1- Importing Libraries

In [ ]:
```
import os
import cv2
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import random
import shutil

import subprocess
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv3D, MaxPooling3D, Flatten, Dens
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix

from moviepy import VideoFileClip
from tqdm import tqdm
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
```

2-Exploratory Data Analysis

In [ ]:

```
# Define dataset paths (update with your actual paths)
DATASET_PATHS = {
    "waving": "/home/student/Documents/Programming-Exercises/projects/H
    "walking": "/home/student/Documents/Programming-Exercises/projects/
    "writing": "/home/student/Documents/Programming-Exercises/projects/
    "calling": "/home/student/Documents/Programming-Exercises/projects/
    "sitting": "/home/student/Documents/Programming-Exercises/projects/
    "standing": "/home/student/Documents/Programming-Exercises/projects
}

# Count videos per class
class_counts = {action: len(os.listdir(path)) for action, path in DATAS

# Convert to lists for plotting
actions, counts = zip(*class_counts.items())

# Plot distribution of action classes
plt.figure(figsize=(10, 5))
sns.barplot(x=list(actions), y=list(counts), palette="viridis")
plt.title("Distribution of Action Classes")
plt.xlabel("Action Classes")
plt.ylabel("Number of Videos")
plt.xticks(rotation=45)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()

# Print number of unique action classes
num_classes = len(class_counts)
print(f"Number of action classes: {num_classes}")
```

```
/tmp/ipykernel_213974/3020151254.py:19: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be r
emoved in v0.14.0. Assign the `x` variable to `hue` and set `legend=F
alse` for the same effect.

  sns.barplot(x=list(actions), y=list(counts), palette="viridis")
```


```
Number of action classes: 6
```

3-Data Preprocessing

a-Conversion of videos from mov to mp4 and taking 30fps

converting all mov extension videos to mp4

CONVERTED_VIDEOS_PATH = "/home/student24/Documents/Review_blocks/Review_Block_4/Deep learning/Assignment/Presentation/converted_videos" os.makedirs(CONVERTED_VIDEOS_PATH, exist_ok=True)

def convert_to_mp4(video_path, output_path): """Convert video to MP4 format.""" command = f"ffmpeg -i '{video_path}' -q:v 0 -q:a 0 '{output_path}' -y" subprocess.run(command, shell=True, stdout=subprocess.PIPE, stderr=subprocess.PIPE)

Convert all videos to MP4

for class_name, class_path in DATASET_PATHS.items(): for video_file in os.listdir(class_path): video_path = os.path.join(class_path, video_file)

```
    if video_file.endswith(".MOV"):  # Convert only MOV files
        mp4_file = video_file.replace(".MOV", ".mp4")
        mp4_path = os.path.join(CONVERTED_VIDEOS_PATH, mp4_fil
e)

        print(f"Converting {video_file} to {mp4_file}...")
        convert_to_mp4(video_path, mp4_path)

    elif video_file.endswith(".mp4"):  # Copy existing MP4s
        mp4_path = os.path.join(CONVERTED_VIDEOS_PATH, video_f
ile)
        os.system(f"cp '{video_path}' '{mp4_path}'")  # Copy t
o new folder
```

print("✅ All videos are now in MP4 format!")

B-Converting all videos to frames

In [ ]:
```
# Paths
CONVERTED_VIDEOS_PATH = "/home/student/Documents/Programming-Exercises/
PROCESSED_FRAMES_PATH = "/home/student/Documents/Programming-Exercises/

# Create processed frames directory
os.makedirs(PROCESSED_FRAMES_PATH, exist_ok=True)

def extract_frames(video_path, class_name, num_frames=30):
    cap = cv2.VideoCapture(video_path)
    total_frames = int(cap.get(cv2.CAP_PROP_FRAME_COUNT))

    if total_frames == 0:
        print(f"⚠️ Skipping {video_path}: No frames detected!")
        return

    frame_idxs = np.linspace(0, total_frames - 1, num_frames, dtype=in
    video_name = os.path.basename(video_path).split('.')[0]  # Remove

    # Ensure frames are saved under processed_frames/class_name/
    class_dir = os.path.join(PROCESSED_FRAMES_PATH, class_name)
    os.makedirs(class_dir, exist_ok=True)

    save_dir = os.path.join(class_dir, video_name)
    os.makedirs(save_dir, exist_ok=True)

    for i, idx in enumerate(frame_idxs):
        cap.set(cv2.CAP_PROP_POS_FRAMES, idx)
        ret, frame = cap.read()
        if not ret:
            break
        frame = cv2.resize(frame, (224, 224))  # Resize to 224x224
        frame_path = os.path.join(save_dir, f"frame_{i:02d}.jpg")
        cv2.imwrite(frame_path, frame)

    cap.release()

# Process all videos in the converted folder
for video_file in os.listdir(CONVERTED_VIDEOS_PATH):
    if video_file.endswith(".mp4"):  # Process only MP4 files
        video_path = os.path.join(CONVERTED_VIDEOS_PATH, video_file)

        # Extract class name from filename (e.g., "calling_01.mp4" → "
        class_name = video_file.split('_')[0]

        print(f"Extracting frames from {video_file} (Class: {class_name
        extract_frames(video_path, class_name)

print("✅ Frame extraction complete! Check 'processed_frames/'")
```

```
Extracting frames from sitting_24.mp4 (Class: sitting)...
Extracting frames from writing_01.mp4 (Class: writing)...
Extracting frames from calling_08.mp4 (Class: calling)...
Extracting frames from writing_27.mp4 (Class: writing)...
Extracting frames from sitting_44.mp4 (Class: sitting)...
Extracting frames from sitting_45.mp4 (Class: sitting)...
Extracting frames from writing_07.mp4 (Class: writing)...
Extracting frames from waving_05.mp4 (Class: waving)...
Extracting frames from walking_13.mp4 (Class: walking)...
Extracting frames from waving_14.mp4 (Class: waving)...
Extracting frames from walking_18.mp4 (Class: walking)...
Extracting frames from sitting_40.mp4 (Class: sitting)...
Extracting frames from walking_32.mp4 (Class: walking)...
```

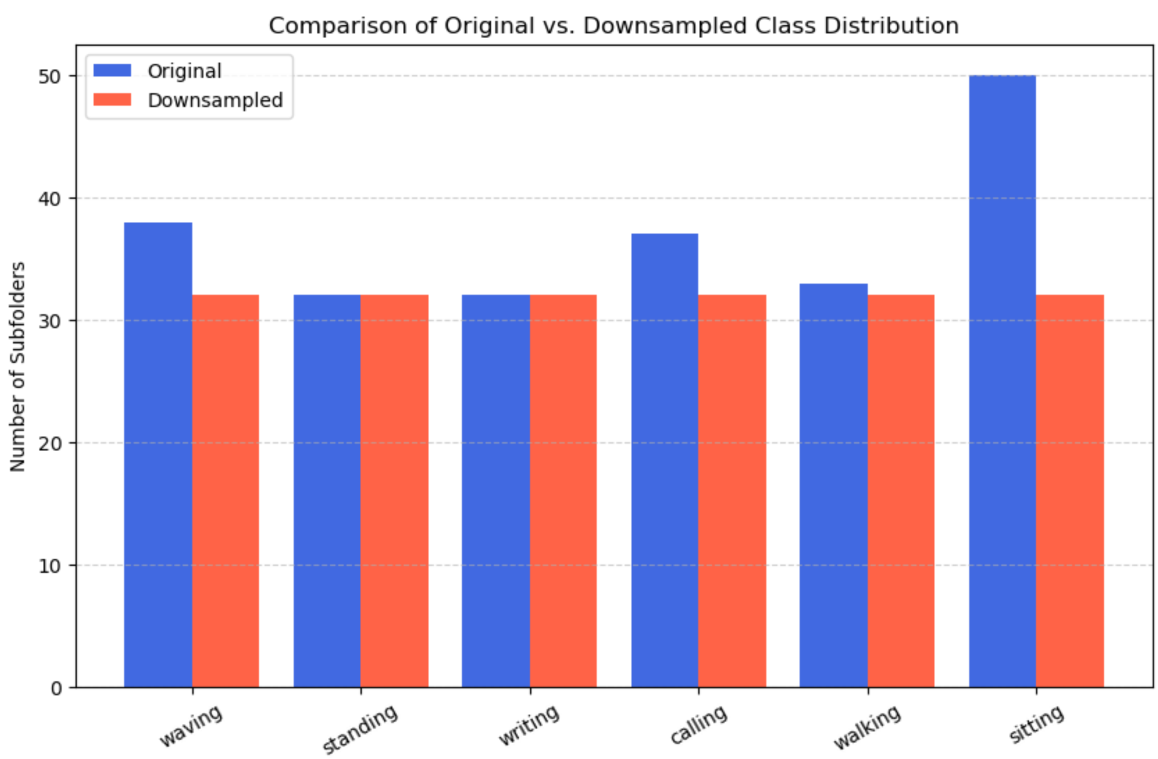
C-Undersampling to ensure uniform class distribution

In [ ]:
```
# Original dataset path
base_path = "/home/student/Documents/Programming-Exercises/projects/Hur

# New folder for downsampled data
downsampled_path = "/home/student/Documents/Programming-Exercises/proje

# Ensure the downsampled directory exists
os.makedirs(downsampled_path, exist_ok=True)

# Get all class folders
class_folders = [f for f in os.listdir(base_path) if os.path.isdir(os.p

# Find the minimum number of subfolders in any class
min_subfolders = min(len(os.listdir(os.path.join(base_path, folder))) f

# Downsample each class
for folder in class_folders:
    folder_path = os.path.join(base_path, folder)
    subfolders = [sf for sf in os.listdir(folder_path) if os.path.isdi

    # Randomly select only `min_subfolders` subfolders
    selected_subfolders = random.sample(subfolders, min_subfolders)

    # Create the corresponding class folder in the downsampled directo
    new_class_path = os.path.join(downsampled_path, folder)
    os.makedirs(new_class_path, exist_ok=True)

    for subfolder in selected_subfolders:
        src_subfolder = os.path.join(folder_path, subfolder)
        dest_subfolder = os.path.join(new_class_path, subfolder)
        shutil.copytree(src_subfolder, dest_subfolder)  # Copy the ent

print(f"Downsampling complete! All classes now have {min_subfolders} su
```

```
Downsampling complete! All classes now have 32 subfolders, saved in /
home/student24/Documents/Review_blocks/Review_Block_4/Deep learning/A
ssignment/Presentation/downsampled.
```

D-Plotting the original class distribution with downsampled class distribution

In [ ]:
```
# Paths
original_path = "/home/student/Documents/Programming-Exercises/project
downsampled_path = "/home/student/Documents/Programming-Exercises/proje

# Get class folders
class_folders = [f for f in os.listdir(original_path) if os.path.isdir

# Count subfolders in each class
original_counts = [len(os.listdir(os.path.join(original_path, folder))
downsampled_counts = [len(os.listdir(os.path.join(downsampled_path, fo

# Plot
x = np.arange(len(class_folders))  # X-axis positions

plt.figure(figsize=(10, 6))
plt.bar(x - 0.2, original_counts, width=0.4, label="Original", color="
plt.bar(x + 0.2, downsampled_counts, width=0.4, label="Downsampled", co

# Labels
plt.xticks(x, class_folders, rotation=30)
plt.ylabel("Number of Subfolders")
plt.title("Comparison of Original vs. Downsampled Class Distribution")
plt.legend()
plt.grid(axis="y", linestyle="--", alpha=0.6)

# Show plot
plt.show()
```



E-Data Augmentation

1-Flipping the videos

2-changing the speed

3-cropping the videos and resizing it back to 224

In [ ]:
```
# Paths
downsampled_path = "/home/student/Documents/Programming-Exercises/proje
augmented_path = "/home/student/Documents/Programming-Exercises/projec

# Ensure augmented directory exists
os.makedirs(augmented_path, exist_ok=True)

# Data augmentation functions
def flip_image(image):
    """ Horizontally flips the image """
    return cv2.flip(image, 1)

def crop_and_resize(image, size=224):
    """ Random crop and resize back to original size """
    h, w, _ = image.shape
    crop_size = int(0.8 * min(h, w))  # Crop 80% of min dimension
    x = random.randint(0, w - crop_size)
    y = random.randint(0, h - crop_size)
    cropped = image[y:y+crop_size, x:x+crop_size]
    return cv2.resize(cropped, (size, size))

def change_video_speed(video_path, output_path, speed_factor):
    """ Change video speed by speed_factor (0.5 = slow, 2.0 = fast) ""
    clip = VideoFileClip(video_path)
    new_clip = clip.fx(vfx.speedx, speed_factor)
    new_clip.write_videofile(output_path, codec="libx264", fps=clip.fps

# Process each class
for class_name in tqdm(os.listdir(downsampled_path), desc="Processing
    class_dir = os.path.join(downsampled_path, class_name)
    new_class_dir = os.path.join(augmented_path, class_name)
    os.makedirs(new_class_dir, exist_ok=True)

    # Process each subfolder (video instance)
    for subfolder in os.listdir(class_dir):
        subfolder_path = os.path.join(class_dir, subfolder)
        new_subfolder_path = os.path.join(new_class_dir, subfolder)
        os.makedirs(new_subfolder_path, exist_ok=True)

        # Process each frame
        for frame_name in os.listdir(subfolder_path):
            frame_path = os.path.join(subfolder_path, frame_name)
            image = cv2.imread(frame_path)

            if image is None:
                continue

            # Save original
            cv2.imwrite(os.path.join(new_subfolder_path, frame_name), i

            # Apply flipping
            flipped = flip_image(image)
            cv2.imwrite(os.path.join(new_subfolder_path, f"flipped_{fra

            # Apply cropping & resize
```

```
            cropped_resized = crop_and_resize(image)
            cv2.imwrite(os.path.join(new_subfolder_path, f"cropped_{fra

print("✅ Augmentation complete! Data saved in 'augmented' folder.")
```

```
Processing Classes: 100%|████████████████████████| 6/6 [00:12<00:00,
2.01s/it]

✅ Augmentation complete! Data saved in 'augmented' folder.
```

4-Splitting Dataset into training and testing

In [44]:

```
def load_data(frame_dir, num_classes, num_frames=16, img_size=(224, 224
    X = []
    y = []
    class_labels = sorted(os.listdir(frame_dir))  # Get action class na
    label_map = {label: idx for idx, label in enumerate(class_labels)}

    for action in class_labels:
        action_path = os.path.join(frame_dir, action)

        for instance in os.listdir(action_path):  # Iterate over video
            instance_path = os.path.join(action_path, instance)

            frame_paths = sorted(os.listdir(instance_path))[:num_frames

            frames = []
            for frame in frame_paths:
                img = cv2.imread(os.path.join(instance_path, frame))  #
                img = cv2.resize(img, img_size)  # Resize to 224x224
                img = img / 255.0  # Normalize pixel values
                frames.append(img)

            if len(frames) == num_frames:  # Ensure complete sequences
                X.append(np.array(frames))  # Store as NumPy array
                y.append(label_map[action])  # Store label

    # Convert to NumPy arrays
    X = np.array(X)
    y = to_categorical(y, num_classes)  # One-hot encode labels

    return X, y, class_labels  # Return class labels
```

In [47]:
```
# to identify the class labels,we output the different classes
frame_dir = "/home/student24/Documents/Review_blocks/Review_Block_4/Dee
num_classes = 6  # Adjust based on your dataset

X, y, class_labels = load_data(frame_dir, num_classes)

# Print class labels
print("Class labels:", class_labels)
```

```
Class labels: ['calling', 'sitting', 'standing', 'walking', 'waving',
'writing']
```

In [12]:
```
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.2
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_si
print(f"Train: {X_train.shape}, Validation: {X_val.shape}, Test: {X_tes
```

```
Train: (153, 16, 224, 224, 3), Validation: (19, 16, 224, 224, 3), Tes
t: (20, 16, 224, 224, 3)
```

5-Creating CNN Model

In [21]:
```
def create_advanced_3dcnn_model(input_shape, num_classes):
    model = Sequential()

    # 3D convolutional layer with 64 filters, kernel size of (3, 3, 3)
    model.add(Conv3D(32, (3, 3, 3), activation='relu', padding='same',
    # 3D max pooling layer with pool size of (2, 2, 2)
    model.add(MaxPooling3D((2, 2, 2)))
    # Batch normalization layer
    model.add(BatchNormalization())

    # Another 3D convolutional layer with 128 filters, kernel size of
    model.add(Conv3D(64, (3, 3, 3), activation='relu', padding='same'))
    # Another 3D max pooling layer with pool size of (2, 2, 2)
    model.add(MaxPooling3D((2, 2, 2)))
    # Another batch normalization layer
    model.add(BatchNormalization())

    # Another 3D convolutional layer with 256 filters, kernel size of
    model.add(Conv3D(98, (3, 3, 3), activation='relu', padding='same'))
    # Another 3D max pooling layer with pool size of (2, 2, 2)
    model.add(MaxPooling3D((2, 2, 2)))
    # Another batch normalization layer
    model.add(BatchNormalization())

    # Flatten layer to flatten the output of the convolutional layers
    model.add(Flatten())
    # Fully connected (dense) layer with 512 units and ReLU activation
    model.add(Dense(128, activation='relu'))
    # Dropout layer with dropout rate of 0.5
    model.add(Dropout(0.2))
    # Output layer with softmax activation for multi-class classificat
    model.add(Dense(num_classes, activation='softmax'))

    # Compile the model with Adam optimizer, categorical crossentropy
    model.compile(optimizer='adam', loss='categorical_crossentropy', me

    return model

# Define the shape of input frames and create the advanced 3D CNN mode
input_shape = (16, 224, 224, 3)
model = create_advanced_3dcnn_model(input_shape, num_classes)
```

In [22]:
```
model.summary()
```

```
Model: "sequential_1"
```

```
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━
━━━━━━┓
┃ Layer (type)                     ┃ Output Shape           ┃       Pa
ram # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━
━━━━━━┩
│ conv3d_3 (Conv3D)                │ (None, 16, 224, 224,   │
2,624 │
│                                  │ 32)                    │
│
├──────────────────────────────────┼────────────────────────┼─────────
──────┤
│ max_pooling3d_3 (MaxPooling3D)   │ (None, 8, 112, 112,    │
0 │
│                                  │ 32)                    │
│
├──────────────────────────────────┼────────────────────────┼─────────
──────┤
│ batch_normalization_3            │ (None, 8, 112, 112,    │
128 │
│ (BatchNormalization)             │ 32)                    │
│
├──────────────────────────────────┼────────────────────────┼─────────
──────┤
│ conv3d_4 (Conv3D)                │ (None, 8, 112, 112,    │        5
5,360 │
│                                  │ 64)                    │
│
├──────────────────────────────────┼────────────────────────┼─────────
──────┤
│ max_pooling3d_4 (MaxPooling3D)   │ (None, 4, 56, 56, 64)  │
0 │
├──────────────────────────────────┼────────────────────────┼─────────
──────┤
│ batch_normalization_4            │ (None, 4, 56, 56, 64)  │
256 │
│ (BatchNormalization)             │                        │
│
├──────────────────────────────────┼────────────────────────┼─────────
──────┤
│ conv3d_5 (Conv3D)                │ (None, 4, 56, 56, 98)  │       16
9,442 │
├──────────────────────────────────┼────────────────────────┼─────────
──────┤
│ max_pooling3d_5 (MaxPooling3D)   │ (None, 2, 28, 28, 98)  │
0 │
├──────────────────────────────────┼────────────────────────┼─────────
```

```
────────┤
│ batch_normalization_5           │ (None, 2, 28, 28, 98)  │
392 │
│ (BatchNormalization)            │                        │
│
├─────────────────────────────────┼────────────────────────┼───────────
────────┤
│ flatten_1 (Flatten)             │ (None, 153664)         │
0 │
├─────────────────────────────────┼────────────────────────┼───────────
────────┤
│ dense_4 (Dense)                 │ (None, 128)            │    19,66
9,120 │
├─────────────────────────────────┼────────────────────────┼───────────
────────┤
│ dropout_2 (Dropout)             │ (None, 128)            │
0 │
├─────────────────────────────────┼────────────────────────┼───────────
────────┤
│ dense_5 (Dense)                 │ (None, 6)              │
774 │
└─────────────────────────────────┴────────────────────────┴───────────
────────┘
```

```
 Total params: 19,898,096 (75.91 MB)

 Trainable params: 19,897,708 (75.90 MB)

 Non-trainable params: 388 (1.52 KB)
```

In [25]:
```
# Train the 3D CNN model with validation
history1 = model.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=20,
    batch_size=8
)

# Evaluate on the test set after training
test_loss, test_accuracy = model.evaluate(X_test, y_test)
print(f"Test Loss: {test_loss:.4f}, Test Accuracy: {test_accuracy:.4f}'
```

```
Epoch 1/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 85s 4s/step - accuracy: 0.9725 - loss: 0.5
941 - val_accuracy: 0.4737 - val_loss: 37.2437
Epoch 2/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 75s 4s/step - accuracy: 0.9666 - loss: 1.4
941 - val_accuracy: 0.4211 - val_loss: 35.4518
Epoch 3/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 62s 3s/step - accuracy: 0.9689 - loss: 0.8
349 - val_accuracy: 0.6842 - val_loss: 22.9164
Epoch 4/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 65s 3s/step - accuracy: 0.9695 - loss: 2.1
735 - val_accuracy: 0.5789 - val_loss: 26.6513
Epoch 5/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 65s 3s/step - accuracy: 0.9724 - loss: 0.3
635 - val_accuracy: 0.5789 - val_loss: 28.7597
Epoch 6/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 64s 3s/step - accuracy: 0.9925 - loss: 0.1
100 - val_accuracy: 0.5263 - val_loss: 23.3851
Epoch 7/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 64s 3s/step - accuracy: 0.9618 - loss: 1.5
311 - val_accuracy: 0.7368 - val_loss: 29.2711
Epoch 8/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 64s 3s/step - accuracy: 0.9629 - loss: 0.5
831 - val_accuracy: 0.5263 - val_loss: 90.7565
Epoch 9/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 64s 3s/step - accuracy: 0.9760 - loss: 1.1
722 - val_accuracy: 0.6842 - val_loss: 16.8705
Epoch 10/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 63s 3s/step - accuracy: 0.9704 - loss: 1.9
987 - val_accuracy: 0.6842 - val_loss: 19.9193
Epoch 11/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 62s 3s/step - accuracy: 0.9260 - loss: 4.6
293 - val_accuracy: 0.4737 - val_loss: 45.7940
Epoch 12/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 63s 3s/step - accuracy: 0.9176 - loss: 5.2
300 - val_accuracy: 0.7895 - val_loss: 46.6961
Epoch 13/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 62s 3s/step - accuracy: 0.9336 - loss: 2.2
154 - val_accuracy: 0.6316 - val_loss: 90.2532
Epoch 14/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 64s 3s/step - accuracy: 0.9273 - loss: 3.7
867 - val_accuracy: 0.4737 - val_loss: 97.7207
Epoch 15/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 64s 3s/step - accuracy: 0.9761 - loss: 0.8
088 - val_accuracy: 0.5789 - val_loss: 38.0017
Epoch 16/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 61s 3s/step - accuracy: 0.9717 - loss: 0.7
816 - val_accuracy: 0.4211 - val_loss: 168.1232
Epoch 17/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 60s 3s/step - accuracy: 0.9658 - loss: 1.2
109 - val_accuracy: 0.5263 - val_loss: 154.8853
Epoch 18/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 60s 3s/step - accuracy: 0.9447 - loss: 3.5
613 - val_accuracy: 0.6842 - val_loss: 42.5931
Epoch 19/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 60s 3s/step - accuracy: 0.9360 - loss: 6.5
```

```
236 - val_accuracy: 0.2632 - val_loss: 200.4634
Epoch 20/20
20/20 ━━━━━━━━━━━━━━━━━━━━ 60s 3s/step - accuracy: 0.9676 - loss: 2.0
181 - val_accuracy: 0.6316 - val_loss: 68.0031
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.7000 - loss: 34.707
7
Test Loss: 34.7077, Test Accuracy: 0.7000
```

In [27]:

```
# Extract accuracy and loss values
train_loss = history1.history['loss']
val_loss = history1.history['val_loss']
train_acc = history1.history['accuracy']
val_acc = history1.history['val_accuracy']

# Number of epochs
epochs = range(1, len(train_loss) + 1)

# Plot Accuracy
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(epochs, train_acc, label='Train Accuracy')
plt.plot(epochs, val_acc, label='Validation Accuracy')
plt.axhline(y=test_accuracy, color='r', linestyle='--', label='Test Acc
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training & Validation Accuracy')
plt.legend()

# Plot Loss
plt.subplot(1, 2, 2)
plt.plot(epochs, train_loss, label='Train Loss')
plt.plot(epochs, val_loss, label='Validation Loss')
plt.axhline(y=test_loss, color='r', linestyle='--', label='Test Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training & Validation Loss')
plt.legend()

plt.tight_layout()
plt.show()
```

Using Transfer learning

In [28]:
```
# Define input shape (16 frames, 224x224, RGB)
input_shape = (16, 224, 224, 3)
num_classes = 6  # Adjust based on your dataset

# Load MobileNetV2 as a feature extractor
base_model = keras.applications.MobileNetV2(
    input_shape=(224, 224, 3),  # Per-frame shape
    include_top=False,
    weights="imagenet"
)

# Freeze the base model to retain pretrained weights
base_model.trainable = False


# Define model input
inputs = keras.Input(shape=input_shape)

# Process each frame independently through MobileNetV2
x = layers.TimeDistributed(base_model)(inputs)

# Reduce spatial dimensions
x = layers.TimeDistributed(layers.GlobalAveragePooling2D())(x)

# Temporal processing using LSTM (captures motion over time)
x = layers.Bidirectional(layers.LSTM(128, return_sequences=False))(x)
x = layers.Dense(128, activation="relu")(x)  # **Apply ReLU activation
x = layers.Dropout(0.3)(x)  # **Apply Dropout correctly**

# **Fix: Connect outputs to x**
outputs = layers.Dense(num_classes, activation="softmax")(x)  # Correc

# Build the model
model1 = keras.Model(inputs=inputs, outputs=outputs)

# Compile model
model1.compile(optimizer="adam",
              loss="categorical_crossentropy",
              metrics=["accuracy"])

# Print model summary
model1.summary()
```

```
Model: "functional_27"
```

Layer (type)	Output Shape	Param #
input_layer_5 (InputLayer)	(None, 16, 224, 224, 3)	0
time_distributed_2 (TimeDistributed)	(None, 16, 7, 7, 1280)	2,257,984
time_distributed_3 (TimeDistributed)	(None, 16, 1280)	0
bidirectional_1 (Bidirectional)	(None, 256)	1,442,816
dense_6 (Dense)	(None, 128)	32,896
dropout_3 (Dropout)	(None, 128)	0
dense_7 (Dense)	(None, 6)	774

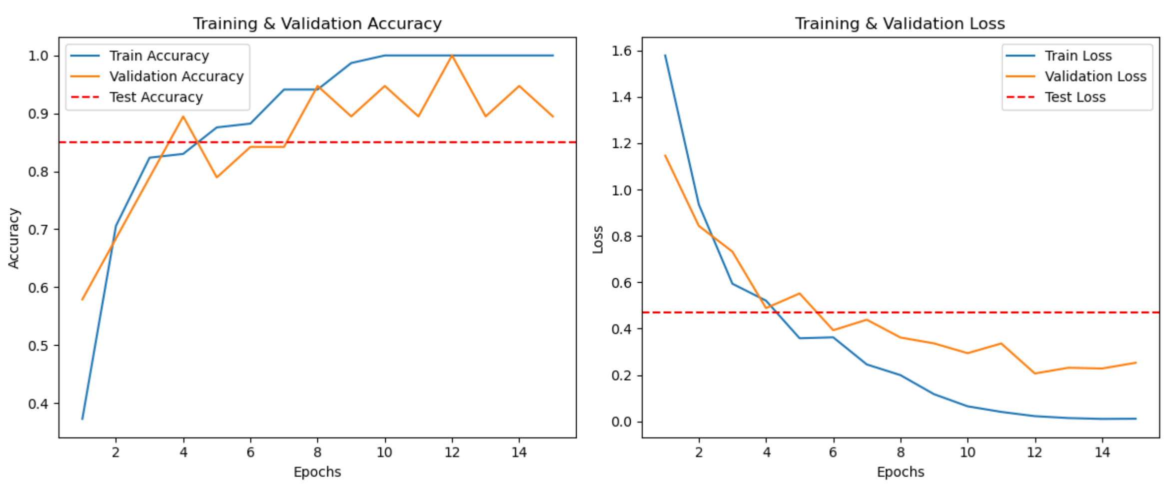
```
Total params: 3,734,470 (14.25 MB)

Trainable params: 1,476,486 (5.63 MB)

Non-trainable params: 2,257,984 (8.61 MB)
```

In [30]:
```
# Train the model with training, validation, and testing
EPOCHS = 15
history = model1.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=EPOCHS,
    batch_size=8
)

# Evaluate on test data
test_loss, test_accuracy = model1.evaluate(X_test, y_test)
print(f"Test Loss: {test_loss:.4f}, Test Accuracy: {test_accuracy:.4f}'

# Save the trained model
model.save("human_action_recognition.h5")
print("✅ Model training complete! Model saved as 'human_action_recogni
```

```
Epoch 1/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 157s 4s/step - accuracy: 0.2469 - loss: 1.
7761 - val_accuracy: 0.5789 - val_loss: 1.1460
Epoch 2/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 60s 3s/step - accuracy: 0.6628 - loss: 1.0
151 - val_accuracy: 0.6842 - val_loss: 0.8429
Epoch 3/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 78s 4s/step - accuracy: 0.7976 - loss: 0.6
461 - val_accuracy: 0.7895 - val_loss: 0.7317
Epoch 4/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 56s 3s/step - accuracy: 0.8332 - loss: 0.5
106 - val_accuracy: 0.8947 - val_loss: 0.4883
Epoch 5/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 46s 2s/step - accuracy: 0.8951 - loss: 0.3
433 - val_accuracy: 0.7895 - val_loss: 0.5515
Epoch 6/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 46s 2s/step - accuracy: 0.8625 - loss: 0.3
742 - val_accuracy: 0.8421 - val_loss: 0.3930
Epoch 7/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 45s 2s/step - accuracy: 0.9188 - loss: 0.3
029 - val_accuracy: 0.8421 - val_loss: 0.4384
Epoch 8/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 46s 2s/step - accuracy: 0.9580 - loss: 0.1
732 - val_accuracy: 0.9474 - val_loss: 0.3614
Epoch 9/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 46s 2s/step - accuracy: 0.9749 - loss: 0.1
339 - val_accuracy: 0.8947 - val_loss: 0.3360
Epoch 10/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 46s 2s/step - accuracy: 1.0000 - loss: 0.0
661 - val_accuracy: 0.9474 - val_loss: 0.2939
Epoch 11/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 46s 2s/step - accuracy: 1.0000 - loss: 0.0
481 - val_accuracy: 0.8947 - val_loss: 0.3358
Epoch 12/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 45s 2s/step - accuracy: 1.0000 - loss: 0.0
236 - val_accuracy: 1.0000 - val_loss: 0.2064
Epoch 13/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 46s 2s/step - accuracy: 1.0000 - loss: 0.0
136 - val_accuracy: 0.8947 - val_loss: 0.2311
Epoch 14/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 46s 2s/step - accuracy: 1.0000 - loss: 0.0
099 - val_accuracy: 0.9474 - val_loss: 0.2278
Epoch 15/15
20/20 ━━━━━━━━━━━━━━━━━━━━ 45s 2s/step - accuracy: 1.0000 - loss: 0.0
105 - val_accuracy: 0.8947 - val_loss: 0.2526
1/1 ━━━━━━━━━━━━━━━━━━━━ 9s 9s/step - accuracy: 0.8500 - loss: 0.4690

WARNING:absl:You are saving your model as an HDF5 file via `model.sav
e()` or `keras.saving.save_model(model)`. This file format is conside
red legacy. We recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model, 'my
_model.keras')`.

Test Loss: 0.4690, Test Accuracy: 0.8500
✅ Model training complete! Model saved as 'human_action_recognition.
h5'.
```

plots for scratch and pretrained models:

In [31]:
```
import matplotlib.pyplot as plt

# Extract accuracy and loss values
train_loss = history.history['loss']
val_loss = history.history['val_loss']
train_acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

# Number of epochs
epochs = range(1, len(train_loss) + 1)

# Plot Accuracy
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(epochs, train_acc, label='Train Accuracy')
plt.plot(epochs, val_acc, label='Validation Accuracy')
plt.axhline(y=test_accuracy, color='r', linestyle='--', label='Test Acc
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training & Validation Accuracy')
plt.legend()

# Plot Loss
plt.subplot(1, 2, 2)
plt.plot(epochs, train_loss, label='Train Loss')
plt.plot(epochs, val_loss, label='Validation Loss')
plt.axhline(y=test_loss, color='r', linestyle='--', label='Test Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training & Validation Loss')
plt.legend()

plt.tight_layout()
plt.show()
```



Prediction power of two models: scratch model and pretrained model

In [32]:
```
# Predict class probabilities for each sample
y_pred_model = model.predict(X_test)
y_pred_model1 = model1.predict(X_test)

# Convert probabilities to class labels (indices of max probability)
y_pred_classes_model = np.argmax(y_pred_model, axis=1)
y_pred_classes_model1 = np.argmax(y_pred_model1, axis=1)

# Convert true labels to class indices
y_true_classes = np.argmax(y_test, axis=1)  # Assuming one-hot encoded
```

```
2025-02-19 22:49:46.529527: W tensorflow/core/kernels/data/prefetch_a
utotuner.cc:52] Prefetch autotuner tried to allocate 192675840 bytes
after encountering the first element of size 192675840 bytes.This alr
eady causes the autotune ram budget to be exceeded. To stay within th
e ram budget, either increase the ram budget or reduce element size

1/1 ━━━━━━━━━━━━━━━━━━━━ 5s 5s/step

2025-02-19 22:49:52.871590: W tensorflow/core/kernels/data/prefetch_a
utotuner.cc:52] Prefetch autotuner tried to allocate 192675840 bytes
after encountering the first element of size 192675840 bytes.This alr
eady causes the autotune ram budget to be exceeded. To stay within th
e ram budget, either increase the ram budget or reduce element size

1/1 ━━━━━━━━━━━━━━━━━━━━ 30s 30s/step
```

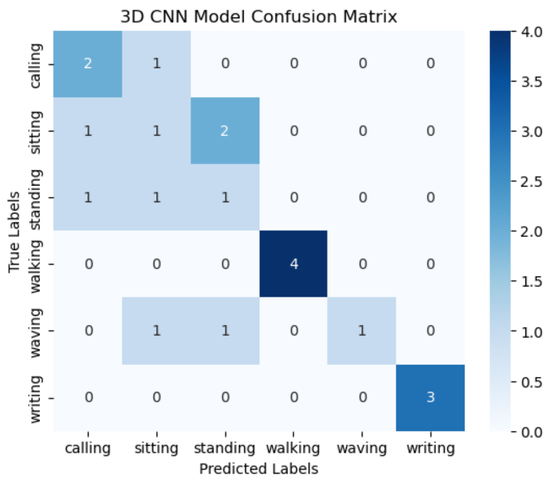
In [33]:
```
# Evaluate accuracy and loss for both models
test_loss_model, test_acc_model = model.evaluate(X_test, y_test)
test_loss_model1, test_acc_model1 = model1.evaluate(X_test, y_test)

print(f"3D CNN Model - Test Loss: {test_loss_model:.4f}, Test Accuracy
print(f"MobileNet Model - Test Loss: {test_loss_model1:.4f}, Test Accu
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.6000 - loss: 36.846
5
1/1 ━━━━━━━━━━━━━━━━━━━━ 5s 5s/step - accuracy: 0.8500 - loss: 0.4690
3D CNN Model - Test Loss: 36.8465, Test Accuracy: 0.6000
MobileNet Model - Test Loss: 0.4690, Test Accuracy: 0.8500
```

In [35]:
```
# Print classification report for 3D CNN Model
print("Classification Report for 3D CNN Model:")
print(classification_report(y_true_classes, y_pred_classes_model, digi

# Print classification report for MobileNet Model
print("Classification Report for MobileNet Model:")
print(classification_report(y_true_classes, y_pred_classes_model1, dig:
```

```
Classification Report for 3D CNN Model:
              precision    recall  f1-score   support

           0     0.5000    0.6667    0.5714         3
           1     0.2500    0.2500    0.2500         4
           2     0.2500    0.3333    0.2857         3
           3     1.0000    1.0000    1.0000         4
           4     1.0000    0.3333    0.5000         3
           5     1.0000    1.0000    1.0000         3

    accuracy                         0.6000        20
   macro avg     0.6667    0.5972    0.6012        20
weighted avg     0.6625    0.6000    0.6036        20

Classification Report for MobileNet Model:
              precision    recall  f1-score   support

           0     0.7500    1.0000    0.8571         3
           1     1.0000    0.7500    0.8571         4
           2     1.0000    0.6667    0.8000         3
           3     1.0000    1.0000    1.0000         4
           4     0.6667    0.6667    0.6667         3
           5     0.7500    1.0000    0.8571         3

    accuracy                         0.8500        20
   macro avg     0.8611    0.8472    0.8397        20
weighted avg     0.8750    0.8500    0.8486        20
```

In [ ]:
```
# Generate confusion matrices
cm_model = confusion_matrix(y_true_classes, y_pred_classes_model)
cm_model1 = confusion_matrix(y_true_classes, y_pred_classes_model1)

# Plot confusion matrices
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# 3D CNN Model Confusion Matrix
sns.heatmap(cm_model, annot=True, fmt="d", cmap="Blues", xticklabels=cl
axes[0].set_title("3D CNN Model Confusion Matrix")
axes[0].set_xlabel("Predicted Labels")
axes[0].set_ylabel("True Labels")

# MobileNet Model Confusion Matrix
sns.heatmap(cm_model1, annot=True, fmt="d", cmap="Oranges", xticklabels
axes[1].set_title("MobileNet Model Confusion Matrix")
axes[1].set_xlabel("Predicted Labels")
axes[1].set_ylabel("True Labels")

plt.show()
```



In [ ]: