## Train

## December 11, 2023

```
[]: PATH = '../Dataset_GISLR/asl-signs/'
     PROCESSED_OUTPUT_PATH = './Dataset_GISLR_Processed/'
     MODEL_VERSION = 'high-perform-test'
     save low performers = True
     save_high_performers = False
[]: import cv2
     import numpy as np
     import pandas as pd
     from PIL import Image
     from ipywidgets import interact, interactive, fixed, interact_manual
     import ipywidgets as widgets
     import mediapipe as mp
     from mediapipe.framework.formats import landmark_pb2
     mp_drawing = mp.solutions.drawing_utils
     mp drawing styles = mp.solutions.drawing styles
     mp_holistic = mp.solutions.holistic
     import numpy as np
     import matplotlib.pyplot as plt
     import math
     import json
     import os
     from sklearn.model_selection import train_test_split
     from tensorflow.keras.utils import to_categorical
     from tensorflow.keras.models import Sequential
     from keras.layers import LSTM, Dense, Dropout, BatchNormalization
     from tensorflow.keras.callbacks import TensorBoard
     from keras.optimizers import Adam
     from keras.callbacks import EarlyStopping, ReduceLROnPlateau
     from tensorflow.keras.mixed_precision import set_global_policy
     import matplotlib.pyplot as plt
     import pandas as pd
     from sklearn.metrics import classification_report
```

import numpy as np

```
⇒f1_score, mean_squared_error, mean_absolute_error
2023-12-02 08:37:44.380617: E
tensorflow/compiler/xla/stream_executor/cuda/cuda_dnn.cc:9342] Unable to
register cuDNN factory: Attempting to register factory for plugin cuDNN when one
has already been registered
2023-12-02 08:37:44.380665: E
tensorflow/compiler/xla/stream_executor/cuda/cuda_fft.cc:609] Unable to register
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
2023-12-02 08:37:44.380683: E
tensorflow/compiler/xla/stream_executor/cuda/cuda_blas.cc:1518] Unable to
register cuBLAS factory: Attempting to register factory for plugin cuBLAS when
one has already been registered
2023-12-02 08:37:44.385081: I tensorflow/core/platform/cpu_feature_guard.cc:182]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild
TensorFlow with the appropriate compiler flags.
/usr/lib/python3/dist-packages/scipy/__init__.py:146: UserWarning: A NumPy
version >=1.17.3 and <1.25.0 is required for this version of SciPy (detected
version 1.26.2
 warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

from sklearn.metrics import accuracy\_score, precision\_score, recall\_score,

Load the Labels from the PreProcessed Data. Optionally filter out labels to remove any identified low performing labels.

```
[]: signs_to_train = [name for name in os.listdir(PROCESSED_OUTPUT_PATH) if os.path.
      →isdir(os.path.join(PROCESSED_OUTPUT_PATH, name))]
     low_performing_labels_file_path = 'low_performing_labels.npy'
     low performing labels = np.array([])
     if os.path.exists(low_performing_labels_file_path):
         low_performing_labels = np.load(low_performing_labels_file_path,__
     →allow_pickle=True)
     print(len(low_performing_labels))
     high performing labels file path = 'high performing labels.npy'
     high_performing_labels = np.array([])
     if os.path.exists(high_performing_labels_file_path):
         high_performing_labels = np.load(high_performing_labels_file_path,_
     →allow_pickle=True)
     print(len(high_performing_labels))
     # remove low performing labels from signs_to_train
     signs_to_train = [x for x in signs_to_train if x not in low_performing_labels]
     print(len(signs_to_train))
```

```
# remove all non high performers
     if (len(high_performing_labels) > 0):
         signs_to_train = [x for x in signs_to_train if x in high_performing_labels]
         print(len(signs_to_train))
     signs_to_train.sort()
     actions = np.array(signs_to_train)
     print(actions)
    197
    53
    ['aunt' 'bird' 'black' 'brother' 'brown' 'bug' 'callonphone' 'cheek'
     'clown' 'cow' 'cute' 'dad' 'doll' 'donkey' 'drink' 'ear' 'eye' 'feet'
     'find' 'fireman' 'flower' 'for' 'frog' 'grandpa' 'grass' 'gum' 'hair'
     'hen' 'home' 'horse' 'lamp' 'mad' 'mom' 'mouse' 'nose' 'owl' 'pig'
     'police' 'radio' 'see' 'shhh' 'shirt' 'sick' 'stairs' 'stuck' 'taste'
     'thirsty' 'tiger' 'uncle' 'water' 'who' 'yucky' 'zebra']
    Load all of the pre processed data
[]: label_map = {label:num for num, label in enumerate(actions)}
     sequences, labels = [], []
     for label_folder in os.listdir(PROCESSED_OUTPUT_PATH):
         label = label folder # Use the folder name as the label
         if (label not in signs_to_train):
             continue
         if (label in low_performing_labels):
             print("Skipping label: ", label)
             continue
         label_folder_path = os.path.join(PROCESSED_OUTPUT_PATH, label_folder)
         # Iterate through the files in the label folder (each file is a sequence)
         for sequence_file in os.listdir(label_folder_path):
             if sequence_file.endswith('.npy'):
                 # Load the sequence from the file
                 sequence = np.load(os.path.join(label_folder_path, sequence_file))
                 # Append the sequence and label to the respective lists
                 sequences.append(sequence)
                 labels.append(label_map[label])
[]: X = np.array(sequences)
     print(X.shape)
```

```
[]: y = to_categorical(labels).astype(int)
     print(y.shape)
    (13288, 53)
    Test train split all of the data
[]: # First, split the data into training and a combined validation/test set
     X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3)
                                                                                  #__
      -Adjust the test_size as needed
     # Now, split the combined validation/test set into separate validation and test
      \hookrightarrowsets
     X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5)
      →# This will split the remaining 30% into two 15% sets
[]: print(y_test.shape)
     print(y_val.shape)
     print(y_train.shape)
    (1994, 53)
    (1993, 53)
    (9301, 53)
    Replace all nan else the model will not train correctly
[]: # Check for NaN values in the datasets
     print(f"NaNs in X_train: {np.isnan(X_train).any()}, NaNs in y_train: {np.

sisnan(y_train).any()}")
     print(f"NaNs in X_val: {np.isnan(X_val).any()}, NaNs in y_val: {np.isnan(y_val).
     print(f"NaNs in X_test: {np.isnan(X_test).any()}, NaNs in y_test: {np.

sisnan(y_test).any()}")
     # Replace NaN values in the datasets
     X_train = np.nan_to_num(X_train)
     y_train = np.nan_to_num(y_train)
     X_val = np.nan_to_num(X_val)
     y_val = np.nan_to_num(y_val)
     X_test = np.nan_to_num(X_test)
     y_test = np.nan_to_num(y_test)
    NaNs in X_train: True, NaNs in y_train: False
    NaNs in X_val: True, NaNs in y_val: False
    NaNs in X_test: True, NaNs in y_test: False
    Build the model WIP
```

(13288, 10, 1662)

```
[]: # v1
     # model = Sequential()
     # model.add(LSTM(64, return_sequences=True, activation='relu',_
     \hookrightarrow input\_shape=(10, 1662)))
     # model.add(LSTM(128, return_sequences=True, activation='relu'))
     # model.add(LSTM(64, return_sequences=False, activation='relu'))
     # model.add(Dense(64, activation='relu'))
     # model.add(Dense(32, activation='relu'))
     # model.add(Dense(actions.shape[0], activation='softmax'))
     # model.compile(optimizer='Adam', loss='categorical_crossentropy',_
      →metrics=['categorical_accuracy'])
     frame length = 1662
     num_classes = actions.shape[0]
     # v2
     model = Sequential()
     model.add(LSTM(128, return_sequences=True, activation='relu', input_shape=(10, u
      →frame_length)))
     model.add(Dropout(0.2))
     model.add(BatchNormalization())
     model.add(LSTM(256, return_sequences=False, activation='relu'))
     model.add(Dropout(0.2))
     model.add(Dense(128, activation='relu'))
     model.add(Dropout(0.2))
     model.add(Dense(num_classes, activation='softmax'))
     # Optimizer with Gradient Clipping
     # optimizer = Adam(learning_rate=0.0001, clipvalue=0.5) # Adjust learning rate_u
      ⇔and clipvalue as needed
     optimizer = Adam(learning_rate=0.001)
     # Compile the model
     model.compile(optimizer=optimizer, loss='categorical_crossentropy', __
      →metrics=['accuracy'])
     # Callbacks
     early_stopping = EarlyStopping(monitor='val_loss', patience=100, verbose=1, __
      →mode='min')
     reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=25,_
      ⇔verbose=1, mode='min', min_lr=0.00001)
```

WARNING:tensorflow:Layer lstm will not use cuDNN kernels since it doesn't meet the criteria. It will use a generic GPU kernel as fallback when running on GPU.

2023-12-02 08:37:54.430084: I tensorflow/compiler/xla/stream\_executor/cuda/cuda\_gpu\_executor.cc:880] could not

open file to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa\_node Your kernel may have been built without NUMA support.

2023-12-02 08:37:54.432988: I

tensorflow/compiler/xla/stream\_executor/cuda/cuda\_gpu\_executor.cc:880] could not open file to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa\_node

Your kernel may have been built without NUMA support.

2023-12-02 08:37:54.433036: I

tensorflow/compiler/xla/stream\_executor/cuda/cuda\_gpu\_executor.cc:880] could not open file to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa\_node Your kernel may have been built without NUMA support.

2023-12-02 08:37:54.434702: I

tensorflow/compiler/xla/stream\_executor/cuda/cuda\_gpu\_executor.cc:880] could not open file to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa\_node Your kernel may have been built without NUMA support.

2023-12-02 08:37:54.434736: I

tensorflow/compiler/xla/stream\_executor/cuda/cuda\_gpu\_executor.cc:880] could not open file to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa\_node Your kernel may have been built without NUMA support.

2023-12-02 08:37:54.434757: I

tensorflow/compiler/xla/stream\_executor/cuda/cuda\_gpu\_executor.cc:880] could not open file to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa\_node Your kernel may have been built without NUMA support.

2023-12-02 08:37:54.719876: I

tensorflow/compiler/xla/stream\_executor/cuda/cuda\_gpu\_executor.cc:880] could not open file to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa\_node Your kernel may have been built without NUMA support.

2023-12-02 08:37:54.719921: I

tensorflow/compiler/xla/stream\_executor/cuda/cuda\_gpu\_executor.cc:880] could not open file to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa\_node Your kernel may have been built without NUMA support.

2023-12-02 08:37:54.719929: I

tensorflow/core/common\_runtime/gpu/gpu\_device.cc:1977] Could not identify NUMA node of platform GPU id 0, defaulting to 0. Your kernel may not have been built with NUMA support.

2023-12-02 08:37:54.719956: I

tensorflow/compiler/xla/stream\_executor/cuda/cuda\_gpu\_executor.cc:880] could not open file to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa\_node Your kernel may have been built without NUMA support.

2023-12-02 08:37:54.719971: I

tensorflow/core/common\_runtime/gpu/gpu\_device.cc:1886] Created device
/job:localhost/replica:0/task:0/device:GPU:0 with 21472 MB memory: -> device:
0, name: NVIDIA GeForce RTX 4090, pci bus id: 0000:01:00.0, compute capability:
8.9

2023-12-02 08:37:55.285017: I tensorflow/tsl/platform/default/subprocess.cc:304] Start cannot spawn child process: No such file or directory

WARNING:tensorflow:Layer lstm\_1 will not use cuDNN kernels since it doesn't meet the criteria. It will use a generic GPU kernel as fallback when running on GPU.

## Train the model

```
[]: # Enable mixed precision
    set_global_policy('mixed_float16')
    epochs = 1000 # Adjust number of epochs as needed
    batch_size = 1024
    history = model.fit(
       X_train, y_train,
        epochs=epochs,
       batch_size=batch_size,
       validation data=(X val, y val),
        callbacks=[early_stopping, reduce_lr]
    )
   INFO:tensorflow:Mixed precision compatibility check (mixed float16): OK
   Your GPU will likely run quickly with dtype policy mixed_float16 as it has
   compute capability of at least 7.0. Your GPU: NVIDIA GeForce RTX 4090, compute
   capability 8.9
   2023-12-02 08:37:55.529626: I
   tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor.cc:880] could not
   open file to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa node
   Your kernel may have been built without NUMA support.
   Epoch 1/1000
   2023-12-02 08:38:00.429825: I tensorflow/compiler/xla/service/service.cc:168]
   XLA service 0x7fb908296f30 initialized for platform CUDA (this does not
   guarantee that XLA will be used). Devices:
   2023-12-02 08:38:00.429869: I tensorflow/compiler/xla/service/service.cc:176]
   StreamExecutor device (0): NVIDIA GeForce RTX 4090, Compute Capability 8.9
   2023-12-02 08:38:00.434596: I
   tensorflow/compiler/mlir/tensorflow/utils/dump mlir util.cc:269] disabling MLIR
   crash reproducer, set env var `MLIR_CRASH_REPRODUCER_DIRECTORY` to enable.
   2023-12-02 08:38:00.449839: I
   tensorflow/compiler/xla/stream_executor/cuda/cuda_dnn.cc:442] Loaded cuDNN
   version 8700
   2023-12-02 08:38:00.518010: I ./tensorflow/compiler/jit/device_compiler.h:186]
   Compiled cluster using XLA! This line is logged at most once for the lifetime
   of the process.
   accuracy: 0.0229 - val_loss: 3.9901 - val_accuracy: 0.0311 - lr: 0.0010
   Epoch 2/1000
   0.0342 - val_loss: 3.9989 - val_accuracy: 0.0216 - lr: 0.0010
   Epoch 3/1000
```

```
0.0483 - val_loss: 4.0058 - val_accuracy: 0.0211 - lr: 0.0010
Epoch 4/1000
0.0654 - val_loss: 3.9937 - val_accuracy: 0.0321 - lr: 0.0010
Epoch 5/1000
0.0840 - val_loss: 3.7521 - val_accuracy: 0.0396 - lr: 0.0010
Epoch 6/1000
0.1028 - val_loss: 3.7308 - val_accuracy: 0.0447 - lr: 0.0010
Epoch 7/1000
0.1229 - val_loss: 3.6293 - val_accuracy: 0.0542 - lr: 0.0010
Epoch 8/1000
0.1404 - val_loss: 3.5763 - val_accuracy: 0.0833 - lr: 0.0010
Epoch 9/1000
0.1584 - val_loss: 3.5610 - val_accuracy: 0.0758 - lr: 0.0010
Epoch 10/1000
0.1866 - val_loss: 3.4611 - val_accuracy: 0.0682 - lr: 0.0010
Epoch 11/1000
0.2046 - val_loss: 3.6399 - val_accuracy: 0.0702 - lr: 0.0010
Epoch 12/1000
0.2120 - val_loss: 3.4201 - val_accuracy: 0.0838 - lr: 0.0010
Epoch 13/1000
0.2437 - val_loss: 4.9064 - val_accuracy: 0.0592 - lr: 0.0010
Epoch 14/1000
0.2666 - val_loss: 3.5530 - val_accuracy: 0.0828 - lr: 0.0010
Epoch 15/1000
0.2720 - val_loss: 3.1892 - val_accuracy: 0.1445 - lr: 0.0010
Epoch 16/1000
0.2949 - val_loss: 3.5145 - val_accuracy: 0.0948 - lr: 0.0010
Epoch 17/1000
0.3104 - val_loss: 4.0417 - val_accuracy: 0.0462 - lr: 0.0010
Epoch 18/1000
0.3257 - val_loss: 3.4919 - val_accuracy: 0.0973 - lr: 0.0010
Epoch 19/1000
```

```
0.3410 - val_loss: 3.4911 - val_accuracy: 0.0768 - lr: 0.0010
Epoch 20/1000
0.3528 - val_loss: 4.7066 - val_accuracy: 0.0622 - lr: 0.0010
Epoch 21/1000
0.3792 - val_loss: 3.6192 - val_accuracy: 0.0973 - lr: 0.0010
Epoch 22/1000
0.3858 - val_loss: 4.0382 - val_accuracy: 0.0853 - lr: 0.0010
Epoch 23/1000
10/10 [============ ] - 1s 92ms/step - loss: 2.0182 - accuracy:
0.3997 - val_loss: 3.4984 - val_accuracy: 0.1209 - lr: 0.0010
Epoch 24/1000
0.4036 - val_loss: 3.6899 - val_accuracy: 0.0993 - lr: 0.0010
Epoch 25/1000
0.4255 - val_loss: 4.0941 - val_accuracy: 0.0768 - lr: 0.0010
Epoch 26/1000
0.4374 - val_loss: 6.8642 - val_accuracy: 0.0336 - lr: 0.0010
Epoch 27/1000
0.4295 - val_loss: 4.4013 - val_accuracy: 0.0587 - lr: 0.0010
Epoch 28/1000
0.4539 - val_loss: 3.5164 - val_accuracy: 0.0848 - lr: 0.0010
Epoch 29/1000
0.4513 - val_loss: 5.1641 - val_accuracy: 0.0467 - lr: 0.0010
Epoch 30/1000
0.4467 - val_loss: 3.1058 - val_accuracy: 0.1681 - lr: 0.0010
Epoch 31/1000
0.4711 - val_loss: 3.5024 - val_accuracy: 0.1706 - lr: 0.0010
Epoch 32/1000
0.4883 - val_loss: 12.4740 - val_accuracy: 0.0426 - lr: 0.0010
Epoch 33/1000
10/10 [============ ] - 1s 71ms/step - loss: 1.7424 - accuracy:
0.4862 - val_loss: 6.0236 - val_accuracy: 0.0748 - lr: 0.0010
Epoch 34/1000
0.4940 - val_loss: 4.4060 - val_accuracy: 0.1099 - lr: 0.0010
Epoch 35/1000
```

```
0.5054 - val_loss: 4.4375 - val_accuracy: 0.0898 - lr: 0.0010
Epoch 36/1000
0.5122 - val_loss: 3.5053 - val_accuracy: 0.1676 - lr: 0.0010
Epoch 37/1000
0.5228 - val_loss: 4.3137 - val_accuracy: 0.1199 - lr: 0.0010
Epoch 38/1000
0.5409 - val_loss: 3.9728 - val_accuracy: 0.1385 - lr: 0.0010
Epoch 39/1000
0.5285 - val_loss: 2.1798 - val_accuracy: 0.3683 - lr: 0.0010
Epoch 40/1000
0.5376 - val_loss: 2.8181 - val_accuracy: 0.2353 - lr: 0.0010
Epoch 41/1000
0.5511 - val_loss: 4.3897 - val_accuracy: 0.1867 - lr: 0.0010
Epoch 42/1000
0.5661 - val_loss: 4.1782 - val_accuracy: 0.1194 - lr: 0.0010
Epoch 43/1000
0.5706 - val_loss: 4.1497 - val_accuracy: 0.1530 - lr: 0.0010
Epoch 44/1000
0.5863 - val_loss: 2.0730 - val_accuracy: 0.4155 - lr: 0.0010
0.5947 - val_loss: 3.1523 - val_accuracy: 0.2358 - lr: 0.0010
Epoch 46/1000
0.5823 - val_loss: 4.4175 - val_accuracy: 0.1661 - lr: 0.0010
Epoch 47/1000
0.5719 - val_loss: 2.6768 - val_accuracy: 0.3111 - lr: 0.0010
Epoch 48/1000
0.5797 - val_loss: 2.1476 - val_accuracy: 0.3859 - lr: 0.0010
Epoch 49/1000
10/10 [============= ] - 1s 72ms/step - loss: 1.2942 - accuracy:
0.6074 - val_loss: 2.2993 - val_accuracy: 0.3457 - lr: 0.0010
Epoch 50/1000
0.6066 - val_loss: 2.5976 - val_accuracy: 0.3773 - lr: 0.0010
Epoch 51/1000
```

```
0.6214 - val_loss: 2.8531 - val_accuracy: 0.3281 - lr: 0.0010
Epoch 52/1000
0.6214 - val_loss: 2.5329 - val_accuracy: 0.3994 - lr: 0.0010
Epoch 53/1000
0.6227 - val_loss: 4.4819 - val_accuracy: 0.1977 - lr: 0.0010
Epoch 54/1000
0.6158 - val_loss: 3.1625 - val_accuracy: 0.2704 - lr: 0.0010
Epoch 55/1000
10/10 [============= ] - 1s 74ms/step - loss: 1.2232 - accuracy:
0.6283 - val_loss: 4.4479 - val_accuracy: 0.1656 - lr: 0.0010
Epoch 56/1000
0.6313 - val_loss: 3.3525 - val_accuracy: 0.2263 - lr: 0.0010
Epoch 57/1000
0.6277 - val_loss: 2.3473 - val_accuracy: 0.3552 - lr: 0.0010
Epoch 58/1000
0.6386 - val_loss: 4.1074 - val_accuracy: 0.1621 - lr: 0.0010
Epoch 59/1000
0.6334 - val_loss: 2.6640 - val_accuracy: 0.3382 - lr: 0.0010
Epoch 60/1000
0.6423 - val_loss: 2.1666 - val_accuracy: 0.3828 - lr: 0.0010
0.6421 - val_loss: 2.5516 - val_accuracy: 0.3387 - lr: 0.0010
Epoch 62/1000
0.6549 - val_loss: 2.8114 - val_accuracy: 0.3056 - lr: 0.0010
Epoch 63/1000
0.6605 - val_loss: 2.3602 - val_accuracy: 0.3723 - lr: 0.0010
Epoch 64/1000
0.6586 - val_loss: 2.3414 - val_accuracy: 0.3904 - lr: 0.0010
Epoch 65/1000
0.6768 - val_loss: 1.9748 - val_accuracy: 0.4596 - lr: 0.0010
Epoch 66/1000
0.6753 - val_loss: 3.4216 - val_accuracy: 0.2679 - lr: 0.0010
Epoch 67/1000
```

```
0.6795 - val_loss: 6.3611 - val_accuracy: 0.1445 - lr: 0.0010
Epoch 68/1000
0.6914 - val_loss: 2.8259 - val_accuracy: 0.3583 - lr: 0.0010
Epoch 69/1000
0.6953 - val_loss: 4.2136 - val_accuracy: 0.2303 - lr: 0.0010
Epoch 70/1000
0.6940 - val_loss: 2.2607 - val_accuracy: 0.4596 - lr: 0.0010
Epoch 71/1000
0.6864 - val_loss: 3.1059 - val_accuracy: 0.2840 - lr: 0.0010
Epoch 72/1000
0.6798 - val_loss: 6.2830 - val_accuracy: 0.1189 - lr: 0.0010
Epoch 73/1000
0.6884 - val_loss: 2.7543 - val_accuracy: 0.4104 - lr: 0.0010
Epoch 74/1000
0.6901 - val_loss: 3.5821 - val_accuracy: 0.2935 - lr: 0.0010
Epoch 75/1000
0.7013 - val_loss: 4.3199 - val_accuracy: 0.2283 - lr: 0.0010
Epoch 76/1000
0.6930 - val_loss: 2.5538 - val_accuracy: 0.4134 - lr: 0.0010
Epoch 77/1000
0.7139 - val_loss: 2.2958 - val_accuracy: 0.4541 - lr: 0.0010
Epoch 78/1000
0.7135 - val_loss: 3.3550 - val_accuracy: 0.3557 - lr: 0.0010
Epoch 79/1000
0.7111 - val_loss: 2.4026 - val_accuracy: 0.4134 - lr: 0.0010
Epoch 80/1000
0.6870 - val_loss: 3.5296 - val_accuracy: 0.2393 - lr: 0.0010
Epoch 81/1000
10/10 [============= ] - 1s 81ms/step - loss: 1.0288 - accuracy:
0.6873 - val_loss: 3.0178 - val_accuracy: 0.3377 - lr: 0.0010
Epoch 82/1000
10/10 [============= ] - 1s 76ms/step - loss: 0.9726 - accuracy:
0.7048 - val_loss: 2.3653 - val_accuracy: 0.3954 - lr: 0.0010
Epoch 83/1000
```

```
0.7166 - val_loss: 2.9368 - val_accuracy: 0.3402 - lr: 0.0010
Epoch 84/1000
0.7195 - val_loss: 4.0249 - val_accuracy: 0.2659 - lr: 0.0010
Epoch 85/1000
0.7159 - val_loss: 5.8567 - val_accuracy: 0.1641 - lr: 0.0010
Epoch 86/1000
0.7099 - val_loss: 3.9650 - val_accuracy: 0.3136 - lr: 0.0010
Epoch 87/1000
10/10 [============ ] - 1s 83ms/step - loss: 0.9080 - accuracy:
0.7220 - val_loss: 3.6757 - val_accuracy: 0.4205 - lr: 0.0010
Epoch 88/1000
0.7185 - val_loss: 2.6092 - val_accuracy: 0.3964 - lr: 0.0010
Epoch 89/1000
0.7409 - val_loss: 3.1556 - val_accuracy: 0.3823 - lr: 0.0010
Epoch 90/1000
0.7431
Epoch 90: ReduceLROnPlateau reducing learning rate to 0.00050000000237487257.
0.7431 - val_loss: 2.8203 - val_accuracy: 0.3813 - lr: 0.0010
Epoch 91/1000
0.7291 - val_loss: 1.7801 - val_accuracy: 0.5178 - lr: 5.0000e-04
0.7485 - val_loss: 2.0921 - val_accuracy: 0.5043 - lr: 5.0000e-04
Epoch 93/1000
0.7660 - val_loss: 1.5526 - val_accuracy: 0.5951 - lr: 5.0000e-04
Epoch 94/1000
0.7691 - val_loss: 2.0692 - val_accuracy: 0.4972 - lr: 5.0000e-04
Epoch 95/1000
0.7707 - val_loss: 1.8038 - val_accuracy: 0.5640 - lr: 5.0000e-04
Epoch 96/1000
10/10 [============= ] - 1s 85ms/step - loss: 0.7413 - accuracy:
0.7705 - val_loss: 2.0722 - val_accuracy: 0.5253 - lr: 5.0000e-04
Epoch 97/1000
0.7784 - val_loss: 1.7349 - val_accuracy: 0.5730 - lr: 5.0000e-04
Epoch 98/1000
```

```
0.7716 - val_loss: 1.7426 - val_accuracy: 0.5615 - lr: 5.0000e-04
Epoch 99/1000
0.7792 - val_loss: 1.5014 - val_accuracy: 0.6237 - lr: 5.0000e-04
Epoch 100/1000
0.7758 - val_loss: 2.2792 - val_accuracy: 0.4536 - lr: 5.0000e-04
Epoch 101/1000
0.7723 - val_loss: 2.4033 - val_accuracy: 0.4681 - lr: 5.0000e-04
Epoch 102/1000
0.7726 - val_loss: 1.9451 - val_accuracy: 0.5304 - lr: 5.0000e-04
Epoch 103/1000
10/10 [============= ] - 1s 81ms/step - loss: 0.7327 - accuracy:
0.7765 - val_loss: 1.8414 - val_accuracy: 0.5745 - lr: 5.0000e-04
Epoch 104/1000
0.7814 - val_loss: 2.1518 - val_accuracy: 0.4867 - lr: 5.0000e-04
Epoch 105/1000
0.7880 - val_loss: 1.4173 - val_accuracy: 0.6563 - lr: 5.0000e-04
Epoch 106/1000
0.7851 - val_loss: 1.9284 - val_accuracy: 0.5354 - lr: 5.0000e-04
Epoch 107/1000
0.7842 - val_loss: 1.8459 - val_accuracy: 0.5840 - lr: 5.0000e-04
0.7801 - val_loss: 1.6991 - val_accuracy: 0.5911 - lr: 5.0000e-04
Epoch 109/1000
0.7844 - val_loss: 1.6777 - val_accuracy: 0.5911 - lr: 5.0000e-04
Epoch 110/1000
0.7829 - val loss: 1.5008 - val accuracy: 0.6197 - lr: 5.0000e-04
Epoch 111/1000
0.7814 - val_loss: 3.5267 - val_accuracy: 0.3879 - lr: 5.0000e-04
Epoch 112/1000
10/10 [============= ] - 1s 84ms/step - loss: 0.7030 - accuracy:
0.7835 - val_loss: 2.3600 - val_accuracy: 0.4812 - lr: 5.0000e-04
Epoch 113/1000
0.7946 - val_loss: 1.4935 - val_accuracy: 0.6523 - lr: 5.0000e-04
Epoch 114/1000
```

```
0.7929 - val_loss: 2.7850 - val_accuracy: 0.4250 - lr: 5.0000e-04
Epoch 115/1000
0.7941 - val_loss: 2.2523 - val_accuracy: 0.4867 - lr: 5.0000e-04
Epoch 116/1000
0.7924 - val_loss: 2.0229 - val_accuracy: 0.5710 - lr: 5.0000e-04
Epoch 117/1000
0.7646 - val_loss: 3.8095 - val_accuracy: 0.3823 - lr: 5.0000e-04
Epoch 118/1000
0.7767 - val_loss: 2.5434 - val_accuracy: 0.4501 - lr: 5.0000e-04
Epoch 119/1000
0.7926 - val_loss: 1.7208 - val_accuracy: 0.5850 - lr: 5.0000e-04
Epoch 120/1000
0.7991 - val_loss: 1.8456 - val_accuracy: 0.5524 - lr: 5.0000e-04
Epoch 121/1000
0.8044 - val_loss: 1.6371 - val_accuracy: 0.6152 - lr: 5.0000e-04
Epoch 122/1000
0.8003 - val_loss: 2.4097 - val_accuracy: 0.4676 - lr: 5.0000e-04
Epoch 123/1000
0.8029 - val_loss: 1.6785 - val_accuracy: 0.6036 - lr: 5.0000e-04
Epoch 124/1000
0.8114 - val_loss: 1.6146 - val_accuracy: 0.6061 - lr: 5.0000e-04
Epoch 125/1000
0.7995 - val_loss: 2.8770 - val_accuracy: 0.4240 - lr: 5.0000e-04
Epoch 126/1000
0.7760 - val_loss: 2.5048 - val_accuracy: 0.4431 - lr: 5.0000e-04
Epoch 127/1000
0.7797 - val_loss: 3.1209 - val_accuracy: 0.3909 - lr: 5.0000e-04
Epoch 128/1000
0.7978 - val_loss: 1.7914 - val_accuracy: 0.5936 - lr: 5.0000e-04
Epoch 129/1000
0.8049 - val_loss: 1.7354 - val_accuracy: 0.5896 - lr: 5.0000e-04
Epoch 130/1000
10/10 [============== ] - ETA: Os - loss: 0.6317 - accuracy:
```

```
0.8068
Epoch 130: ReduceLROnPlateau reducing learning rate to 0.0002500000118743628.
0.8068 - val_loss: 1.7700 - val_accuracy: 0.6046 - lr: 5.0000e-04
Epoch 131/1000
0.8224 - val_loss: 1.5718 - val_accuracy: 0.6006 - lr: 2.5000e-04
Epoch 132/1000
0.8252 - val_loss: 1.4502 - val_accuracy: 0.6548 - lr: 2.5000e-04
Epoch 133/1000
0.8254 - val_loss: 1.3111 - val_accuracy: 0.7030 - lr: 2.5000e-04
Epoch 134/1000
10/10 [============ ] - 1s 79ms/step - loss: 0.5627 - accuracy:
0.8293 - val_loss: 1.6107 - val_accuracy: 0.6152 - lr: 2.5000e-04
Epoch 135/1000
0.8294 - val_loss: 1.5372 - val_accuracy: 0.6543 - lr: 2.5000e-04
Epoch 136/1000
0.8270 - val_loss: 1.3902 - val_accuracy: 0.6839 - lr: 2.5000e-04
Epoch 137/1000
0.8222 - val_loss: 1.4410 - val_accuracy: 0.6729 - lr: 2.5000e-04
Epoch 138/1000
0.8297 - val_loss: 1.4287 - val_accuracy: 0.6959 - lr: 2.5000e-04
Epoch 139/1000
0.8369 - val_loss: 1.4379 - val_accuracy: 0.6864 - lr: 2.5000e-04
Epoch 140/1000
0.8380 - val_loss: 1.4818 - val_accuracy: 0.6713 - lr: 2.5000e-04
Epoch 141/1000
0.8308 - val_loss: 1.6933 - val_accuracy: 0.6272 - lr: 2.5000e-04
Epoch 142/1000
0.8342 - val_loss: 1.8863 - val_accuracy: 0.5921 - lr: 2.5000e-04
Epoch 143/1000
10/10 [============ ] - 1s 72ms/step - loss: 0.5504 - accuracy:
0.8336 - val_loss: 1.2888 - val_accuracy: 0.7195 - lr: 2.5000e-04
Epoch 144/1000
0.8327 - val_loss: 1.8144 - val_accuracy: 0.6187 - lr: 2.5000e-04
Epoch 145/1000
```

```
0.8368 - val_loss: 1.2976 - val_accuracy: 0.7045 - lr: 2.5000e-04
Epoch 146/1000
0.8309 - val_loss: 1.6727 - val_accuracy: 0.6372 - lr: 2.5000e-04
Epoch 147/1000
0.8436 - val_loss: 1.5105 - val_accuracy: 0.6834 - lr: 2.5000e-04
Epoch 148/1000
0.8477 - val_loss: 1.4269 - val_accuracy: 0.7015 - lr: 2.5000e-04
Epoch 149/1000
0.8417 - val_loss: 1.5292 - val_accuracy: 0.6618 - lr: 2.5000e-04
Epoch 150/1000
10/10 [============= ] - 1s 89ms/step - loss: 0.5245 - accuracy:
0.8402 - val_loss: 2.0989 - val_accuracy: 0.5815 - lr: 2.5000e-04
Epoch 151/1000
0.8395 - val_loss: 1.8333 - val_accuracy: 0.6267 - lr: 2.5000e-04
Epoch 152/1000
0.8330 - val_loss: 2.3368 - val_accuracy: 0.5263 - 1r: 2.5000e-04
Epoch 153/1000
0.8335 - val_loss: 2.5298 - val_accuracy: 0.5309 - lr: 2.5000e-04
Epoch 154/1000
0.8373 - val_loss: 1.2990 - val_accuracy: 0.7175 - lr: 2.5000e-04
Epoch 155/1000
0.8393 - val_loss: 1.4652 - val_accuracy: 0.6949 - lr: 2.5000e-04
Epoch 156/1000
0.8477 - val_loss: 1.3322 - val_accuracy: 0.7180 - lr: 2.5000e-04
Epoch 157/1000
0.8389 - val_loss: 1.6873 - val_accuracy: 0.6463 - lr: 2.5000e-04
Epoch 158/1000
0.8394 - val_loss: 2.0717 - val_accuracy: 0.5750 - lr: 2.5000e-04
Epoch 159/1000
10/10 [============ ] - 1s 75ms/step - loss: 0.5362 - accuracy:
0.8321 - val_loss: 1.7989 - val_accuracy: 0.6247 - lr: 2.5000e-04
Epoch 160/1000
0.8386 - val_loss: 1.4313 - val_accuracy: 0.6994 - lr: 2.5000e-04
Epoch 161/1000
```

```
0.8389 - val_loss: 1.4663 - val_accuracy: 0.6994 - lr: 2.5000e-04
Epoch 162/1000
0.8466 - val_loss: 1.3695 - val_accuracy: 0.7210 - lr: 2.5000e-04
Epoch 163/1000
0.8468 - val_loss: 1.8780 - val_accuracy: 0.6116 - lr: 2.5000e-04
Epoch 164/1000
0.8496 - val_loss: 1.5349 - val_accuracy: 0.6663 - lr: 2.5000e-04
Epoch 165/1000
10/10 [============ ] - 1s 90ms/step - loss: 0.4979 - accuracy:
0.8414 - val_loss: 1.3911 - val_accuracy: 0.7035 - lr: 2.5000e-04
Epoch 166/1000
10/10 [============= ] - 1s 79ms/step - loss: 0.5081 - accuracy:
0.8446 - val_loss: 1.8783 - val_accuracy: 0.6402 - lr: 2.5000e-04
Epoch 167/1000
0.8416 - val_loss: 2.3452 - val_accuracy: 0.5263 - lr: 2.5000e-04
Epoch 168/1000
0.8437
Epoch 168: ReduceLROnPlateau reducing learning rate to 0.0001250000059371814.
0.8437 - val_loss: 2.1829 - val_accuracy: 0.5886 - lr: 2.5000e-04
Epoch 169/1000
0.8492 - val_loss: 1.3812 - val_accuracy: 0.6924 - lr: 1.2500e-04
Epoch 170/1000
0.8429 - val_loss: 1.5853 - val_accuracy: 0.6984 - lr: 1.2500e-04
Epoch 171/1000
0.8578 - val_loss: 1.4123 - val_accuracy: 0.7205 - lr: 1.2500e-04
Epoch 172/1000
0.8559 - val_loss: 1.3743 - val_accuracy: 0.7230 - lr: 1.2500e-04
Epoch 173/1000
0.8586 - val_loss: 1.3640 - val_accuracy: 0.7230 - lr: 1.2500e-04
Epoch 174/1000
10/10 [============ ] - 1s 73ms/step - loss: 0.4772 - accuracy:
0.8559 - val_loss: 1.2681 - val_accuracy: 0.7336 - lr: 1.2500e-04
Epoch 175/1000
10/10 [============= ] - 1s 73ms/step - loss: 0.4694 - accuracy:
0.8583 - val_loss: 1.4537 - val_accuracy: 0.6959 - lr: 1.2500e-04
Epoch 176/1000
```

```
0.8523 - val_loss: 1.2918 - val_accuracy: 0.7416 - lr: 1.2500e-04
Epoch 177/1000
0.8585 - val_loss: 1.4493 - val_accuracy: 0.6954 - lr: 1.2500e-04
Epoch 178/1000
0.8583 - val_loss: 1.3686 - val_accuracy: 0.7316 - lr: 1.2500e-04
Epoch 179/1000
0.8552 - val_loss: 1.2498 - val_accuracy: 0.7456 - lr: 1.2500e-04
Epoch 180/1000
0.8631 - val_loss: 1.4519 - val_accuracy: 0.7075 - lr: 1.2500e-04
Epoch 181/1000
10/10 [============= ] - 1s 75ms/step - loss: 0.4623 - accuracy:
0.8601 - val_loss: 1.4561 - val_accuracy: 0.7030 - lr: 1.2500e-04
Epoch 182/1000
0.8621 - val_loss: 1.3670 - val_accuracy: 0.7215 - lr: 1.2500e-04
Epoch 183/1000
0.8624 - val_loss: 1.3968 - val_accuracy: 0.7100 - lr: 1.2500e-04
Epoch 184/1000
0.8620 - val_loss: 1.3724 - val_accuracy: 0.7175 - lr: 1.2500e-04
Epoch 185/1000
0.8574 - val_loss: 1.5897 - val_accuracy: 0.6739 - lr: 1.2500e-04
Epoch 186/1000
0.8624 - val_loss: 1.4769 - val_accuracy: 0.7010 - lr: 1.2500e-04
Epoch 187/1000
0.8597 - val_loss: 1.3072 - val_accuracy: 0.7466 - lr: 1.2500e-04
Epoch 188/1000
0.8630 - val_loss: 1.5170 - val_accuracy: 0.6889 - lr: 1.2500e-04
Epoch 189/1000
0.8657 - val_loss: 1.2950 - val_accuracy: 0.7381 - lr: 1.2500e-04
Epoch 190/1000
10/10 [============ ] - 1s 75ms/step - loss: 0.4422 - accuracy:
0.8633 - val_loss: 1.3444 - val_accuracy: 0.7301 - lr: 1.2500e-04
Epoch 191/1000
0.8595 - val_loss: 1.3588 - val_accuracy: 0.7346 - lr: 1.2500e-04
Epoch 192/1000
```

```
0.8601 - val_loss: 1.4414 - val_accuracy: 0.7280 - lr: 1.2500e-04
Epoch 193/1000
0.8628 - val_loss: 1.4800 - val_accuracy: 0.7175 - lr: 1.2500e-04
Epoch 194/1000
0.8629 - val_loss: 1.4272 - val_accuracy: 0.7346 - lr: 1.2500e-04
Epoch 195/1000
0.8631 - val_loss: 1.4113 - val_accuracy: 0.7291 - lr: 1.2500e-04
Epoch 196/1000
0.8613 - val_loss: 1.7839 - val_accuracy: 0.6739 - lr: 1.2500e-04
Epoch 197/1000
0.8614 - val_loss: 1.6032 - val_accuracy: 0.7025 - lr: 1.2500e-04
Epoch 198/1000
0.8672 - val_loss: 1.3494 - val_accuracy: 0.7321 - lr: 1.2500e-04
Epoch 199/1000
0.8732 - val_loss: 1.4432 - val_accuracy: 0.7190 - lr: 1.2500e-04
Epoch 200/1000
0.8743 - val_loss: 1.4368 - val_accuracy: 0.7155 - lr: 1.2500e-04
Epoch 201/1000
0.8656 - val_loss: 1.3738 - val_accuracy: 0.7321 - lr: 1.2500e-04
0.8682 - val_loss: 1.4616 - val_accuracy: 0.7110 - lr: 1.2500e-04
Epoch 203/1000
0.8756 - val_loss: 1.4906 - val_accuracy: 0.7155 - lr: 1.2500e-04
Epoch 204/1000
10/10 [============== ] - ETA: Os - loss: 0.4306 - accuracy:
Epoch 204: ReduceLROnPlateau reducing learning rate to 6.25000029685907e-05.
0.8676 - val_loss: 1.3672 - val_accuracy: 0.7301 - lr: 1.2500e-04
Epoch 205/1000
10/10 [============= ] - 1s 87ms/step - loss: 0.4199 - accuracy:
0.8684 - val_loss: 1.4129 - val_accuracy: 0.7275 - lr: 6.2500e-05
Epoch 206/1000
0.8732 - val_loss: 1.3314 - val_accuracy: 0.7386 - lr: 6.2500e-05
Epoch 207/1000
```

```
0.8735 - val_loss: 1.3239 - val_accuracy: 0.7511 - lr: 6.2500e-05
Epoch 208/1000
0.8742 - val_loss: 1.3606 - val_accuracy: 0.7376 - lr: 6.2500e-05
Epoch 209/1000
0.8719 - val_loss: 1.4158 - val_accuracy: 0.7306 - lr: 6.2500e-05
Epoch 210/1000
0.8714 - val_loss: 1.2933 - val_accuracy: 0.7491 - lr: 6.2500e-05
Epoch 211/1000
0.8745 - val_loss: 1.3167 - val_accuracy: 0.7466 - lr: 6.2500e-05
Epoch 212/1000
10/10 [============ ] - 1s 83ms/step - loss: 0.4046 - accuracy:
0.8762 - val_loss: 1.3867 - val_accuracy: 0.7341 - lr: 6.2500e-05
Epoch 213/1000
0.8680 - val_loss: 1.3514 - val_accuracy: 0.7551 - lr: 6.2500e-05
Epoch 214/1000
0.8731 - val_loss: 1.3811 - val_accuracy: 0.7416 - lr: 6.2500e-05
Epoch 215/1000
0.8726 - val_loss: 1.3973 - val_accuracy: 0.7296 - lr: 6.2500e-05
Epoch 216/1000
0.8735 - val_loss: 1.4108 - val_accuracy: 0.7401 - lr: 6.2500e-05
Epoch 217/1000
0.8698 - val_loss: 1.4965 - val_accuracy: 0.7265 - lr: 6.2500e-05
Epoch 218/1000
0.8761 - val_loss: 1.3957 - val_accuracy: 0.7301 - lr: 6.2500e-05
Epoch 219/1000
0.8780 - val_loss: 1.3475 - val_accuracy: 0.7411 - lr: 6.2500e-05
Epoch 220/1000
0.8698 - val_loss: 1.3514 - val_accuracy: 0.7386 - lr: 6.2500e-05
Epoch 221/1000
10/10 [============ ] - 1s 87ms/step - loss: 0.4121 - accuracy:
0.8743 - val_loss: 1.3512 - val_accuracy: 0.7401 - lr: 6.2500e-05
Epoch 222/1000
0.8795 - val_loss: 1.3618 - val_accuracy: 0.7321 - lr: 6.2500e-05
Epoch 223/1000
```

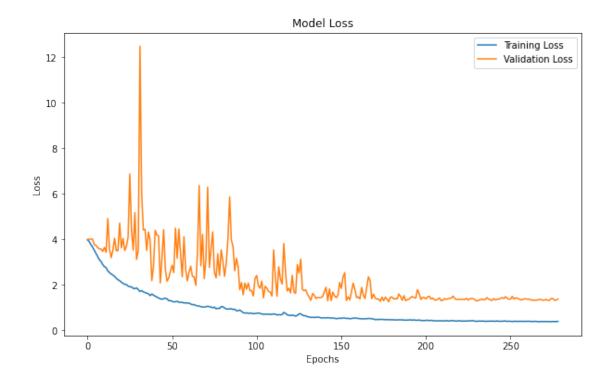
```
0.8775 - val_loss: 1.3527 - val_accuracy: 0.7456 - lr: 6.2500e-05
Epoch 224/1000
0.8786 - val_loss: 1.3443 - val_accuracy: 0.7431 - lr: 6.2500e-05
Epoch 225/1000
0.8786 - val_loss: 1.3996 - val_accuracy: 0.7275 - lr: 6.2500e-05
Epoch 226/1000
0.8704 - val_loss: 1.3261 - val_accuracy: 0.7451 - lr: 6.2500e-05
Epoch 227/1000
10/10 [============= ] - 1s 75ms/step - loss: 0.4052 - accuracy:
0.8755 - val_loss: 1.3752 - val_accuracy: 0.7391 - lr: 6.2500e-05
Epoch 228/1000
0.8722 - val_loss: 1.3983 - val_accuracy: 0.7331 - lr: 6.2500e-05
Epoch 229/1000
0.8712
Epoch 229: ReduceLROnPlateau reducing learning rate to 3.125000148429535e-05.
0.8712 - val_loss: 1.3839 - val_accuracy: 0.7291 - lr: 6.2500e-05
Epoch 230/1000
0.8804 - val_loss: 1.3327 - val_accuracy: 0.7396 - lr: 3.1250e-05
Epoch 231/1000
0.8782 - val_loss: 1.2840 - val_accuracy: 0.7471 - lr: 3.1250e-05
Epoch 232/1000
0.8780 - val_loss: 1.3074 - val_accuracy: 0.7466 - lr: 3.1250e-05
Epoch 233/1000
0.8779 - val_loss: 1.3352 - val_accuracy: 0.7456 - lr: 3.1250e-05
Epoch 234/1000
0.8736 - val_loss: 1.3660 - val_accuracy: 0.7426 - lr: 3.1250e-05
Epoch 235/1000
0.8741 - val_loss: 1.3368 - val_accuracy: 0.7471 - lr: 3.1250e-05
Epoch 236/1000
0.8823 - val_loss: 1.3433 - val_accuracy: 0.7441 - lr: 3.1250e-05
Epoch 237/1000
10/10 [============= ] - 1s 74ms/step - loss: 0.3936 - accuracy:
0.8796 - val_loss: 1.4280 - val_accuracy: 0.7376 - lr: 3.1250e-05
Epoch 238/1000
```

```
0.8783 - val_loss: 1.3677 - val_accuracy: 0.7436 - lr: 3.1250e-05
Epoch 239/1000
0.8781 - val_loss: 1.3375 - val_accuracy: 0.7466 - lr: 3.1250e-05
Epoch 240/1000
0.8781 - val_loss: 1.3056 - val_accuracy: 0.7461 - lr: 3.1250e-05
Epoch 241/1000
0.8757 - val_loss: 1.3906 - val_accuracy: 0.7331 - lr: 3.1250e-05
Epoch 242/1000
0.8817 - val_loss: 1.3279 - val_accuracy: 0.7421 - lr: 3.1250e-05
Epoch 243/1000
0.8771 - val_loss: 1.3637 - val_accuracy: 0.7351 - lr: 3.1250e-05
Epoch 244/1000
0.8812 - val_loss: 1.3565 - val_accuracy: 0.7416 - lr: 3.1250e-05
Epoch 245/1000
0.8770 - val_loss: 1.3953 - val_accuracy: 0.7516 - lr: 3.1250e-05
Epoch 246/1000
0.8799 - val_loss: 1.4296 - val_accuracy: 0.7451 - lr: 3.1250e-05
Epoch 247/1000
0.8755 - val_loss: 1.3914 - val_accuracy: 0.7456 - lr: 3.1250e-05
Epoch 248/1000
0.8785 - val_loss: 1.4735 - val_accuracy: 0.7255 - lr: 3.1250e-05
Epoch 249/1000
0.8798 - val_loss: 1.4053 - val_accuracy: 0.7386 - lr: 3.1250e-05
Epoch 250/1000
0.8789 - val_loss: 1.3613 - val_accuracy: 0.7406 - lr: 3.1250e-05
Epoch 251/1000
0.8797 - val_loss: 1.3664 - val_accuracy: 0.7481 - lr: 3.1250e-05
Epoch 252/1000
10/10 [============ ] - 1s 71ms/step - loss: 0.3759 - accuracy:
0.8860 - val_loss: 1.4851 - val_accuracy: 0.7316 - lr: 3.1250e-05
Epoch 253/1000
0.8770 - val_loss: 1.3693 - val_accuracy: 0.7436 - lr: 3.1250e-05
Epoch 254/1000
10/10 [============= ] - ETA: Os - loss: 0.3848 - accuracy:
```

```
0.8823
Epoch 254: ReduceLROnPlateau reducing learning rate to 1.5625000742147677e-05.
0.8823 - val_loss: 1.4202 - val_accuracy: 0.7265 - lr: 3.1250e-05
Epoch 255/1000
0.8774 - val_loss: 1.3991 - val_accuracy: 0.7326 - lr: 1.5625e-05
Epoch 256/1000
0.8799 - val_loss: 1.3768 - val_accuracy: 0.7441 - lr: 1.5625e-05
Epoch 257/1000
10/10 [============ ] - 1s 76ms/step - loss: 0.3909 - accuracy:
0.8783 - val_loss: 1.3264 - val_accuracy: 0.7501 - lr: 1.5625e-05
Epoch 258/1000
10/10 [============= ] - 1s 83ms/step - loss: 0.3904 - accuracy:
0.8818 - val_loss: 1.3495 - val_accuracy: 0.7436 - lr: 1.5625e-05
Epoch 259/1000
0.8818 - val_loss: 1.3734 - val_accuracy: 0.7446 - lr: 1.5625e-05
Epoch 260/1000
0.8799 - val_loss: 1.3787 - val_accuracy: 0.7451 - lr: 1.5625e-05
Epoch 261/1000
0.8825 - val_loss: 1.3607 - val_accuracy: 0.7511 - lr: 1.5625e-05
Epoch 262/1000
0.8813 - val_loss: 1.3616 - val_accuracy: 0.7496 - lr: 1.5625e-05
Epoch 263/1000
0.8804 - val_loss: 1.3331 - val_accuracy: 0.7486 - lr: 1.5625e-05
Epoch 264/1000
0.8849 - val_loss: 1.3200 - val_accuracy: 0.7481 - lr: 1.5625e-05
Epoch 265/1000
0.8780 - val_loss: 1.3150 - val_accuracy: 0.7496 - lr: 1.5625e-05
Epoch 266/1000
0.8826 - val_loss: 1.3206 - val_accuracy: 0.7461 - lr: 1.5625e-05
Epoch 267/1000
0.8853 - val_loss: 1.3267 - val_accuracy: 0.7471 - lr: 1.5625e-05
Epoch 268/1000
0.8843 - val_loss: 1.3497 - val_accuracy: 0.7451 - lr: 1.5625e-05
Epoch 269/1000
```

```
Epoch 270/1000
  0.8833 - val_loss: 1.3188 - val_accuracy: 0.7481 - lr: 1.5625e-05
  Epoch 271/1000
  0.8830 - val_loss: 1.3173 - val_accuracy: 0.7491 - lr: 1.5625e-05
  Epoch 272/1000
  0.8824 - val_loss: 1.3520 - val_accuracy: 0.7446 - lr: 1.5625e-05
  Epoch 273/1000
  0.8824 - val_loss: 1.3159 - val_accuracy: 0.7501 - lr: 1.5625e-05
  Epoch 274/1000
  10/10 [============= ] - 1s 89ms/step - loss: 0.3733 - accuracy:
  0.8864 - val_loss: 1.3117 - val_accuracy: 0.7551 - lr: 1.5625e-05
  Epoch 275/1000
  0.8853 - val_loss: 1.3879 - val_accuracy: 0.7451 - lr: 1.5625e-05
  Epoch 276/1000
  0.8802 - val_loss: 1.3871 - val_accuracy: 0.7436 - lr: 1.5625e-05
  Epoch 277/1000
  0.8835 - val_loss: 1.3131 - val_accuracy: 0.7556 - lr: 1.5625e-05
  Epoch 278/1000
  0.8838 - val_loss: 1.3273 - val_accuracy: 0.7521 - lr: 1.5625e-05
  Epoch 279/1000
  10/10 [=============== ] - ETA: Os - loss: 0.3857 - accuracy:
  0.8814
  Epoch 279: ReduceLROnPlateau reducing learning rate to 1e-05.
  0.8814 - val_loss: 1.3669 - val_accuracy: 0.7401 - lr: 1.5625e-05
  Epoch 279: early stopping
  Gather metrics
[]: plt.figure(figsize=(10, 6))
   plt.plot(history.history['loss'], label='Training Loss')
   plt.plot(history.history['val_loss'], label='Validation Loss')
   plt.title('Model Loss')
   plt.ylabel('Loss')
   plt.xlabel('Epochs')
   plt.legend()
   plt.show()
```

0.8818 - val\_loss: 1.3420 - val\_accuracy: 0.7446 - lr: 1.5625e-05



## []: model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 10, 128)	916992
dropout (Dropout)	(None, 10, 128)	0
<pre>batch_normalization (Batch Normalization)</pre>	(None, 10, 128)	512
lstm_1 (LSTM)	(None, 256)	394240
<pre>dropout_1 (Dropout)</pre>	(None, 256)	0
dense (Dense)	(None, 128)	32896
<pre>dropout_2 (Dropout)</pre>	(None, 128)	0
dense_1 (Dense)	(None, 53)	6837

\_\_\_\_\_

Total params: 1351477 (5.16 MB)

```
Trainable params: 1351221 (5.15 MB) Non-trainable params: 256 (1.00 KB)
```

\_\_\_\_\_\_

Store the model data for later use in the Inference

```
[]: model_dir = 'model-' + MODEL_VERSION + '/'
model_name = 'model-' + MODEL_VERSION + '.h5'
model.save(model_dir + model_name)
labels_name = 'labels-' + MODEL_VERSION + '.npy'
np.save(model_dir + labels_name, actions)

df_csv = pd.DataFrame(actions)
labels_csv_name = 'labels-' + MODEL_VERSION + '.csv'
df_csv.to_csv(model_dir + labels_csv_name, index=False)

/home/user/.local/lib/python3.10/site-
packages/keras/src/engine/training.py:3079: UserWarning: You are saving your
model as an HDF5 file via `model.save()`. This file format is considered legacy.
We recommend using instead the native Keras format, e.g.
```

me recommend using instead the filter
imodel.save('my\_model.keras')
saving\_api.save\_model(

```
[]: predictions = model.predict(X_test)
     predicted_classes = np.argmax(predictions, axis=1)
     true_classes = np.argmax(y_test, axis=1)
     accuracy = accuracy_score(true_classes, predicted_classes)
     precision = precision_score(true_classes, predicted_classes, average='weighted')
     recall = recall_score(true_classes, predicted_classes, average='weighted')
     f1 = f1_score(true_classes, predicted_classes, average='weighted')
     report = classification_report(true_classes, predicted_classes,_
      →target_names=actions)
     with open(model_dir + 'model_metrics.txt', 'w') as file:
         file.write(f"Accuracy: {accuracy}\n")
         file.write(f"Precision: {precision}\n")
         file.write(f"Recall: {recall}\n")
         file.write(f"F1 Score: {f1}\n")
         file.write(f"\nClassification Report:\n{report}")
     print(report)
```

```
63/63 [======== ] - 1s 11ms/step
           precision recall f1-score
                                      support
      aunt
               0.92
                        0.83
                                0.87
                                          41
      bird
               0.85
                        0.72
                                0.78
                                          46
     black
               0.74
                        0.70
                                0.72
                                          20
```

brother	0.61	0.67	0.64	21
				44
brown	0.86	0.95	0.90	
bug	0.87	0.82	0.85	40
callonphone	0.81	0.71	0.76	42
cheek	0.69	0.67	0.68	36
clown	0.84	0.84	0.84	61
COW	0.76	0.74	0.75	46
cute	0.90	0.76	0.83	34
dad	0.60	0.68	0.64	38
doll	0.78	0.58	0.67	43
donkey	0.61	0.79	0.69	34
drink	0.76	0.70	0.73	37
ear	0.83	0.89	0.86	44
eye	0.81	0.69	0.75	32
feet	0.82	0.85	0.84	39
find	0.86	0.76	0.81	33
fireman	0.64	0.81	0.71	37
flower	0.79	0.74	0.76	35
for	0.81	0.55	0.65	31
frog	0.83	0.78	0.81	37
grandpa	0.63	0.65	0.64	26
grass	0.74	0.72	0.73	32
gum	0.69	0.80	0.74	44
hair	0.85	0.79	0.81	42
hen	0.82	0.66	0.73	41
home	0.57	0.71	0.63	24
horse	0.81	0.68	0.74	50
lamp	0.53	0.55	0.54	31
mad	0.53	0.55	0.54	31
mom	0.66	0.66	0.66	35
mouse	0.66	0.71	0.68	58
nose	0.95	0.83	0.89	42
owl	0.86	0.80	0.83	46
pig	0.82	0.86	0.84	36
police	0.79	0.78	0.79	54
radio	0.78	0.86	0.82	44
see	0.76	0.93	0.84	41
shhh	0.78	0.90	0.83	48
shirt	0.63	0.94	0.76	18
sick	0.83	0.83	0.83	29
stairs	0.72	0.66	0.69	35
stuck	0.68	0.71	0.70	21
taste	0.78	0.86	0.82	37
thirsty	0.69	0.72	0.71	25
tiger	0.74	0.72	0.73	36
uncle	0.77	0.79	0.78	52
water	0.88	0.88	0.88	48
who	0.70	0.77	0.73	48

```
0.72
                                 0.75
                                           0.73
                                                        24
           zebra
                                           0.76
                                                      1994
        accuracy
                                 0.75
                                           0.75
                                                      1994
       macro avg
                       0.76
    weighted avg
                       0.77
                                 0.76
                                           0.76
                                                      1994
[]: if (save_high_performers):
         # Generate the classification report
         report = classification report(true classes, predicted classes,
      →target_names=actions, output_dict=True)
         # Convert report to a DataFrame
         report_df = pd.DataFrame(report).transpose()
         # The last few rows are overall metrics (accuracy, macro avg, weighted \Box
      →avg), so we remove them
         report_df = report_df[:-3]
         # Display the DataFrame sorted by F1-score
         report_df_sorted = report_df.sort_values(by='f1-score')
         high_performance_threshold = 0.82 # Define your threshold
         high_performing_categories = report_df_sorted[report_df_sorted['f1-score']_
      high_performance_threshold]
         print(high performing categories.count())
         print(high_performing_categories)
         high_performing_labels = high_performing_categories.index.to_numpy()
         print(high_performing_labels)
         np.save(model_dir + 'high_performing_labels.npy', high_performing_labels)
    precision
                 15
    recall
                 15
    f1-score
                 15
    support
                 15
    dtype: int64
           precision
                        recall f1-score support
```

0.80

0.780488 0.864865 0.820513

0.896552 0.764706 0.825397

0.827586 0.827586 0.827586 0.860465 0.804348 0.831461

0.781818 0.895833 0.834951

0.760000 0.926829 0.835165

0.825000 0.846154 0.835443

clown 0.836066 0.836066 0.836066

taste

cute

sick

owl shhh

see

feet

yucky

0.64

0.71

25

37.0

34.0

29.0

46.0

48.0

41.0

39.0

61.0

```
36.0
           0.815789 0.861111 0.837838
    pig
    bug
           0.868421 0.825000 0.846154
                                            40.0
           0.829787 0.886364 0.857143
                                            44.0
    ear
    aunt 0.918919 0.829268 0.871795
                                           41.0
    water 0.875000 0.875000 0.875000
                                            48.0
           0.945946 0.833333 0.886076
                                            42.0
    nose
    brown 0.857143 0.954545 0.903226
                                             44.0
    ['taste' 'cute' 'sick' 'owl' 'shhh' 'see' 'feet' 'clown' 'pig' 'bug' 'ear'
     'aunt' 'water' 'nose' 'brown']
[]: if (save low performers):
         # Generate the classification report
        report = classification report(true classes, predicted classes,
      →target_names=actions, output_dict=True)
        # Convert report to a DataFrame
        report_df = pd.DataFrame(report).transpose()
        # The last few rows are overall metrics (accuracy, macro avg, weighted)
      →avg), so we remove them
        report_df = report_df[:-3]
         # Display the DataFrame sorted by F1-score
        report_df_sorted = report_df.sort_values(by='f1-score')
        low_performance_threshold = 0.6 # Define your threshold
        low_performing_categories = report_df_sorted[report_df_sorted['f1-score'] <__</pre>
      →low performance threshold]
        print(low performing categories.count())
        print(low_performing_categories)
        low_performing_labels = low_performing_categories.index.to_numpy()
        print(low_performing_labels)
        np.save(model_dir + 'low_performing_labels.npy', low_performing_labels)
[]: res = model.predict(X_test)
[]: test_index = 10
    print(actions[np.argmax(res[test_index])])
    print(actions[np.argmax(y_test[test_index])])
```