Sign_Language_Detection_Project_Eyoha

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#Sign Language Detection

##Abstract This project focuses on developing a deep learning model to accurately predict and classify hand gestures, representing words, and numbers in American Sign Language. With a primary aim to facilitate communication with deaf children, especially those born to hearing parents unfamiliar with ASL, the project leverages a comprehensive dataset comprising hand landmarks extracted from video frames. Utilizing advanced image processing techniques and machine learning algorithms, the model interprets hand positions, movements, and finger configurations to translate sign language into text. The goal of this project is to learn more aboout CV and deep learning techneques in the context of ASL while creating a an effective solution for people who use ASL.

##Introduction Background Communication barriers between deaf individuals and those unfamiliar with sign language pose significant challenges. Particularly, deaf children born to hearing parents often face communication gaps, as many parents do not initially know sign language. This project aims to bridge this gap by leveraging technology to translate American Sign Language into text, thus aiding parents, educators, and caregivers in learning and interacting more effectively with deaf children.

Objectives The primary objective of this project is to develop a deep learning-based model capable of accurately detecting and classifying ASL signs. The model will interpret hand gestures, including the position, movement, and orientation of hands and fingers, to translate these into corresponding textual representations.

Dataset and Methods The dataset for this project is sourced from a Kaggle competition, comprising landmark data extracted from videos using the MediaPipe holistic model. This data includes normalized spatial coordinates for hand landmarks, which are the critical features for model training. The project will employ various image processing techniques, such as edge detection and finger positioning analysis, alongside deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to interpret these signs. The model's performance will be evaluated using accuracy, precision, recall, and F1-score metrics, and the final model will be converted into TensorFlow Lite format for practical deployment.

Step 1: Setup Environment and Dependencies

[ ]:
```
!pip install tensorflow numpy pandas matplotlib scikit-learn opencv-python
```

[ ]:
```
import tensorflow as tf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```python
import pyarrow.parquet as pq
import cv2
import os
from sklearn.model_selection import train_test_split
```

Step 2: Data Acquisition and Loading

[ ]:
```python
from google.colab import files
files.upload()  # This will allow us to upload the kaggle.json file
```

```
<IPython.core.display.HTML object>
```

```
Saving kaggle.json to kaggle.json
```

[ ]:
```
{'kaggle.json':
b'{"username":"yoha00","key":"009129d68ea830c0102186e43b0dd39f"}'}
```

[ ]:
```python
# setting up kaggle environment
!mkdir ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
```

[ ]:
```python
# now we use the kaggle API to download the asl dataset
!kaggle competitions download -c asl-signs
```

```
Downloading asl-signs.zip to /content
100% 37.4G/37.4G [21:21<00:00, 39.4MB/s]
100% 37.4G/37.4G [21:21<00:00, 31.3MB/s]
```

[ ]:
```python
# Unzip the downloaded file
!unzip asl-signs.zip
```

[ ]:
```python
#looking at the file structure
!ls
```

```
asl-signs.zip  sample_data                      train.csv
kaggle.json    sign_to_prediction_index_map.json  train_landmark_files
```

[ ]:
```python
# Taking a look at the train.csv
df = pd.read_csv('/content/train.csv')
df.head()
```

[ ]:
```
                                        path  participant_id  sequence_id  \
0  train_landmark_files/26734/1000035562.parquet           26734   1000035562
1  train_landmark_files/28656/1000106739.parquet           28656   1000106739
2   train_landmark_files/16069/100015657.parquet           16069    100015657
3  train_landmark_files/25571/1000210073.parquet           25571   1000210073
4  train_landmark_files/62590/1000240708.parquet           62590   1000240708

    sign
```

```
0    blow
1    wait
2   cloud
3    bird
4    owie
```

###Evaluation

Based on the structure above it looks like we have a number of participants in the data set who have each taken part in signing a word. Denoted by their participant ID.

We can also see that there are multiple signes in the data set that are denoted by their sign ID each corriponding to a participant_id and a parquet file for the landmark data.

[ ]:
```
# Taking a look at the sign_to_prediction_index_map.json file
df = pd.read_csv('/content/sign_to_prediction_index_map.json')
df.head()
```

[ ]:
```
Empty DataFrame
Columns: [{"TV": 0,  "after": 1,  "airplane": 2,  "all": 3,  "alligator": 4,
"animal": 5,  "another": 6,  "any": 7,  "apple": 8,  "arm": 9,  "aunt": 10,
"awake": 11,  "backyard": 12,  "bad": 13,  "balloon": 14,  "bath": 15,
"because": 16,  "bed": 17,  "bedroom": 18,  "bee": 19,  "before": 20,  "beside":
21,  "better": 22,  "bird": 23,  "black": 24,  "blow": 25,  "blue": 26,  "boat":
27,  "book": 28,  "boy": 29,  "brother": 30,  "brown": 31,  "bug": 32,  "bye":
33,  "callonphone": 34,  "can": 35,  "car": 36,  "carrot": 37,  "cat": 38,
"cereal": 39,  "chair": 40,  "cheek": 41,  "child": 42,  "chin": 43,
"chocolate": 44,  "clean": 45,  "close": 46,  "closet": 47,  "cloud": 48,
"clown": 49,  "cow": 50,  "cowboy": 51,  "cry": 52,  "cut": 53,  "cute": 54,
"dad": 55,  "dance": 56,  "dirty": 57,  "dog": 58,  "doll": 59,  "donkey": 60,
"down": 61,  "drawer": 62,  "drink": 63,  "drop": 64,  "dry": 65,  "dryer": 66,
"duck": 67,  "ear": 68,  "elephant": 69,  "empty": 70,  "every": 71,  "eye": 72,
"face": 73,  "fall": 74,  "farm": 75,  "fast": 76,  "feet": 77,  "find": 78,
"fine": 79,  "finger": 80,  "finish": 81,  "fireman": 82,  "first": 83,  "fish":
84,  "flag": 85,  "flower": 86,  "food": 87,  "for": 88,  "frenchfries": 89,
"frog": 90,  "garbage": 91,  "gift": 92,  "giraffe": 93,  "girl": 94,  "give":
95,  "glasswindow": 96,  "go": 97,  "goose": 98,  "grandma": 99, …]
Index: []

[0 rows x 250 columns]
```

[ ]:
```
#After unzipping we have a folder named train_landmark_files in our current␣
↪directory with the following files
!ls '/content/train_landmark_files'
```

```
16069   2044    25571   27610   29302   32319   36257   37779   49445   55372   62590
18796   22343   26734   28656   30680   34503   37055   4718    53618   61333
```

```
[ ]: #Example of file count in one of our folders
!ls -l '/content/train_landmark_files/16069' | wc -l
!ls -l '/content/train_landmark_files/18796' | wc -l
```

```
4849
3503
```

```
[ ]: #Based in vusila inspcetion it seems like all of the folders have the same data␣
↪type a Parquet file
#Let's look at one of the files
!file "/content/train_landmark_files/16069/100015657.parquet"
```

```
/content/train_landmark_files/16069/100015657.parquet: Apache Parquet
```

#Exploratory Data Analysis

For the Exploratory Data Analysis, we'll focus on understanding the train.csv file's contents and characteristics.

> Basic Descriptive Statistics: This includes counts, means, and other statistical measures that give a quick overview of the data.
>
> Missing Values Check: To ensure the integrity of the dataset, we will check for any missing values.
>
> Visualization of Sign Distribution: A visual representation (such as a histogram or bar chart) to show the distribution of different signs in the dataset.

Additionally, we'll analyze:

> The number of unique signs in the dataset.
>
> The number of unique participants.
>
> The distribution of the number of .parquet files (landmark files) per sign, focusing on the top 20 signs with the most files

```
[ ]: # Lets start by creating our data frame

# Load the train.csv file into a DataFrame
train_csv_path = '/content/train.csv'
train_df = pd.read_csv(train_csv_path)
```

```
[ ]: #Show basic Descriptive Statistics
basic_stats = train_df.describe(include='all')
basic_stats
```

```
[ ]:                                              path  participant_id  \
count                                           94477    94477.000000
unique                                          94477             NaN
top     train_landmark_files/26734/1000035562.parquet             NaN
freq                                                1             NaN
mean                                              NaN    33678.632366
```

```
std                                                 NaN    16138.124387
min                                                 NaN     2044.000000
25%                                                 NaN    25571.000000
50%                                                 NaN    32319.000000
75%                                                 NaN    49445.000000
max                                                 NaN    62590.000000

         sequence_id    sign
count   9.447700e+04   94477
unique           NaN     250
top              NaN  listen
freq             NaN     415
mean    2.149377e+09     NaN
std     1.239239e+09     NaN
min     8.528200e+04     NaN
25%     1.078076e+09     NaN
50%     2.154240e+09     NaN
75%     3.218820e+09     NaN
max     4.294915e+09     NaN
```

[ ]:
```python
# Number of Unique Signs in the data set
unique_signs_count = train_df['sign'].nunique()
unique_signs_count
```

[ ]: 250

[ ]:
```python
#  Next we calculate the number of unique participants in the dataset.
unique_participants_count = train_df['participant_id'].nunique()
unique_participants_count
```

[ ]: 21

[ ]:
```python
# To understand which signs have the most data points, we look at the␣
↪distribution of .parquet files per sign.
parquets_per_sign = train_df['sign'].value_counts().head(20)
parquets_per_sign
```

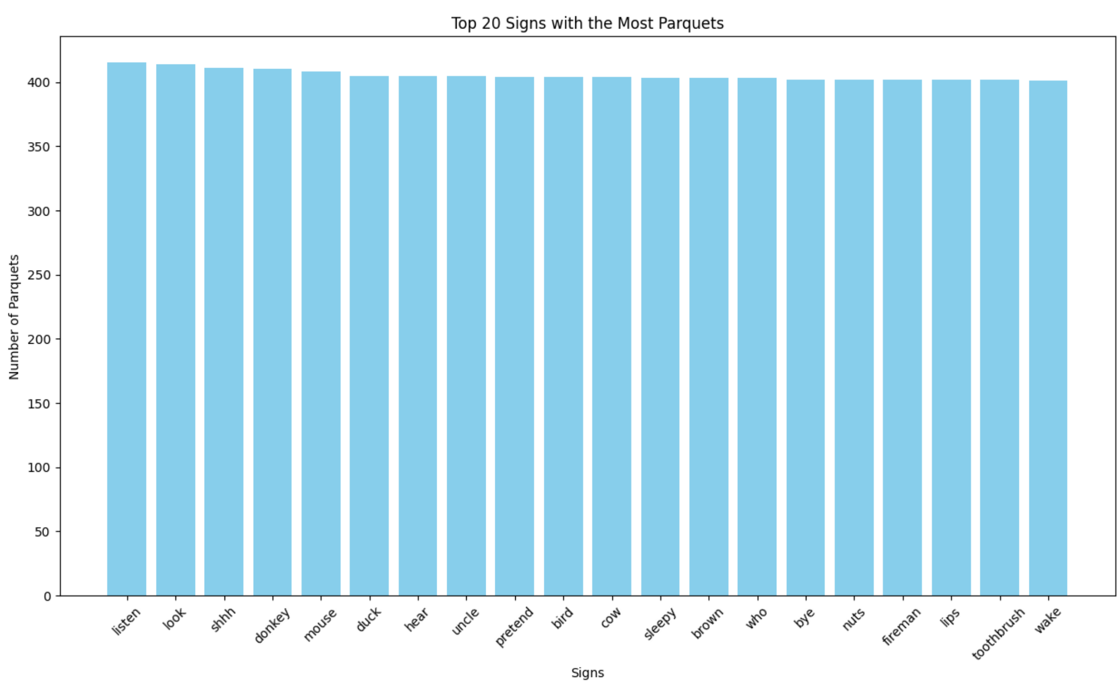
[ ]:
```
listen        415
look          414
shhh          411
donkey        410
mouse         408
duck          405
hear          405
uncle         405
pretend       404
bird          404
```

```
cow            404
sleepy         403
brown          403
who            403
bye            402
nuts           402
fireman        402
lips           402
toothbrush     402
wake           401
Name: sign, dtype: int64
```

[ ]:
```python
# To better visualize this we plot the distribution the top 20 signs

# Preparing data for visualization
top_signs = parquets_per_sign.index.tolist()
top_signs_counts = parquets_per_sign.values.tolist()

# Visualization code
plt.figure(figsize=(15, 8))
plt.bar(top_signs, top_signs_counts, color='skyblue')
plt.xlabel('Signs')
plt.ylabel('Number of Parquets')
plt.title('Top 20 Signs with the Most Parquets')
plt.xticks(rotation=45)
plt.show()
```



```
[ ]: # Final lets check for missing values
missing_values = train_df.isnull().sum()
missing_values
```

```
[ ]: path              0
participant_id    0
sequence_id       0
sign              0
dtype: int64
```

TODO add more analysis for EDA in relation to parquet files ##Data pre-processing

next step is data pre-processing. This phase involves preparing the .parquet files in the train_landmark_files folder, which contain the landmark data for the sign language gestures, for model training.

```
[ ]: # Reading the .praquet files

# Example of reading a single .parquet file
file_path = 'train_landmark_files/16069/100015657.parquet'  # Replace with␣
↪actual file path
parquet_data = pd.read_parquet(file_path)
parquet_data.head()
parquet_data.shape
```

```
[ ]: (57015, 7)
```

```
[ ]: # Now lets read all of the .parquet files in the train_landmark_files folder
# We'll save the processed files in a log file incase we need to restart the␣
↪process
# We'll use the log file to skip files that have already been processed
# We'll save prgress of our process in a batch file every 2000 files

import os
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
import datetime

def read_log(log_path):
    if os.path.exists(log_path):
        with open(log_path, 'r') as file:
            processed_files = file.read().splitlines()
        return set(processed_files)
    else:
        return set()
```

```
def update_log(log_path, file_name):
    with open(log_path, 'a') as file:
        file.write(file_name + '\n')

root_folder = '/content/train_landmark_files'
scaler = MinMaxScaler()
batch_size = 2000
log_path = 'processed_files_log.txt'
processed_files = read_log(log_path)

for subfolder in os.listdir(root_folder):
    subfolder_path = os.path.join(root_folder, subfolder)
    if os.path.isdir(subfolder_path):
        all_data = pd.DataFrame()
        file_count = 0

        for file in os.listdir(subfolder_path):
            if file in processed_files:
                continue  # Skip if the file is already processed

            file_path = os.path.join(subfolder_path, file)
            parquet_data = pd.read_parquet(file_path)
            data_of_interest = parquet_data[parquet_data['type'].
↪isin(['left_hand', 'right_hand', 'pose'])].copy()
            data_of_interest[['x', 'y', 'z']] = scaler.
↪fit_transform(data_of_interest[['x', 'y', 'z']])
            sequence_id = int(file.split('.')[0])
            data_of_interest['sequence_id'] = sequence_id
            all_data = pd.concat([all_data, data_of_interest],␣
↪ignore_index=True)

            update_log(log_path, file)  # Update the log
            file_count += 1
            if file_count >= batch_size:
                break

        batch_filename = f'batch_{len(processed_files)//batch_size}.csv'
        all_data.to_csv(batch_filename, index=False)
        print(f"Batch {len(processed_files)//batch_size} saved. Timestamp:␣
↪{datetime.datetime.now()}")
```

[ ]:

```
# prompt: how check csv file

import pandas as pd

# Read the CSV file
df = pd.read_csv('/content/batch_0 (2).csv')
```

```python
# Check the shape of the DataFrame
print('\n check the shape of the DataFrame:')
print(df.shape)

# Check the column names
print( '\n check the column names:')
print(df.columns)

# Check the data types of each column
print('\n check the data types of each column:')
print(df.dtypes)

# Check the missing values
print('\n check the missing values:')
print(df.isnull().sum())

# Check the unique values in each column
print('\n check the unique values in each column:')
for column in df.columns:
    print(df[column].unique())

# Check the distribution of each column
print('\n check the distribution of each column:')
for column in df.columns:
    print(df[column].value_counts())
```

```
 check the shape of the DataFrame:
(6854100, 8)

 check the column names:
Index(['frame', 'row_id', 'type', 'landmark_index', 'x', 'y', 'z',
       'sequence_id'],
      dtype='object')

 check the data types of each column:
frame               int64
row_id             object
type               object
landmark_index      int64
x                 float64
y                 float64
z                 float64
sequence_id         int64
dtype: object

 check the missing values:
```

```
frame                   0
row_id                  0
type                    0
landmark_index          0
x                 2611371
y                 2611371
z                 2611371
sequence_id             0
dtype: int64

 check the unique values in each column:
[ 28  29  30  31  32  33  34  35  36  37  38  39  40  41  42  43  44  45
  46   0   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16
  17  18  19  20  21  22  23  24  25  26  27  47  48  49  50  51  52  53
  54  55  56  57  58  59  60  61  62  63  64  65  66  67  68  69  70  71
  72  73  74  75  76  77  78  79  80  81  82  83  84  85  86  87  88  89
  90  91  92  93  94  95  96  97  98  99 100 101 102 103 104 105 106 107
 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125
 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 143
 144 145 146 147 148 149 150 151 152 153 154 155 156 157 158 159 160 161
 162 163 164 165 166 167 168 169 170 171 172 173 174 175 176 177 178 179
 180 181 182 183 184 185 186 187 188 189 190 191 192 193 194 195 196 197
 198 199 200 201 202 203 204 205 206 207 208 209 210 211 212 213 214 215
 216 217 218 219 220 221 222 223 224 225 226 227 228 229 230 231 232 233
 234 235 236 237 238 239 240 241 242 243 244 245 246 247 248 249 250 251
 252 253 254 255 256 257 258 259 260 261 262 263 264 265 266 267 268 269
 270 271 272 273 274 275 276 277 278 279 280 281 282 283 284 285 286 287
 288 289 290 291 292 293 294 295 296 297 298 299 300 301 302 303 304 305
 306 307 308 309 310 311 312 313 314 315 316 317 318 319 320 321 322 323
 324 325 326 327 328 329 330 331 332 333 334 335 336 337 338 339 340 341
 342 343 344 345 346 347 348 349 350 351 352 353 354 355 356 357 358 359
 360 361 362 363 364 365 366 367 368]
['28-left_hand-0' '28-left_hand-1' '28-left_hand-2' …
 '368-right_hand-18' '368-right_hand-19' '368-right_hand-20']
['left_hand' 'pose' 'right_hand']
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28 29 30 31 32]
[       nan 0.45774874 0.49702824 … 0.24177278 0.25391836 0.25731359]
[       nan 0.05357234 0.02111482 … 0.11386584 0.12666472 0.1371545 ]
[       nan 0.26440656 0.27806687 … 0.56036613 0.56105648 0.56260731]
[ 775017794 2374631589 1809269714 …  461538069 2403863845 3520591614]

 check the distribution of each column:
31      104100
32      104100
33      103725
34      103200
30      102900
```

```
        …
355        75
354        75
353        75
352        75
368        75
Name: frame, Length: 369, dtype: int64
32-left_hand-18      1388
31-right_hand-2      1388
31-right_hand-0      1388
31-pose-32           1388
31-pose-31           1388
                     …
357-pose-27             1
357-pose-26             1
357-pose-25             1
357-pose-24             1
368-right_hand-20       1
Name: row_id, Length: 27675, dtype: int64
pose          3015804
left_hand     1919148
right_hand    1919148
Name: type, dtype: int64
0     274164
11    274164
20    274164
19    274164
18    274164
17    274164
1     274164
15    274164
14    274164
13    274164
12    274164
16    274164
10    274164
8     274164
7     274164
6     274164
5     274164
4     274164
3     274164
2     274164
9     274164
27     91388
31     91388
30     91388
29     91388
```

```
28     91388
22     91388
26     91388
25     91388
24     91388
23     91388
21     91388
32     91388
Name: landmark_index, dtype: int64
0.000000    2000
1.000000    1939
1.000000      60
0.851977       2
0.341960       2
            …
0.445724       1
0.479908       1
0.502889       1
0.521004       1
0.257314       1
Name: x, Length: 4237907, dtype: int64
0.000000    2000
1.000000    1806
1.000000     145
1.000000      49
0.009188       3
            …
0.145814       1
0.163988       1
0.182917       1
0.147290       1
0.137155       1
Name: y, Length: 4237438, dtype: int64
0.000000    2000
1.000000    1996
1.000000       4
0.656015       2
0.768214       2
            …
0.568731       1
0.564664       1
0.557889       1
0.551387       1
0.562607       1
Name: z, Length: 4238532, dtype: int64
2235701764    21375
3896074830    18525
2047975791    18450
```

```
1478297125    18375
1863870271    18225
              ...
3304912458      225
1868735223      150
1142420711      150
2189530106      150
617950465       150
Name: sequence_id, Length: 2000, dtype: int64
```

Data Shape and Columns:

The DataFrame has 6,854,100 rows and 8 columns. This is a large dataset, so efficient processing and memory management will be crucial.

Data Types: Most columns are of expected types (integers and floats). Ensure these types align with the intended use in the model.

Missing Values: Columns 'x', 'y', and 'z' have 2,611,371 missing values each. We'll handel these missing values by replacing them with 0's.

Unique Values and Distribution: The distribution of values in columns like 'frame', 'row_id', 'type', and 'landmark_index' indicates a wide range of data points. The 'type' column suggests data from three categories: 'left_hand', 'right_hand', and 'pose'.

The distribution of 'sequence_id' shows how many data points are available per sequence.

0.0.1 Feature Engineering

1. **Landmark Aggregation**: For each frame and each type (left hand, right hand, pose), we would like to create a feature vector that aggregateates the landmark data. This means creating a single feature vector per frame per type that encapsulates all the landmarks.
2. **Temporal Features**: Since this is time-series data (sequential data across frames), we'll be creating features that capture the temporal aspect, like the change in position of landmarks from one frame to the next.

Then we will reshape the data into a format that can be fed into the model.

Reshaping Data: We reshape the data into a suitable format. For sequence models like LSTM or GRU (common in handling time-series data), we need to structure the data into sequences.

[ ]:
```python
# Pull lables from train.csv

# Read the train.csv file
train_df = pd.read_csv('/content/train.csv')

# Create a dictionary mapping from sequence_id to sign label
sign_labels = dict(zip(train_df['sequence_id'], train_df['sign']))
```

[ ]:
```python
# Sample data for demonstration (replace with your actual DataFrame)
import pandas as pd
```

```python
import numpy as np

sequence_length = 20


def create_temporal_features(df):
    # Calculating differences in coordinates for each landmark
    df[['x_diff', 'y_diff', 'z_diff']] = df.groupby(['sequence_id', 'type',
 ↪'landmark_index'])[['x', 'y', 'z']].diff().fillna(0)
    temporal_features = []
    for (sequence_id, frame, typ), group in df.groupby(['sequence_id', 'frame',
 ↪'type']):
        sorted_group = group.sort_values(by='landmark_index')
        differences = sorted_group[['x_diff', 'y_diff', 'z_diff']].values.
 ↪flatten()
        temporal_features.append((sequence_id, frame, typ, differences))
    return pd.DataFrame(temporal_features, columns=['sequence_id', 'frame',
 ↪'type', 'Features'])
temporal_data = create_temporal_features(df)

# Function to validate features
# This code will check if the feature vectors for a given frame and sequence_id
 ↪in our dataset align with the expected structure.
def validate_features(temporal_data, sequence_id, frame, expected_features):
    frame_data = temporal_data[(temporal_data['sequence_id'] == sequence_id) &
 ↪(temporal_data['frame'] == frame)]
    for _, row in frame_data.iterrows():
        features = row['Features']
        if len(features) != expected_features[row['type']]:
            return False, f"Mismatch in features for type {row['type']} at
 ↪frame {frame} of sequence {sequence_id}"
    return True, "All features are correctly structured"

# Feature lengths for each type
expected_feature_lengths = {
    'left_hand': 63,  # 21 landmarks * 3 coordinates
    'right_hand': 63,
    'pose': 99  # 33 landmarks * 3 coordinates
}

# Validate for a particular frame and sequence_id
validation_result = validate_features(temporal_data, sequence_id=1, frame=0,
 ↪expected_features=expected_feature_lengths)
print(validation_result)
```

```
(True, 'All features are correctly structured')
```

[ ]:

```python
from tensorflow.keras.preprocessing.sequence import pad_sequences

sequence_length = 20

def structure_data_for_lstm(temporal_data, sequence_length, sign_labels):
    sequences = []
    labels = []

    for sequence_id in temporal_data['sequence_id'].unique():
        sequence_data = temporal_data[temporal_data['sequence_id'] ==␣
↪sequence_id]
        label = sign_labels.get(sequence_id)
        if label is None:
            continue

        feature_vectors = []
        for frame in range(sequence_data['frame'].max() + 1):
            frame_data = sequence_data[sequence_data['frame'] == frame]
            feature_vector = np.zeros(225)  # Initialize with zeros
            # [Your code to create feature_vector for each type]
            for typ in ['left_hand', 'right_hand', 'pose']:
                type_data = frame_data[frame_data['type'] == typ]['Features']
                if not type_data.empty:
                    type_features = type_data.iloc[0]  # Assumes each type only␣
↪has one row per frame
                    # Check if type_features has the expected number of elements
                    expected_length = 63 if typ in ['left_hand', 'right_hand']␣
↪else 99  # 99 for pose
                    if len(type_features) == expected_length:
                        start_index = 0 if typ == 'left_hand' else (63 if typ␣
↪== 'right_hand' else 126)
                        feature_vector[start_index:start_index +␣
↪expected_length] = type_features
                    else:
                        # Handle the case where type_features is not as long as␣
↪expected
                        print(f"Warning: Missing data for {typ} in sequence␣
↪{sequence_id}, frame {frame}")

            feature_vectors.append(feature_vector)

        # Padding the sequence
        feature_vectors_padded = pad_sequences([feature_vectors],␣
↪maxlen=sequence_length, padding='post', dtype='float32')[0]

        sequences.append(feature_vectors_padded)
```

```
        labels.append(label)

    return np.array(sequences), np.array(labels)

sequences, labels = structure_data_for_lstm(temporal_data, sequence_length,␣
↪sign_labels)
```

0.1 Model Building

0.1.1 Number of Features

we have 21 unique landmarks for each hand and 33 landmarks for the pose. For each landmark, we have x, y, z coordinates. Thus, for each type (left hand, right hand, pose), you have 21 * 3 = 63 features for hands and 33 * 3 = 99 features for pose. If you're using all these features, n_features would be 63 (left hand) + 63 (right hand) + 99 (pose) = 225.

[ ]:
```
# we use TensorFlow and Keras to define the LSTM model.
# The model architecture can be simple to start with, and then we can expand or␣
↪modify it based on the model's performance.

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout

# We are using 225 features and we are classifying into 'n_classes' categories
n_features = 225
n_classes = len(np.unique(labels))  # Calculate the number of unique labels

# Define the sequence length (number of frames per sequence)


# Define the LSTM model
model = Sequential([
    LSTM(50, return_sequences=True, input_shape=(sequence_length, n_features)),
    Dropout(0.2),
    LSTM(50),
    Dropout(0.2),
    Dense(n_classes, activation='softmax')  # Use 'softmax' for multi-class␣
↪classification
])

# Output the number of classes and model summary
print(f"Number of classes: {n_classes}")
model.summary()
```

```
Number of classes: 250
Model: "sequential_8"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
```

```
=================================================================
 lstm_16 (LSTM)              (None, 20, 50)            55200

 dropout_16 (Dropout)        (None, 20, 50)            0

 lstm_17 (LSTM)              (None, 50)                20200

 dropout_17 (Dropout)        (None, 50)                0

 dense_10 (Dense)            (None, 250)               12750

=================================================================
Total params: 88150 (344.34 KB)
Trainable params: 88150 (344.34 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[ ]:
```
# Compile the Model
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',␣
↪metrics=['accuracy'])
```

[ ]:
```
# Data Preparation for Training



# Split the data into training and validation sets.
# The split is 80% for training and 20% for validation.
from sklearn.model_selection import train_test_split

X_train, X_val, y_train, y_val = train_test_split(sequences, labels,␣
↪test_size=0.2, random_state=64)

# Check the shapes and types of the training and validation data
print(X_train.shape, X_train.dtype)
print(y_train.shape, y_train.dtype)
print(X_val.shape, X_val.dtype)
print(y_val.shape, y_val.dtype)
```

```
(1600, 20, 225) float32
(1600,) <U12
(400, 20, 225) float32
(400,) <U12
```

We can see from the data that the labels are encoded as integers but the features are strings. We need to convert them to integers.

[ ]:
```
from sklearn.preprocessing import LabelEncoder

# Create the label encoder
```

```python
label_encoder = LabelEncoder()

# Fit the encoder to your labels (all labels in dataset)
label_encoder.fit(np.concatenate((y_train, y_val), axis=0))

# Transform the training and validation labels
y_train_encoded = label_encoder.transform(y_train)
y_val_encoded = label_encoder.transform(y_val)

# Check the shapes and types again
print(y_train_encoded.shape, y_train_encoded.dtype)
print(y_val_encoded.shape, y_val_encoded.dtype)
```

```
(1600,) int64
(400,) int64
```

[ ]:
```python
# Model Training
history = model.fit(
    X_train, y_train_encoded,  # Use integer-encoded labels for training
    validation_data=(X_val, y_val_encoded),  # Use integer-encoded labels for
 ↪validation
    epochs=10,
    batch_size=32
)
```

```
Epoch 1/10
50/50 [==============================] - 4s 24ms/step - loss: 5.5225 - accuracy:
0.0031 - val_loss: 5.5216 - val_accuracy: 0.0125
Epoch 2/10
50/50 [==============================] - 0s 8ms/step - loss: 5.5165 - accuracy:
0.0088 - val_loss: 5.5251 - val_accuracy: 0.0025
Epoch 3/10
50/50 [==============================] - 0s 8ms/step - loss: 5.5025 - accuracy:
0.0056 - val_loss: 5.5253 - val_accuracy: 0.0000e+00
Epoch 4/10
50/50 [==============================] - 0s 8ms/step - loss: 5.4840 - accuracy:
0.0075 - val_loss: 5.5361 - val_accuracy: 0.0125
Epoch 5/10
50/50 [==============================] - 0s 8ms/step - loss: 5.4560 - accuracy:
0.0075 - val_loss: 5.5195 - val_accuracy: 0.0075
Epoch 6/10
50/50 [==============================] - 0s 8ms/step - loss: 5.4141 - accuracy:
0.0081 - val_loss: 5.5085 - val_accuracy: 0.0200
Epoch 7/10
50/50 [==============================] - 0s 8ms/step - loss: 5.3680 - accuracy:
0.0119 - val_loss: 5.4855 - val_accuracy: 0.0150
Epoch 8/10
50/50 [==============================] - 0s 8ms/step - loss: 5.3079 - accuracy:
```

```
0.0169 - val_loss: 5.4679 - val_accuracy: 0.0100
Epoch 9/10
50/50 [==============================] - 0s 8ms/step - loss: 5.2490 - accuracy:
0.0219 - val_loss: 5.4706 - val_accuracy: 0.0075
Epoch 10/10
50/50 [==============================] - 0s 8ms/step - loss: 5.1830 - accuracy:
0.0244 - val_loss: 5.4722 - val_accuracy: 0.0200
```

Changing model architecture to Bidirectional LSTM to see if that improves performance

[ ]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout, Bidirectional
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.optimizers import RMSprop
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras.regularizers import l1_l2


n_features = 225
n_classes = len(np.unique(labels))

regularizer = l1_l2(l1=0.01, l2=0.01)  # Example regularization parameters,␣
↪these may need tuning


model = Sequential([
    Bidirectional(LSTM(200, return_sequences=True,␣
↪input_shape=(sequence_length, n_features))),
    Dropout(0.7),
    Bidirectional(LSTM(200)),
    Dropout(0.7),
    Dense(100, activation='relu', kernel_regularizer=regularizer),
    Dense(n_classes, activation='softmax')
])

# Using a custom learning rate
#optimizer = Adam(learning_rate=0.0001)

#model.compile(optimizer=optimizer, loss='sparse_categorical_crossentropy',␣
↪metrics=['accuracy'])

optimizer = RMSprop(learning_rate=0.0001)
model.compile(optimizer=optimizer, loss='sparse_categorical_crossentropy',␣
↪metrics=['accuracy'])
sample_input = np.random.random((1, sequence_length, n_features))
model(sample_input)

model.summary()
```

```
Model: "sequential_23"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 bidirectional_30 (Bidirect  (1, 20, 400)              681600
 ional)

 dropout_45 (Dropout)        (1, 20, 400)              0

 bidirectional_31 (Bidirect  (1, 400)                  961600
 ional)

 dropout_46 (Dropout)        (1, 400)                  0

 dense_37 (Dense)            (1, 100)                  40100

 dense_38 (Dense)            (1, 250)                  25250

=================================================================
Total params: 1708550 (6.52 MB)
Trainable params: 1708550 (6.52 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[ ]:
```
model = Sequential([
    LSTM(100, input_shape=(sequence_length, n_features)),
    Dropout(0.5),
    Dense(n_classes, activation='softmax')
])

# Using a custom learning rate
optimizer = Adam(learning_rate=0.001)
model.compile(optimizer=optimizer, loss='sparse_categorical_crossentropy',␣
 ↪metrics=['accuracy'])

#model(sample_input)

model.summary()
```

```
Model: "sequential_24"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_42 (LSTM)              (None, 100)               130400

 dropout_47 (Dropout)        (None, 100)               0

 dense_39 (Dense)            (None, 250)               25250
```

```
=================================================================
Total params: 155650 (608.01 KB)
Trainable params: 155650 (608.01 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[ ]:
```python
#Data preprocessing
from sklearn.preprocessing import StandardScaler

# Assuming 'sequences' is your data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train.reshape(-1, X_train.shape[-1])).
 ↪reshape(X_train.shape)
X_val_scaled = scaler.transform(X_val.reshape(-1, X_val.shape[-1])).
 ↪reshape(X_val.shape)
```

[ ]:
```python
#training procedure
from tensorflow.keras.callbacks import EarlyStopping

early_stopping = EarlyStopping(monitor='val_loss', patience=3,␣
 ↪restore_best_weights=True)
model_checkpoint = ModelCheckpoint('best_model.h5', monitor='val_loss',␣
 ↪save_best_only=True)


history = model.fit(
    X_train_scaled, y_train_encoded,
    validation_data=(X_val_scaled, y_val_encoded),
    epochs=50,  # Increased epochs
    batch_size=16,  # Adjusted batch size
    callbacks=[early_stopping]
)
```

```
Epoch 1/50
100/100 [==============================] - 1s 6ms/step - loss: 0.2296 -
accuracy: 0.9737 - val_loss: 6.5063 - val_accuracy: 0.0375
Epoch 2/50
100/100 [==============================] - 1s 6ms/step - loss: 0.1969 -
accuracy: 0.9837 - val_loss: 6.5250 - val_accuracy: 0.0375
Epoch 3/50
100/100 [==============================] - 1s 5ms/step - loss: 0.2051 -
accuracy: 0.9725 - val_loss: 6.6032 - val_accuracy: 0.0500
Epoch 4/50
100/100 [==============================] - 1s 5ms/step - loss: 0.2072 -
accuracy: 0.9669 - val_loss: 6.5575 - val_accuracy: 0.0400
```

Based on the above, we can see that the training accuracy is increasing over epochs,

the validation accuracy is decreasing over epochs, and the validation loss is increasing over epochs which can be interprated as the following:

Increasing Training Accuracy: The model's training accuracy is increasing over epochs, which is a positive sign. It suggests that the model is learning from the training data.

Validation Accuracy Not Keeping Pace: However, the validation accuracy is much lower and doesn't increase at the same rate. This could be a sign of overfitting, where the model learns the training data too well, including its noise and outliers, but does not generalize well to new, unseen data.

Rising Validation Loss: The increasing validation loss further supports the possibility of overfitting.

To address these issues, we will consider adding the following steps:

Regularization: Implement dropout layers or L2 regularization to prevent overfitting. Data Augmentation: If possible, augment your data to introduce more variability and help the model generalize better.

Early Stopping: Implement early stopping to terminate training when the validation loss starts to increase, preventing overfitting.

Hyperparameter Tuning: Optimize Model Architecture and Tune LSTM Units Adjust the number of units in LSTM layers. Sometimes fewer units can help the model generalize better.

Layer Adjustments: Experiment with adding or removing layers to find a better architecture balance

[ ]:
```python
# accounting for class imbalance

from sklearn.utils.class_weight import compute_class_weight

class_weights = compute_class_weight('balanced', classes=np.
 ↪unique(y_train_encoded), y=y_train_encoded)
class_weight_dict = dict(enumerate(class_weights))

history = model.fit(
    X_train_scaled, y_train_encoded,
    validation_data=(X_val_scaled, y_val_encoded),
    epochs=50,
    batch_size=8,
    class_weight=class_weight_dict,
    callbacks=[early_stopping]
)
```

```
Epoch 1/50
200/200 [==============================] - 7s 18ms/step - loss: 3.9584 -
accuracy: 0.1863 - val_loss: 5.3828 - val_accuracy: 0.0525
Epoch 2/50
200/200 [==============================] - 2s 11ms/step - loss: 3.3910 -
accuracy: 0.2262 - val_loss: 5.5687 - val_accuracy: 0.0450
```

```
Epoch 3/50
200/200 [==============================] - 2s 11ms/step - loss: 2.6470 -
accuracy: 0.3675 - val_loss: 5.7771 - val_accuracy: 0.0525
Epoch 4/50
200/200 [==============================] - 2s 12ms/step - loss: 1.9898 -
accuracy: 0.4919 - val_loss: 6.5177 - val_accuracy: 0.0700
```

more changes to see if it improves performance

[ ]:
```python
from sklearn.preprocessing import MinMaxScaler

# Assuming 'X_train' and 'X_val' are your training and validation sets
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train.reshape(-1, X_train.shape[-1])).
    ↪reshape(X_train.shape)
X_val_scaled = scaler.transform(X_val.reshape(-1, X_val.shape[-1])).
    ↪reshape(X_val.shape)
```

[ ]:
```python
from tensorflow.keras.layers import GRU

model = Sequential([
    Bidirectional(GRU(100, return_sequences=True, input_shape=(sequence_length,␣
    ↪n_features))),
    Dropout(0.3),
    Bidirectional(GRU(100)),
    Dropout(0.3),
    Dense(100, activation='relu'),
    Dense(n_classes, activation='softmax')
])

model.compile(optimizer=optimizer, loss='sparse_categorical_crossentropy',␣
    ↪metrics=['accuracy'])
sample_input = np.random.random((1, sequence_length, n_features))
model(sample_input)

model.summary()
```

```
Model: "sequential_13"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 bidirectional_12 (Bidirect  (1, 20, 200)              196200
 ional)

 dropout_26 (Dropout)        (1, 20, 200)              0

 bidirectional_13 (Bidirect  (1, 200)                  181200
 ional)
```

```
 dropout_27 (Dropout)        (1, 200)                 0


 dense_18 (Dense)            (1, 100)                 20100


 dense_19 (Dense)            (1, 250)                 25250

=================================================================
Total params: 422750 (1.61 MB)
Trainable params: 422750 (1.61 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[ ]:
```python
from tensorflow.keras.callbacks import ModelCheckpoint

checkpoint = ModelCheckpoint('best_model.h5', monitor='val_loss',
 ↪save_best_only=True)

# Add 'checkpoint' to the callbacks list in model.fit
history = model.fit(
    X_train_scaled, y_train_encoded,
    validation_data=(X_val_scaled, y_val_encoded),
    epochs=50,
    batch_size=64,
    callbacks=[early_stopping, checkpoint]  # Add 'checkpoint' here
)
```

```
Epoch 1/50
25/25 [==============================] - 8s 72ms/step - loss: 5.5545 - accuracy:
0.0031 - val_loss: 5.5231 - val_accuracy: 0.0050
Epoch 2/50
11/25 [============>…] - ETA: 0s - loss: 5.5209 - accuracy:
0.0043

/usr/local/lib/python3.10/dist-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. `model.save('my_model.keras')`.
  saving_api.save_model(

25/25 [==============================] - 0s 13ms/step - loss: 5.5398 - accuracy:
0.0031 - val_loss: 5.5309 - val_accuracy: 0.0000e+00
Epoch 3/50
25/25 [==============================] - 0s 13ms/step - loss: 5.5237 - accuracy:
0.0044 - val_loss: 5.5427 - val_accuracy: 0.0025
Epoch 4/50
25/25 [==============================] - 0s 14ms/step - loss: 5.5232 - accuracy:
0.0044 - val_loss: 5.5409 - val_accuracy: 0.0050
Epoch 5/50
```

```
25/25 [==============================] - 0s 13ms/step - loss: 5.5200 - accuracy:
0.0056 - val_loss: 5.5386 - val_accuracy: 0.0050
Epoch 6/50
25/25 [==============================] - 0s 14ms/step - loss: 5.5133 - accuracy:
0.0044 - val_loss: 5.5446 - val_accuracy: 0.0000e+00
Epoch 7/50
25/25 [==============================] - 0s 13ms/step - loss: 5.5175 - accuracy:
0.0044 - val_loss: 5.5502 - val_accuracy: 0.0025
Epoch 8/50
25/25 [==============================] - 0s 14ms/step - loss: 5.5062 - accuracy:
0.0056 - val_loss: 5.5680 - val_accuracy: 0.0000e+00
Epoch 9/50
25/25 [==============================] - 0s 14ms/step - loss: 5.5011 - accuracy:
0.0075 - val_loss: 5.5471 - val_accuracy: 0.0100
Epoch 10/50
25/25 [==============================] - 0s 14ms/step - loss: 5.5115 - accuracy:
0.0050 - val_loss: 5.5499 - val_accuracy: 0.0100
Epoch 11/50
25/25 [==============================] - 0s 14ms/step - loss: 5.5037 - accuracy:
0.0050 - val_loss: 5.5581 - val_accuracy: 0.0100
```

At this point we can see that the mdoel is overfitting. If we had more time we would see if we could improve the model by applying more regularization, data augmentation, and hyperparameter tuning.

At this point we're going to try another more complex archetecture to see if that improves performance. In the next phase we'll expore transformer models with the same dataset.