16ms/step - loss: 1.2044 - accuracy: 0.4556 - val\_loss: 1.2295 - val\_accuracy: 0.4493  
Epoch 29/300  
218/218 [=====] - 3s 14ms/step - loss: 1.1899 - accuracy: 0.4615 - val\_loss: 1.2126 - val\_accuracy: 0.4360  
Epoch 30/300  
218/218 [=====] - 3s 15ms/step - loss: 1.2003 - accuracy: 0.4537 - val\_loss: 1.2128 - val\_accuracy: 0.4593  
Epoch 31/300  
218/218 [=====] - 3s 15ms/step - loss: 1.1867 - accuracy: 0.4664 - val\_loss: 1.2029 - val\_accuracy: 0.4687  
Epoch 32/300  
218/218 [=====] - 3s 15ms/step - loss: 1.1817 - accuracy: 0.4733 - val\_loss: 1.2153 - val\_accuracy: 0.4193  
Epoch 33/300  
218/218 [=====] - 3s 14ms/step - loss: 1.1787 - accuracy: 0.4726 - val\_loss: 1.1927 - val\_accuracy: 0.4700  
Epoch 34/300  
218/218 [=====] - 3s 15ms/step - loss: 1.1686 - accuracy: 0.4772 - val\_loss: 1.2066 - val\_accuracy: 0.4473

Epoch 35/300  
218/218 [=====] - 3s 15ms/step - loss: 1.1747 - accuracy: 0.4825 - val\_loss: 1.1915 - val\_accuracy: 0.4747  
Epoch 36/300  
218/218 [=====] - 3s 15ms/step - loss: 1.1660 - accuracy: 0.4819 - val\_loss: 1.1909 - val\_accuracy: 0.4513  
Epoch 37/300  
218/218 [=====] - 3s 14ms/step - loss: 1.1577 - accuracy: 0.4825 - val\_loss: 1.2013 - val\_accuracy: 0.4567  
Epoch 38/300  
218/218 [=====] - 3s 14ms/step - loss: 1.1555 - accuracy: 0.4898 - val\_loss: 1.1875 - val\_accuracy: 0.4800  
Epoch 39/300  
218/218 [=====] - 3s 14ms/step - loss: 1.1356 - accuracy: 0.5032 - val\_loss: 1.1509 - val\_accuracy: 0.4987  
Epoch 40/300  
218/218 [=====] - 3s 14ms/step - loss: 1.1382 - accuracy: 0.5109 - val\_loss: 1.1679 - val\_accuracy: 0.4813  
Epoch 41/300  
218/218 [=====] - 3s 14ms/step - loss: 1.1493 - accuracy: 0.5033 - val\_loss: 1.1466 - val\_accuracy: 0.5233  
Epoch 42/300  
218/218 [=====] - 3s 14ms/step - loss: 1.1235 - accuracy: 0.5155 - val\_loss: 1.1349 - val\_accuracy: 0.5247  
Epoch 43/300  
218/218 [=====] - 4s 16ms/step - loss: 1.1241 - accuracy: 0.5168 - val\_loss: 1.1264 - val\_accuracy: 0.5153  
Epoch 44/300  
218/218 [=====] - 3s 14ms/step - loss: 1.1172 - accuracy: 0.5240 - val\_loss: 1.1199 - val\_accuracy: 0.5347  
Epoch 45/300  
218/218 [=====] - 3s 15ms/step - loss: 1.1101 - accuracy: 0.5306 - val\_loss: 1.1233 - val\_accuracy: 0.5227  
Epoch 46/300  
218/218 [=====] - 3s 15ms/step - loss: 1.1086 - accuracy: 0.5280 - val\_loss: 1.1228 - val\_accuracy: 0.5260  
Epoch 47/300  
218/218 [=====] - 3s 15ms/step - loss: 1.1130 - accuracy: 0.5323 - val\_loss: 1.1104 - val\_accuracy: 0.5173  
Epoch 48/300  
218/218 [=====] - 3s 15ms/step - loss: 1.0981 - accuracy: 0.5421 - val\_loss: 1.1077 - val\_accuracy: 0.5333  
Epoch 49/300  
218/218 [=====] - 3s 15ms/step - loss: 1.1007 - accuracy: 0.5297 - val\_loss: 1.1121 - val\_accuracy: 0.5320  
Epoch 50/300  
218/218 [=====] - 3s 15ms/step - loss: 1.0872 - accuracy: 0.5394 - val\_loss: 1.0993 - val\_accuracy: 0.5600  
Epoch 51/300  
218/218 [=====] - 3s 15ms/step - loss: 1.0763 - accuracy: 0.5457 - val\_loss: 1.0881 - val\_accuracy: 0.5567  
Epoch 52/300  
218/218 [=====] - 3s 14ms/step - loss: 1.0754 - accuracy: 0.5543 - val\_loss: 1.0767 - val\_accuracy: 0.5593  
Epoch 53/300  
218/218 [=====] - 3s 14ms/step - loss: 1.0785 - ac

curacy: 0.5507 - val\_loss: 1.0654 - val\_accuracy: 0.5687  
Epoch 54/300  
218/218 [=====] - 3s 14ms/step - loss: 1.0780 - ac  
curacy: 0.5507 - val\_loss: 1.0614 - val\_accuracy: 0.5533  
Epoch 55/300  
218/218 [=====] - 3s 15ms/step - loss: 1.0595 - ac  
curacy: 0.5585 - val\_loss: 1.0747 - val\_accuracy: 0.5653  
Epoch 56/300  
218/218 [=====] - 3s 15ms/step - loss: 1.0625 - ac  
curacy: 0.5583 - val\_loss: 1.0577 - val\_accuracy: 0.5447  
Epoch 57/300  
218/218 [=====] - 3s 15ms/step - loss: 1.0499 - ac  
curacy: 0.5601 - val\_loss: 1.0412 - val\_accuracy: 0.5653  
Epoch 58/300  
218/218 [=====] - 3s 15ms/step - loss: 1.0552 - ac  
curacy: 0.5649 - val\_loss: 1.0378 - val\_accuracy: 0.5700  
Epoch 59/300  
218/218 [=====] - 3s 15ms/step - loss: 1.0462 - ac  
curacy: 0.5661 - val\_loss: 1.0221 - val\_accuracy: 0.5807  
Epoch 60/300  
218/218 [=====] - 3s 15ms/step - loss: 1.0331 - ac  
curacy: 0.5716 - val\_loss: 1.0317 - val\_accuracy: 0.5680  
Epoch 61/300  
218/218 [=====] - 3s 15ms/step - loss: 1.0399 - ac  
curacy: 0.5727 - val\_loss: 1.0149 - val\_accuracy: 0.5887  
Epoch 62/300  
218/218 [=====] - 3s 15ms/step - loss: 1.0330 - ac  
curacy: 0.5753 - val\_loss: 1.0180 - val\_accuracy: 0.5827  
Epoch 63/300  
218/218 [=====] - 3s 15ms/step - loss: 1.0382 - ac  
curacy: 0.5823 - val\_loss: 1.0146 - val\_accuracy: 0.5827  
Epoch 64/300  
218/218 [=====] - 3s 16ms/step - loss: 1.0276 - ac  
curacy: 0.5770 - val\_loss: 0.9921 - val\_accuracy: 0.5913  
Epoch 65/300  
218/218 [=====] - 3s 14ms/step - loss: 1.0179 - ac  
curacy: 0.5879 - val\_loss: 1.0140 - val\_accuracy: 0.5673  
Epoch 66/300  
218/218 [=====] - 3s 14ms/step - loss: 1.0159 - ac  
curacy: 0.5812 - val\_loss: 0.9827 - val\_accuracy: 0.5973  
Epoch 67/300  
218/218 [=====] - 3s 14ms/step - loss: 1.0095 - ac  
curacy: 0.5891 - val\_loss: 0.9887 - val\_accuracy: 0.6107  
Epoch 68/300  
218/218 [=====] - 3s 15ms/step - loss: 1.0017 - ac  
curacy: 0.5898 - val\_loss: 0.9859 - val\_accuracy: 0.5967  
Epoch 69/300  
218/218 [=====] - 3s 15ms/step - loss: 0.9987 - ac  
curacy: 0.5981 - val\_loss: 0.9772 - val\_accuracy: 0.6160  
Epoch 70/300  
218/218 [=====] - 3s 14ms/step - loss: 1.0044 - ac  
curacy: 0.5953 - val\_loss: 0.9594 - val\_accuracy: 0.6187  
Epoch 71/300  
218/218 [=====] - 3s 16ms/step - loss: 0.9993 - ac  
curacy: 0.5909 - val\_loss: 0.9747 - val\_accuracy: 0.6113  
Epoch 72/300

218/218 [=====] - 3s 15ms/step - loss: 1.0034 - accuracy: 0.5914 - val\_loss: 0.9672 - val\_accuracy: 0.6300  
Epoch 73/300  
218/218 [=====] - 3s 16ms/step - loss: 0.9914 - accuracy: 0.5953 - val\_loss: 0.9646 - val\_accuracy: 0.6280  
Epoch 74/300  
218/218 [=====] - 3s 15ms/step - loss: 0.9867 - accuracy: 0.6026 - val\_loss: 0.9425 - val\_accuracy: 0.6287  
Epoch 75/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9857 - accuracy: 0.5980 - val\_loss: 0.9492 - val\_accuracy: 0.6247  
Epoch 76/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9766 - accuracy: 0.6019 - val\_loss: 0.9416 - val\_accuracy: 0.6233  
Epoch 77/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9677 - accuracy: 0.6069 - val\_loss: 0.9531 - val\_accuracy: 0.6147  
Epoch 78/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9521 - accuracy: 0.6114 - val\_loss: 0.9284 - val\_accuracy: 0.6200  
Epoch 79/300  
218/218 [=====] - 3s 15ms/step - loss: 0.9755 - accuracy: 0.6098 - val\_loss: 0.9257 - val\_accuracy: 0.6340  
Epoch 80/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9587 - accuracy: 0.6096 - val\_loss: 0.9299 - val\_accuracy: 0.6180  
Epoch 81/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9618 - accuracy: 0.6122 - val\_loss: 0.9382 - val\_accuracy: 0.6400  
Epoch 82/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9433 - accuracy: 0.6191 - val\_loss: 0.9188 - val\_accuracy: 0.6320  
Epoch 83/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9577 - accuracy: 0.6111 - val\_loss: 0.9246 - val\_accuracy: 0.6320  
Epoch 84/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9548 - accuracy: 0.6128 - val\_loss: 0.8958 - val\_accuracy: 0.6480  
Epoch 85/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9483 - accuracy: 0.6263 - val\_loss: 0.8905 - val\_accuracy: 0.6413  
Epoch 86/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9617 - accuracy: 0.6108 - val\_loss: 0.8969 - val\_accuracy: 0.6527  
Epoch 87/300  
218/218 [=====] - 3s 15ms/step - loss: 0.9498 - accuracy: 0.6267 - val\_loss: 0.8967 - val\_accuracy: 0.6480  
Epoch 88/300  
218/218 [=====] - 3s 15ms/step - loss: 0.9456 - accuracy: 0.6134 - val\_loss: 0.8981 - val\_accuracy: 0.6447  
Epoch 89/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9494 - accuracy: 0.6132 - val\_loss: 0.8953 - val\_accuracy: 0.6360  
Epoch 90/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9390 - accuracy: 0.6233 - val\_loss: 0.8784 - val\_accuracy: 0.6447

Epoch 91/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9453 - accuracy: 0.6167 - val\_loss: 0.8902 - val\_accuracy: 0.6420  
Epoch 92/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9368 - accuracy: 0.6204 - val\_loss: 0.8958 - val\_accuracy: 0.6353  
Epoch 93/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9331 - accuracy: 0.6310 - val\_loss: 0.8938 - val\_accuracy: 0.6447  
Epoch 94/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9345 - accuracy: 0.6264 - val\_loss: 0.8774 - val\_accuracy: 0.6480  
Epoch 95/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9241 - accuracy: 0.6303 - val\_loss: 0.8753 - val\_accuracy: 0.6587  
Epoch 96/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9313 - accuracy: 0.6302 - val\_loss: 0.8929 - val\_accuracy: 0.6447  
Epoch 97/300  
218/218 [=====] - 3s 15ms/step - loss: 0.9311 - accuracy: 0.6307 - val\_loss: 0.8948 - val\_accuracy: 0.6427  
Epoch 98/300  
218/218 [=====] - 3s 16ms/step - loss: 0.9347 - accuracy: 0.6287 - val\_loss: 0.8800 - val\_accuracy: 0.6373  
Epoch 99/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9240 - accuracy: 0.6351 - val\_loss: 0.8899 - val\_accuracy: 0.6407  
Epoch 100/300  
218/218 [=====] - 3s 15ms/step - loss: 0.9180 - accuracy: 0.6299 - val\_loss: 0.8936 - val\_accuracy: 0.6380  
Epoch 101/300  
218/218 [=====] - 3s 15ms/step - loss: 0.9224 - accuracy: 0.6356 - val\_loss: 0.8694 - val\_accuracy: 0.6573  
Epoch 102/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9200 - accuracy: 0.6361 - val\_loss: 0.8829 - val\_accuracy: 0.6427  
Epoch 103/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9252 - accuracy: 0.6338 - val\_loss: 0.8786 - val\_accuracy: 0.6393  
Epoch 104/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9285 - accuracy: 0.6290 - val\_loss: 0.8868 - val\_accuracy: 0.6493  
Epoch 105/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9032 - accuracy: 0.6366 - val\_loss: 0.8827 - val\_accuracy: 0.6333  
Epoch 106/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9035 - accuracy: 0.6352 - val\_loss: 0.8669 - val\_accuracy: 0.6700  
Epoch 107/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9063 - accuracy: 0.6385 - val\_loss: 0.8633 - val\_accuracy: 0.6533  
Epoch 108/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9074 - accuracy: 0.6372 - val\_loss: 0.8580 - val\_accuracy: 0.6527  
Epoch 109/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9171 - ac

curacy: 0.6299 - val\_loss: 0.8571 - val\_accuracy: 0.6753  
Epoch 110/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9001 - ac  
curacy: 0.6467 - val\_loss: 0.8469 - val\_accuracy: 0.6647  
Epoch 111/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9083 - ac  
curacy: 0.6326 - val\_loss: 0.8562 - val\_accuracy: 0.6553  
Epoch 112/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9064 - ac  
curacy: 0.6358 - val\_loss: 0.8592 - val\_accuracy: 0.6580  
Epoch 113/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8957 - ac  
curacy: 0.6411 - val\_loss: 0.8361 - val\_accuracy: 0.6653  
Epoch 114/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8912 - ac  
curacy: 0.6481 - val\_loss: 0.8464 - val\_accuracy: 0.6673  
Epoch 115/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9073 - ac  
curacy: 0.6424 - val\_loss: 0.8586 - val\_accuracy: 0.6560  
Epoch 116/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9029 - ac  
curacy: 0.6421 - val\_loss: 0.8502 - val\_accuracy: 0.6607  
Epoch 117/300  
218/218 [=====] - 3s 14ms/step - loss: 0.9008 - ac  
curacy: 0.6478 - val\_loss: 0.8452 - val\_accuracy: 0.6593  
Epoch 118/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8920 - ac  
curacy: 0.6497 - val\_loss: 0.8317 - val\_accuracy: 0.6740  
Epoch 119/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8969 - ac  
curacy: 0.6448 - val\_loss: 0.8531 - val\_accuracy: 0.6580  
Epoch 120/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8928 - ac  
curacy: 0.6501 - val\_loss: 0.8450 - val\_accuracy: 0.6633  
Epoch 121/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8928 - ac  
curacy: 0.6481 - val\_loss: 0.8441 - val\_accuracy: 0.6513  
Epoch 122/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8966 - ac  
curacy: 0.6468 - val\_loss: 0.8444 - val\_accuracy: 0.6620  
Epoch 123/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8912 - ac  
curacy: 0.6478 - val\_loss: 0.8398 - val\_accuracy: 0.6473  
Epoch 124/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8901 - ac  
curacy: 0.6401 - val\_loss: 0.8177 - val\_accuracy: 0.6647  
Epoch 125/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8904 - ac  
curacy: 0.6451 - val\_loss: 0.8372 - val\_accuracy: 0.6753  
Epoch 126/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8898 - ac  
curacy: 0.6409 - val\_loss: 0.8351 - val\_accuracy: 0.6587  
Epoch 127/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8872 - ac  
curacy: 0.6503 - val\_loss: 0.8351 - val\_accuracy: 0.6680  
Epoch 128/300

218/218 [=====] - 3s 14ms/step - loss: 0.8766 - accuracy: 0.6579 - val\_loss: 0.8316 - val\_accuracy: 0.6760  
Epoch 129/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8911 - accuracy: 0.6480 - val\_loss: 0.8288 - val\_accuracy: 0.6680  
Epoch 130/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8792 - accuracy: 0.6438 - val\_loss: 0.8332 - val\_accuracy: 0.6707  
Epoch 131/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8684 - accuracy: 0.6559 - val\_loss: 0.8165 - val\_accuracy: 0.6720  
Epoch 132/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8778 - accuracy: 0.6536 - val\_loss: 0.8223 - val\_accuracy: 0.6787  
Epoch 133/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8645 - accuracy: 0.6628 - val\_loss: 0.8365 - val\_accuracy: 0.6673  
Epoch 134/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8770 - accuracy: 0.6537 - val\_loss: 0.8285 - val\_accuracy: 0.6707  
Epoch 135/300  
218/218 [=====] - 4s 16ms/step - loss: 0.8835 - accuracy: 0.6532 - val\_loss: 0.8322 - val\_accuracy: 0.6613  
Epoch 136/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8697 - accuracy: 0.6570 - val\_loss: 0.8322 - val\_accuracy: 0.6680  
Epoch 137/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8748 - accuracy: 0.6537 - val\_loss: 0.8191 - val\_accuracy: 0.6760  
Epoch 138/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8652 - accuracy: 0.6569 - val\_loss: 0.8331 - val\_accuracy: 0.6673  
Epoch 139/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8734 - accuracy: 0.6566 - val\_loss: 0.8306 - val\_accuracy: 0.6733  
Epoch 140/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8675 - accuracy: 0.6539 - val\_loss: 0.8267 - val\_accuracy: 0.6747  
Epoch 141/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8735 - accuracy: 0.6595 - val\_loss: 0.8348 - val\_accuracy: 0.6787  
Epoch 142/300  
218/218 [=====] - 3s 16ms/step - loss: 0.8632 - accuracy: 0.6612 - val\_loss: 0.8191 - val\_accuracy: 0.6720  
Epoch 143/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8559 - accuracy: 0.6605 - val\_loss: 0.8340 - val\_accuracy: 0.6753  
Epoch 144/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8550 - accuracy: 0.6609 - val\_loss: 0.8101 - val\_accuracy: 0.6780  
Epoch 145/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8545 - accuracy: 0.6638 - val\_loss: 0.8196 - val\_accuracy: 0.6727  
Epoch 146/300  
218/218 [=====] - 3s 16ms/step - loss: 0.8616 - accuracy: 0.6639 - val\_loss: 0.8012 - val\_accuracy: 0.6847

Epoch 147/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8641 - accuracy: 0.6652 - val\_loss: 0.8185 - val\_accuracy: 0.6847  
Epoch 148/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8506 - accuracy: 0.6655 - val\_loss: 0.8199 - val\_accuracy: 0.6747  
Epoch 149/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8440 - accuracy: 0.6701 - val\_loss: 0.8176 - val\_accuracy: 0.6807  
Epoch 150/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8453 - accuracy: 0.6688 - val\_loss: 0.8117 - val\_accuracy: 0.6873  
Epoch 151/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8474 - accuracy: 0.6710 - val\_loss: 0.8127 - val\_accuracy: 0.6727  
Epoch 152/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8617 - accuracy: 0.6672 - val\_loss: 0.8074 - val\_accuracy: 0.6873  
Epoch 153/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8620 - accuracy: 0.6631 - val\_loss: 0.8065 - val\_accuracy: 0.6840  
Epoch 154/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8484 - accuracy: 0.6672 - val\_loss: 0.8223 - val\_accuracy: 0.6720  
Epoch 155/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8476 - accuracy: 0.6649 - val\_loss: 0.8126 - val\_accuracy: 0.6733  
Epoch 156/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8544 - accuracy: 0.6602 - val\_loss: 0.8142 - val\_accuracy: 0.6833  
Epoch 157/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8564 - accuracy: 0.6649 - val\_loss: 0.8077 - val\_accuracy: 0.6787  
Epoch 158/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8532 - accuracy: 0.6707 - val\_loss: 0.8185 - val\_accuracy: 0.6720  
Epoch 159/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8497 - accuracy: 0.6677 - val\_loss: 0.8079 - val\_accuracy: 0.6827  
Epoch 160/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8532 - accuracy: 0.6714 - val\_loss: 0.8115 - val\_accuracy: 0.6793  
Epoch 161/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8457 - accuracy: 0.6691 - val\_loss: 0.8274 - val\_accuracy: 0.6800  
Epoch 162/300  
218/218 [=====] - 3s 16ms/step - loss: 0.8462 - accuracy: 0.6661 - val\_loss: 0.8115 - val\_accuracy: 0.6907  
Epoch 163/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8336 - accuracy: 0.6693 - val\_loss: 0.8123 - val\_accuracy: 0.6787  
Epoch 164/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8325 - accuracy: 0.6698 - val\_loss: 0.7994 - val\_accuracy: 0.6847  
Epoch 165/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8440 - accuracy: 0.6698 - val\_loss: 0.7994 - val\_accuracy: 0.6847



curacy: 0.6662 - val\_loss: 0.8121 - val\_accuracy: 0.6860  
Epoch 166/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8322 - ac  
curacy: 0.6773 - val\_loss: 0.7937 - val\_accuracy: 0.6960  
Epoch 167/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8472 - ac  
curacy: 0.6694 - val\_loss: 0.7945 - val\_accuracy: 0.6867  
Epoch 168/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8404 - ac  
curacy: 0.6736 - val\_loss: 0.8104 - val\_accuracy: 0.6893  
Epoch 169/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8144 - ac  
curacy: 0.6764 - val\_loss: 0.8099 - val\_accuracy: 0.6873  
Epoch 170/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8482 - ac  
curacy: 0.6624 - val\_loss: 0.8267 - val\_accuracy: 0.6807  
Epoch 171/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8246 - ac  
curacy: 0.6766 - val\_loss: 0.8021 - val\_accuracy: 0.6980  
Epoch 172/300  
218/218 [=====] - 3s 16ms/step - loss: 0.8475 - ac  
curacy: 0.6677 - val\_loss: 0.7989 - val\_accuracy: 0.6907  
Epoch 173/300  
218/218 [=====] - 3s 16ms/step - loss: 0.8215 - ac  
curacy: 0.6744 - val\_loss: 0.7995 - val\_accuracy: 0.6880  
Epoch 174/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8460 - ac  
curacy: 0.6658 - val\_loss: 0.7989 - val\_accuracy: 0.6980  
Epoch 175/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8281 - ac  
curacy: 0.6753 - val\_loss: 0.7841 - val\_accuracy: 0.7000  
Epoch 176/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8322 - ac  
curacy: 0.6793 - val\_loss: 0.8024 - val\_accuracy: 0.6793  
Epoch 177/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8373 - ac  
curacy: 0.6753 - val\_loss: 0.7986 - val\_accuracy: 0.6880  
Epoch 178/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8278 - ac  
curacy: 0.6793 - val\_loss: 0.7926 - val\_accuracy: 0.6887  
Epoch 179/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8267 - ac  
curacy: 0.6724 - val\_loss: 0.7980 - val\_accuracy: 0.6887  
Epoch 180/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8219 - ac  
curacy: 0.6861 - val\_loss: 0.8141 - val\_accuracy: 0.6827  
Epoch 181/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8173 - ac  
curacy: 0.6862 - val\_loss: 0.7946 - val\_accuracy: 0.6887  
Epoch 182/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8296 - ac  
curacy: 0.6763 - val\_loss: 0.7824 - val\_accuracy: 0.7000  
Epoch 183/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8358 - ac  
curacy: 0.6717 - val\_loss: 0.7904 - val\_accuracy: 0.6887  
Epoch 184/300

218/218 [=====] - 3s 14ms/step - loss: 0.8003 - accuracy: 0.6912 - val\_loss: 0.7849 - val\_accuracy: 0.6853  
Epoch 185/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8127 - accuracy: 0.6802 - val\_loss: 0.7966 - val\_accuracy: 0.6920  
Epoch 186/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8278 - accuracy: 0.6772 - val\_loss: 0.7958 - val\_accuracy: 0.6987  
Epoch 187/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8022 - accuracy: 0.6869 - val\_loss: 0.7979 - val\_accuracy: 0.6913  
Epoch 188/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8121 - accuracy: 0.6819 - val\_loss: 0.7994 - val\_accuracy: 0.6853  
Epoch 189/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8315 - accuracy: 0.6708 - val\_loss: 0.7895 - val\_accuracy: 0.6907  
Epoch 190/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8261 - accuracy: 0.6843 - val\_loss: 0.7963 - val\_accuracy: 0.6927  
Epoch 191/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8102 - accuracy: 0.6875 - val\_loss: 0.7918 - val\_accuracy: 0.6800  
Epoch 192/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8142 - accuracy: 0.6825 - val\_loss: 0.7829 - val\_accuracy: 0.6840  
Epoch 193/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8187 - accuracy: 0.6812 - val\_loss: 0.7874 - val\_accuracy: 0.6927  
Epoch 194/300  
218/218 [=====] - 3s 14ms/step - loss: 0.8091 - accuracy: 0.6895 - val\_loss: 0.7932 - val\_accuracy: 0.6980  
Epoch 195/300  
218/218 [=====] - 4s 17ms/step - loss: 0.7962 - accuracy: 0.6889 - val\_loss: 0.7708 - val\_accuracy: 0.7073  
Epoch 196/300  
218/218 [=====] - 4s 19ms/step - loss: 0.8132 - accuracy: 0.6751 - val\_loss: 0.7964 - val\_accuracy: 0.6987  
Epoch 197/300  
218/218 [=====] - 3s 16ms/step - loss: 0.8008 - accuracy: 0.6921 - val\_loss: 0.7975 - val\_accuracy: 0.7007  
Epoch 198/300  
218/218 [=====] - 4s 16ms/step - loss: 0.7931 - accuracy: 0.6858 - val\_loss: 0.7893 - val\_accuracy: 0.6953  
Epoch 199/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8154 - accuracy: 0.6816 - val\_loss: 0.7822 - val\_accuracy: 0.6967  
Epoch 200/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8058 - accuracy: 0.6874 - val\_loss: 0.7844 - val\_accuracy: 0.6953  
Epoch 201/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8170 - accuracy: 0.6793 - val\_loss: 0.7749 - val\_accuracy: 0.6940  
Epoch 202/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8239 - accuracy: 0.6769 - val\_loss: 0.7814 - val\_accuracy: 0.6967

Epoch 203/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7947 - accuracy: 0.6974 - val\_loss: 0.7917 - val\_accuracy: 0.6833  
Epoch 204/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8142 - accuracy: 0.6826 - val\_loss: 0.7879 - val\_accuracy: 0.6993  
Epoch 205/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8207 - accuracy: 0.6773 - val\_loss: 0.7804 - val\_accuracy: 0.7047  
Epoch 206/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8062 - accuracy: 0.6846 - val\_loss: 0.7917 - val\_accuracy: 0.6947  
Epoch 207/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8185 - accuracy: 0.6868 - val\_loss: 0.7834 - val\_accuracy: 0.6973  
Epoch 208/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8031 - accuracy: 0.6898 - val\_loss: 0.7828 - val\_accuracy: 0.7140  
Epoch 209/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8019 - accuracy: 0.6816 - val\_loss: 0.7952 - val\_accuracy: 0.6980  
Epoch 210/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8113 - accuracy: 0.6832 - val\_loss: 0.7946 - val\_accuracy: 0.7013  
Epoch 211/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8034 - accuracy: 0.6874 - val\_loss: 0.7900 - val\_accuracy: 0.6933  
Epoch 212/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7868 - accuracy: 0.6912 - val\_loss: 0.7852 - val\_accuracy: 0.6940  
Epoch 213/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8103 - accuracy: 0.6862 - val\_loss: 0.7932 - val\_accuracy: 0.6913  
Epoch 214/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8057 - accuracy: 0.6841 - val\_loss: 0.7882 - val\_accuracy: 0.6827  
Epoch 215/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8061 - accuracy: 0.6886 - val\_loss: 0.7858 - val\_accuracy: 0.6960  
Epoch 216/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8000 - accuracy: 0.6912 - val\_loss: 0.7990 - val\_accuracy: 0.6933  
Epoch 217/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7949 - accuracy: 0.6908 - val\_loss: 0.7805 - val\_accuracy: 0.7033  
Epoch 218/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7924 - accuracy: 0.7013 - val\_loss: 0.7933 - val\_accuracy: 0.6900  
Epoch 219/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7944 - accuracy: 0.6977 - val\_loss: 0.7838 - val\_accuracy: 0.7020  
Epoch 220/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7961 - accuracy: 0.6905 - val\_loss: 0.7958 - val\_accuracy: 0.6960  
Epoch 221/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8037 - ac

curacy: 0.6937 - val\_loss: 0.7798 - val\_accuracy: 0.6967  
Epoch 222/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7902 - ac  
curacy: 0.6938 - val\_loss: 0.7805 - val\_accuracy: 0.7100  
Epoch 223/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7910 - ac  
curacy: 0.6996 - val\_loss: 0.8013 - val\_accuracy: 0.6860  
Epoch 224/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7959 - ac  
curacy: 0.6862 - val\_loss: 0.7726 - val\_accuracy: 0.7033  
Epoch 225/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7895 - ac  
curacy: 0.6974 - val\_loss: 0.7804 - val\_accuracy: 0.7020  
Epoch 226/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7857 - ac  
curacy: 0.6958 - val\_loss: 0.7907 - val\_accuracy: 0.6947  
Epoch 227/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7949 - ac  
curacy: 0.6930 - val\_loss: 0.7842 - val\_accuracy: 0.6947  
Epoch 228/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7760 - ac  
curacy: 0.7034 - val\_loss: 0.7833 - val\_accuracy: 0.6893  
Epoch 229/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7888 - ac  
curacy: 0.6947 - val\_loss: 0.7745 - val\_accuracy: 0.6987  
Epoch 230/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7857 - ac  
curacy: 0.6898 - val\_loss: 0.7810 - val\_accuracy: 0.7033  
Epoch 231/300  
218/218 [=====] - 4s 17ms/step - loss: 0.7878 - ac  
curacy: 0.6974 - val\_loss: 0.7680 - val\_accuracy: 0.7080  
Epoch 232/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7885 - ac  
curacy: 0.6960 - val\_loss: 0.7849 - val\_accuracy: 0.7007  
Epoch 233/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7808 - ac  
curacy: 0.6958 - val\_loss: 0.7803 - val\_accuracy: 0.7027  
Epoch 234/300  
218/218 [=====] - 3s 15ms/step - loss: 0.8025 - ac  
curacy: 0.6864 - val\_loss: 0.7728 - val\_accuracy: 0.7160  
Epoch 235/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7765 - ac  
curacy: 0.7042 - val\_loss: 0.7765 - val\_accuracy: 0.7093  
Epoch 236/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7921 - ac  
curacy: 0.6931 - val\_loss: 0.7571 - val\_accuracy: 0.7127  
Epoch 237/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7819 - ac  
curacy: 0.6955 - val\_loss: 0.7729 - val\_accuracy: 0.7153  
Epoch 238/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7865 - ac  
curacy: 0.6958 - val\_loss: 0.7722 - val\_accuracy: 0.7120  
Epoch 239/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7827 - ac  
curacy: 0.6924 - val\_loss: 0.7738 - val\_accuracy: 0.7120  
Epoch 240/300

218/218 [=====] - 3s 14ms/step - loss: 0.7883 - accuracy: 0.6955 - val\_loss: 0.7809 - val\_accuracy: 0.7060  
Epoch 241/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7885 - accuracy: 0.6954 - val\_loss: 0.7805 - val\_accuracy: 0.7073  
Epoch 242/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7938 - accuracy: 0.6922 - val\_loss: 0.7896 - val\_accuracy: 0.7100  
Epoch 243/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7833 - accuracy: 0.6940 - val\_loss: 0.7702 - val\_accuracy: 0.7100  
Epoch 244/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7860 - accuracy: 0.7013 - val\_loss: 0.7783 - val\_accuracy: 0.7067  
Epoch 245/300  
218/218 [=====] - 4s 17ms/step - loss: 0.7848 - accuracy: 0.6934 - val\_loss: 0.7831 - val\_accuracy: 0.7107  
Epoch 246/300  
218/218 [=====] - 4s 18ms/step - loss: 0.7934 - accuracy: 0.6905 - val\_loss: 0.7670 - val\_accuracy: 0.7227  
Epoch 247/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7823 - accuracy: 0.6941 - val\_loss: 0.7670 - val\_accuracy: 0.7073  
Epoch 248/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7749 - accuracy: 0.7056 - val\_loss: 0.7864 - val\_accuracy: 0.6960  
Epoch 249/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7709 - accuracy: 0.7070 - val\_loss: 0.7611 - val\_accuracy: 0.7133  
Epoch 250/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7763 - accuracy: 0.7011 - val\_loss: 0.7634 - val\_accuracy: 0.7167  
Epoch 251/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7714 - accuracy: 0.6957 - val\_loss: 0.7571 - val\_accuracy: 0.7080  
Epoch 252/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7743 - accuracy: 0.6968 - val\_loss: 0.7765 - val\_accuracy: 0.7080  
Epoch 253/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7687 - accuracy: 0.7032 - val\_loss: 0.7812 - val\_accuracy: 0.7093  
Epoch 254/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7860 - accuracy: 0.6970 - val\_loss: 0.7713 - val\_accuracy: 0.7213  
Epoch 255/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7687 - accuracy: 0.7057 - val\_loss: 0.7505 - val\_accuracy: 0.7153  
Epoch 256/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7743 - accuracy: 0.6955 - val\_loss: 0.7613 - val\_accuracy: 0.7113  
Epoch 257/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7733 - accuracy: 0.7089 - val\_loss: 0.7638 - val\_accuracy: 0.7093  
Epoch 258/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7662 - accuracy: 0.7004 - val\_loss: 0.7738 - val\_accuracy: 0.7113

Epoch 259/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7748 - accuracy: 0.7060 - val\_loss: 0.7614 - val\_accuracy: 0.7067  
Epoch 260/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7774 - accuracy: 0.7003 - val\_loss: 0.7770 - val\_accuracy: 0.7027  
Epoch 261/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7577 - accuracy: 0.7088 - val\_loss: 0.7674 - val\_accuracy: 0.7173  
Epoch 262/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7704 - accuracy: 0.6980 - val\_loss: 0.7681 - val\_accuracy: 0.7100  
Epoch 263/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7767 - accuracy: 0.6983 - val\_loss: 0.7647 - val\_accuracy: 0.7160  
Epoch 264/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7677 - accuracy: 0.7019 - val\_loss: 0.7717 - val\_accuracy: 0.7033  
Epoch 265/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7934 - accuracy: 0.6993 - val\_loss: 0.7482 - val\_accuracy: 0.7193  
Epoch 266/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7698 - accuracy: 0.7004 - val\_loss: 0.7708 - val\_accuracy: 0.7147  
Epoch 267/300  
218/218 [=====] - 4s 17ms/step - loss: 0.7769 - accuracy: 0.7055 - val\_loss: 0.7570 - val\_accuracy: 0.7040  
Epoch 268/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7549 - accuracy: 0.7036 - val\_loss: 0.7565 - val\_accuracy: 0.7087  
Epoch 269/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7721 - accuracy: 0.6986 - val\_loss: 0.7735 - val\_accuracy: 0.7020  
Epoch 270/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7726 - accuracy: 0.6981 - val\_loss: 0.7740 - val\_accuracy: 0.7060  
Epoch 271/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7788 - accuracy: 0.6983 - val\_loss: 0.7652 - val\_accuracy: 0.7120  
Epoch 272/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7774 - accuracy: 0.7014 - val\_loss: 0.7718 - val\_accuracy: 0.7167  
Epoch 273/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7675 - accuracy: 0.7046 - val\_loss: 0.7724 - val\_accuracy: 0.7147  
Epoch 274/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7695 - accuracy: 0.7026 - val\_loss: 0.7682 - val\_accuracy: 0.7100  
Epoch 275/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7650 - accuracy: 0.7029 - val\_loss: 0.7778 - val\_accuracy: 0.7060  
Epoch 276/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7732 - accuracy: 0.7029 - val\_loss: 0.7809 - val\_accuracy: 0.7033  
Epoch 277/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7732 - ac

curacy: 0.7027 - val\_loss: 0.7703 - val\_accuracy: 0.7007  
Epoch 278/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7691 - ac  
curacy: 0.7046 - val\_loss: 0.7699 - val\_accuracy: 0.7167  
Epoch 279/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7570 - ac  
curacy: 0.7029 - val\_loss: 0.7591 - val\_accuracy: 0.7113  
Epoch 280/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7739 - ac  
curacy: 0.6993 - val\_loss: 0.7622 - val\_accuracy: 0.7140  
Epoch 281/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7543 - ac  
curacy: 0.7034 - val\_loss: 0.7614 - val\_accuracy: 0.7173  
Epoch 282/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7723 - ac  
curacy: 0.7055 - val\_loss: 0.7574 - val\_accuracy: 0.7060  
Epoch 283/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7607 - ac  
curacy: 0.7129 - val\_loss: 0.7503 - val\_accuracy: 0.7193  
Epoch 284/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7732 - ac  
curacy: 0.6944 - val\_loss: 0.7693 - val\_accuracy: 0.7027  
Epoch 285/300  
218/218 [=====] - 3s 14ms/step - loss: 0.7660 - ac  
curacy: 0.6968 - val\_loss: 0.7675 - val\_accuracy: 0.7133  
Epoch 286/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7517 - ac  
curacy: 0.7151 - val\_loss: 0.7482 - val\_accuracy: 0.7213  
Epoch 287/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7707 - ac  
curacy: 0.7039 - val\_loss: 0.7610 - val\_accuracy: 0.7113  
Epoch 288/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7680 - ac  
curacy: 0.7017 - val\_loss: 0.7626 - val\_accuracy: 0.7167  
Epoch 289/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7527 - ac  
curacy: 0.7086 - val\_loss: 0.7659 - val\_accuracy: 0.7187  
Epoch 290/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7696 - ac  
curacy: 0.7001 - val\_loss: 0.7622 - val\_accuracy: 0.7153  
Epoch 291/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7628 - ac  
curacy: 0.7065 - val\_loss: 0.7657 - val\_accuracy: 0.7067  
Epoch 292/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7536 - ac  
curacy: 0.7065 - val\_loss: 0.7678 - val\_accuracy: 0.7053  
Epoch 293/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7564 - ac  
curacy: 0.7091 - val\_loss: 0.7646 - val\_accuracy: 0.7107  
Epoch 294/300  
218/218 [=====] - 3s 16ms/step - loss: 0.7580 - ac  
curacy: 0.7091 - val\_loss: 0.7542 - val\_accuracy: 0.7140  
Epoch 295/300  
218/218 [=====] - 3s 15ms/step - loss: 0.7521 - ac  
curacy: 0.7109 - val\_loss: 0.7635 - val\_accuracy: 0.7160  
Epoch 296/300

```
218/218 [=====] - 3s 15ms/step - loss: 0.7527 - ac
curacy: 0.7060 - val_loss: 0.7545 - val_accuracy: 0.7220
Epoch 297/300
169/218 [=====>.....] - ETA: 0s - loss: 0.7493 - accurac
y: 0.7110
```

## (vi)(CNN-Attention) Visualizing the accuracy and loss trajectory

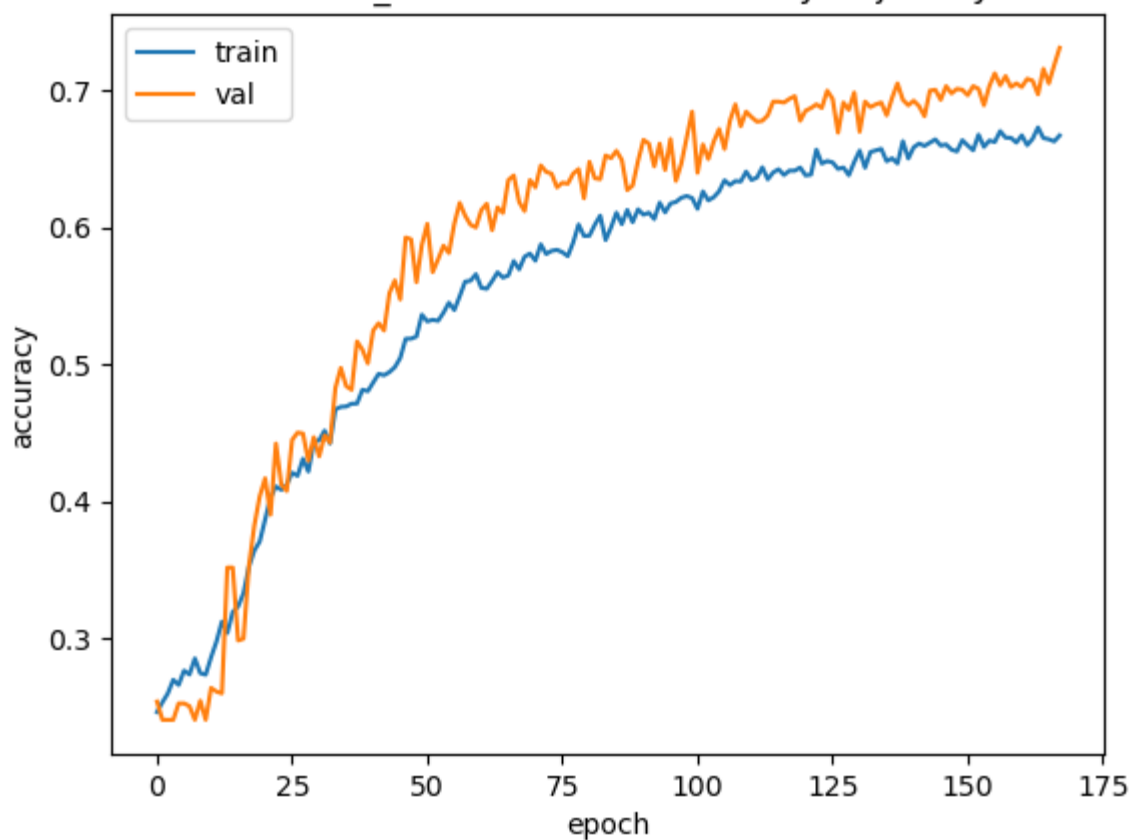
```
In [ ]: import matplotlib.pyplot as plt

# Plotting accuracy trajectory
plt.plot(hybrid_cnn_lstm_model_results.history['accuracy'])
plt.plot(hybrid_cnn_lstm_model_results.history['val_accuracy'])
plt.title('CNN-Self_attention model accuracy trajectory')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()

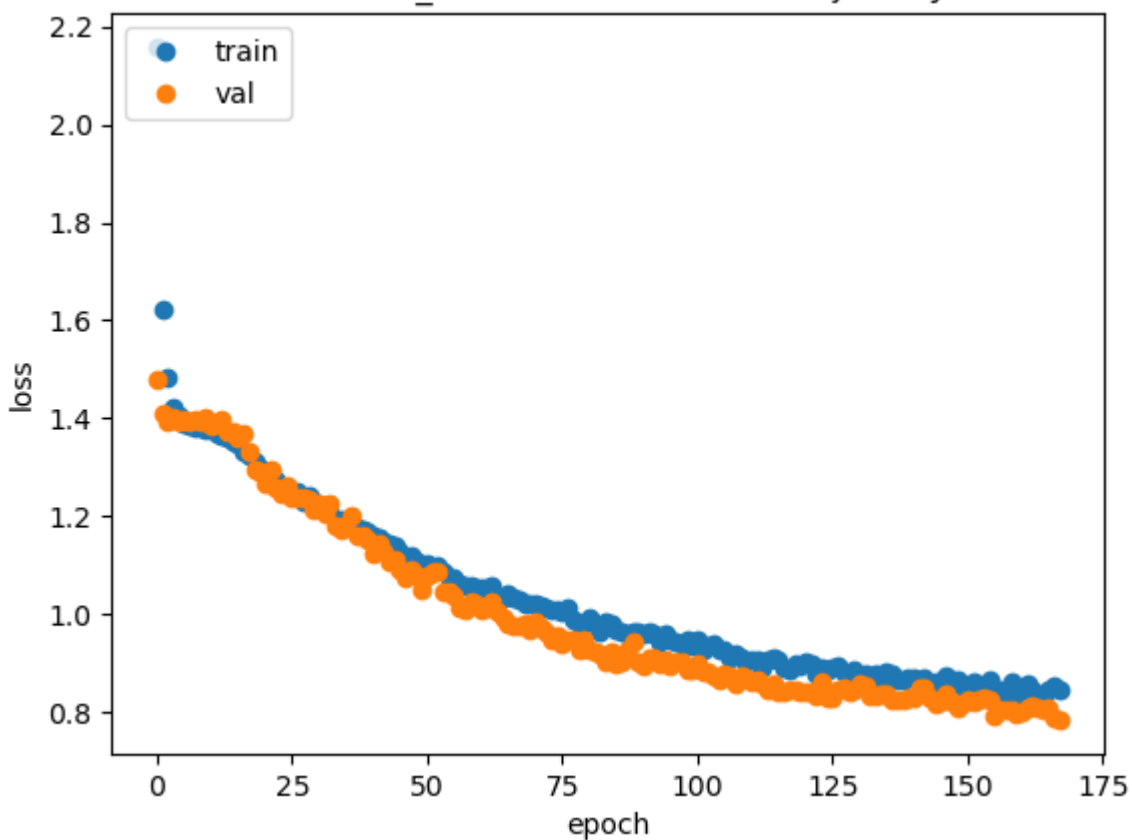
# Plotting loss trajectory
plt.plot(hybrid_cnn_lstm_model_results.history['loss'], 'o')
plt.plot(hybrid_cnn_lstm_model_results.history['val_loss'], 'o')
plt.title('CNN-Self_attention model loss trajectory')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```



CNN-Self\_attention model accuracy trajectory



CNN-Self\_attention model loss trajectory



## (vii)(CNN-Self-Attention) Testing the performance of the hybrid CNN-Self-Attention model on the held out test set

```
In [ ]: ## Testing the hybrid CNN-LSTM model

hybrid_cnn_lstm_score = hybrid_cnn_lstm_model.evaluate(x_test, y_test, verbose=0)
print('Test accuracy of the hybrid CNN-attention model:', hybrid_cnn_lstm_score)

Test accuracy of the hybrid CNN-attention model: 0.6805869340896606
```

```
In [ ]:
```