Human Activity Recognition Using Machine Learning Techniques

A PROJECT REPORT

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Under the guidance of,

Mr. Lakshmisha S Krishna

in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND TECHNOLOGY
[ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING]

At

GAIN MORE KNOWLEDGE
REACH GREATER HEIGHTS

PRESIDENCY UNIVERSITY

BENGALURU

JANUARY 2024

PRESIDENCY UNIVERSITY

SCHOOL OF COMPUTER SCIENCE ENGINEERING

CERTIFICATE

This is to certify that the Project report **“Human Activity Recognition Using Machine Learning Techniques”** being submitted by “Mohammed Zaid Khan, Ankita Yeleswarapu, Jeevan R” bearing roll numbers “20201CST0003, 20201CST0038, 20201CST0039” in partial fulfilment of requirement for the award of degree of Bachelor of Technology in Computer Science and Technology [Artificial intelligence and Machine learning] is a bonafide work carried out under my supervision.

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DECLARATION

We hereby declare that the work, which is being presented in the project report entitled **Human Activity Recognition Using Machine Learning Techniques** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **Computer Science and Technology [Artificial intelligence and Machine learning]**, is a record of our own investigations carried under the guidance of **Mr. Lakshmisha S Krishna, Assistant Professor, School of Computer Science Engineering & Information Science, Presidency University, Bengaluru.**

We have not submitted the matter presented in this report anywhere for the award of any other Degree.

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ABSTRACT

Human Activity Recognition (HAR) using machine learning algorithms has received a lot of attention due to its vast applications in healthcare, smart settings, and human-computer interaction. This research article gives a detailed analysis of current improvements in HAR methodology, with a focus on the application of multiple machine learning approaches for accurate and efficient activity classification.

This project aims to provide researchers, practitioners, and enthusiasts with a comprehensive understanding of the current landscape of HAR using machine learning techniques. By synthesizing existing knowledge, identifying research gaps, and discussing future directions, this paper contributes to the ongoing efforts to advance the field of Human Activity Recognition and encourages the development of more accurate and adaptable systems for understanding human behavior.

By focusing on the UNF101 repository, this research contributes a practical and context-specific perspective to the broader field of HAR. The findings aim to inform researchers and practitioners about the challenges and opportunities associated with applying machine learning techniques to unconstrained activity recognition scenarios, ultimately fostering advancements in the development of more robust and adaptable systems for understanding human behavior.

ACKNOWLEDGEMENT

First of all, we indebted to the **GOD ALMIGHTY** for giving me an opportunity to excel in our efforts to complete this project on time.

We express our sincere thanks to our respected dean **Dr. Md. Sameeruddin Khan**, Dean, School of Computer Science Engineering & Information Science, Presidency University for getting us permission to undergo the project.

We record our heartfelt gratitude to our beloved Associate Deans **Dr. Kalaiarasan C and Dr. Shakkeera L,** School of Computer Science Engineering & Information Science, Presidency University and **Dr. A. Jayachandran**. Head of the Department, School of Computer Science Engineering, Presidency University for rendering timely help for the successful completion of this project.

We are greatly indebted to our guide **Mr. Lakshmisha S Krishna, Assistant Professor**, School of Computer Science Engineering & Information Science, Presidency University for his inspirational guidance, and valuable suggestions and for providing us a chance to express our technical capabilities in every respect for the completion of the project work.

We would like to convey our gratitude and heartfelt thanks to the University Project-II Coordinators **Dr. Sanjeev P Kaulgud, Dr. Mrutyunjaya MS** and also the department Project Coordinators **Dr. Manjula H M, Mr. Yamanappa**.

We thank our family and friends for the strong support and inspiration they have provided us in bringing out this project.

Mohammed Zaid Khan
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CHAPTER-1

INTRODUCTION

1.1 Introduction

Human Activity Recognition (HAR) has emerged as a pivotal research area in various fields ranging from technical to medical. The ability to automatically identify and interpret human activities from sensor data holds tremendous potential across a multitude of applications, ranging from healthcare and assistive technologies to security, smart environments, and beyond. As our world becomes increasingly connected and data-rich, the demand for systems capable of understanding and responding to human behavior has grown exponentially.

Convolutional neural networks bring a fresh perspective to human activity recognition by reinventing how systems extract meaningful signals and understand patterns within motion data. Rather than relying on manually defined features, these networks independently discover the informative components hidden inside raw sensor readings. In doing so, they develop a nuanced awareness of the subtle characteristics that distinguish one activity from another, much like how people intuitively parse human movement. The convolutional filters specifically allow the networks to pinpoint localized motifs within the data, making them attuned to fine variations in movement that may escape traditional analyses. Additionally, the spatial positions of the informative features matter less to these networks - they care more about the sequential flow. This means small changes in where someone places a sensor on their body doesn't obstruct the network's capacity to make sense of the data. Their flexibility and scalability primes them to greatly advance activity recognition.

In this paper, we’ve used UC101 dataset for training and testing the data. UCF101's diverse and realistic dataset from YouTube videos is a valuable asset for Human Activity Recognition (HAR) research. Considering its large-scale collection, emphasis on temporal dynamics, and inclusion numerous activities, it provides a good a foundation for training and testing robust HAR models. The dataset's open-source nature and accessibility stimulate further interdependence, accelerating enhancements in HAR approaches with practical applications.

1.1.1 Scope of Human Activity Recognition

Human activity recognition (HAR) has a broad profound and plays an essential role in applications in a wide range of disciplines. External and wearable sensors are used to recognize human activities. Cameras and other external sensors are used to collect the user's tracing, pose, salient body parts, relevant objects, scene context, and so on. It provides real-time patient monitoring and early detection of health issues in healthcare. HAR advances assistive technologies for those with disabilities and helps with sports performance analysis and injury prevention. The automated detection of illicit behavior boosts security, while smart environment become versatile and efficient. Improved workplace safety benefits industrial settings, and behavioral research provides insights into society dynamics. The incorporation of HAR into wearable devices and Internet of Things technology broadens its potential impact on human-computer interaction, urban planning, and other areas. The numerous uses of HAR demonstrate its importance in enhancing several elements of human life and industry.

1.2 Software Requirements

Operating System	: Windows 10
Programming	: Python3

1.3 Hardware Requirements

Operating System	: Windows 10
Processor	: Intel(R) Core(TM) i7-1065G7 CPU @ 1.30GHz
RAM	: 08.00 GB
SSD	: 512GB

CHAPTER-2

LITERATURE SURVEY

Sl No.	Author Name and Year	Title	Findings
1	H. Yang, X. Wen, Y. Geng, Y. Wang, X. Wang and C. Lu,(2022)	A Multi-Position Joint Angle Dataset for Human Activity Recognition Using Wearable Sensors	Methods that reliably recognize a variety of human actions, underscoring the potential of wearable sensor technologies for reliable activity.
2	F. Zhou, R. Wang, H. Su and S. Xu(2022)	A Human Activity Recognition Model Based on Wearable Sensor	The combination of CNN and RNN architectures enhances the model's ability to recognize and classify specific actions in the dataset.
3	I. Stolovas, S. Suárez, D. Pereyra, F. De Izaguirre and V. Cabrera(2021)	Human activity recognition using machine learning techniques in a low-resource embedded system,	To successfully forecast activities from accelerometer data, the system makes use of statistical properties, dimensionality reduction (Linear Discriminant Analysis), and SVM classification.
4	Q. Jian, S. Guo, P. Chen, P. Wu and G. Cui(2021)	A Robust Real-time Human Activity Recognition method Based on Attention-Augmented GRU	AASC surpasses traditional GRU models in terms of accuracy and robustness by leveraging attention processes to facilitate efficient temporal connection learning .
5	M. Atikuzzaman, T. R. Rahman, E. Wazed, M. P. Hossain and M. Z. Islam(2020)	Human Activity Recognition System from Different Poses with CNN,	Obtained excellent scores for pose and activity detection accuracy. The stated processing speed is significant since it suggests real-time application potential.
6	N. Amin Choudhury, S. Moulik and S. Choudhury(2020)	Cloud-based Real-time and Remote Human Activity Recognition System using Wearable Sensors	Could correctly classify different human activities at a rate of nine, which is especially useful when taking wearables and cloud computing .
7	R. Saini and V. Maan(2020)	Human Activity and Gesture Recognition: A Review,	CNNs have demonstrated success in accurately recognizing a variety of human actions.
8	M. S. H. Bhuiyan, N. S. Patwary, P. K. Saha and M. T. Hossain(2020)	Sensor-Based Human Activity Recognition: A Comparative Study of Machine Learning Techniques,	Combining (PCA) with (RF) on phone accelerometer data produced the best results in terms of HAR accuracy.
9	L. Xie, J. Tian, G. Ding and Q. Zhao(2018)	Human activity recognition method based on inertial sensor and barometer,	The testing results, which accurately detect human activities based on the given sensor data, show how effective the system is.
10	E. Kim, S. Helal and D. Cook(2010)	Human Activity Recognition and Pattern Discovery	The study distinguishes between broad systems that recognize activity using predetermined models and those that use sensor data analysis.

CHAPTER-3

RESEARCH GAPS OF EXISTING METHODS

Current activity tracking tools still fall short in matching the fluid flexibility of human movement. Methods that work well in controlled settings often get tripped up by natural variety. The ultimate goal remains out of reach: systems that can keep up with the complexity of life.

Real-time recognition still strains many algorithms, even though timely responses matter in safety applications. And we attachment trackers in so many unique places, but data quality and placement inconsistencies continue causing trouble.

There’s still progress to make before activity tracking can adapt to diverse abilities, bodies, environments - all the richness of living. Closing these gaps will take creativity, but will uncover new potentials. More flexible, quick-thinking systems would revolutionize applications from healthcare to wearables and beyond. The open questions invite collaborative innovation so one day, trackers can handle life’s every variation.

CHAPTER-4

PROPOSED MOTHODOLOGY

Data Importing:

Open the UCF101 dataset and load the video clips for each of the 101 action categories. Form image patterns by taking the frames out of the video footage. This would be regarded for specific applications.

Extraction of Features and choosing appropriate CNN model for classification:

Features are extracted from the dataset in accordance to the model. The most suitable architecture for video classification is CNN I3D (Inflated 3D CNNs) and is hence used.

Training the data:

The dataset used for training the data is UCF101. Hence, we check the labeling of the data with the use of Kinetics and hence display it for ease access.

Testing the data:

The trained model is tested with the use of sample videos which then displays the probabilistic percentage of the possible labels associated with the video. The one with the highest probability is associated with the video and is hence verified.

CHAPTER-5

OBJECTIVES

- Develop CNN-based models with the primary objective of improving the accuracy and recognition rates in human activity recognition, ensuring more precise identification of various activities.
- Design CNN architectures that exhibit robustness to environmental conditions, such as changes in lighting, background, and different sensor configurations.
- Prioritize the optimization of CNN models for real-time processing to address latency challenges associated with streaming sensor data.
- Create CNN models capable of effectively recognizing a broad spectrum of human activities, promoting versatility and applicability in various contexts and scenarios.
- Investigate the application of transfer learning to leverage pre-trained CNN models on large datasets, potentially enhancing the performance of HAR models. This aims to capitalize on learned features from diverse sources and domains.

CHAPTER-6

SYSTEM DESIGN & IMPLEMENTATION

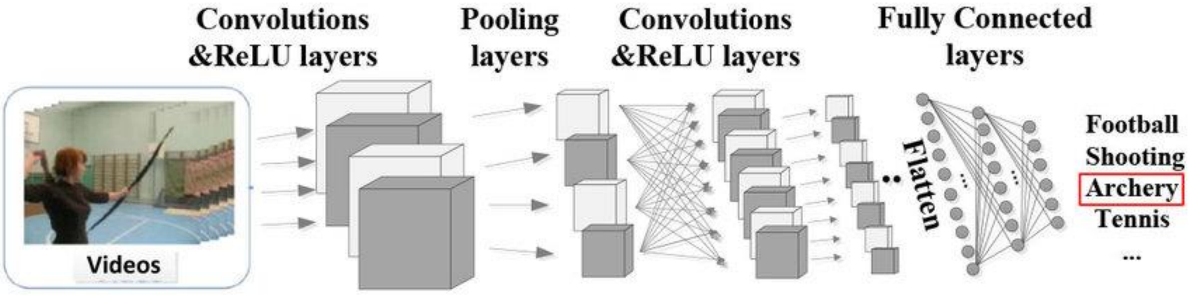


Fig 1.1: CNN Architecture for Image Classification

Firstly, the UCF101 dataset is downloaded and preprocessing is performed. This ensures that the data from the video is well segmented into required and desirable frames and clip length. Kinetics URL is used to authorize and label the data.

Perform data preprocessing steps, such as resizing frames, normalizing pixel values, and potentially extracting optical flow or other relevant features. Split the dataset into training, validation, and test sets.

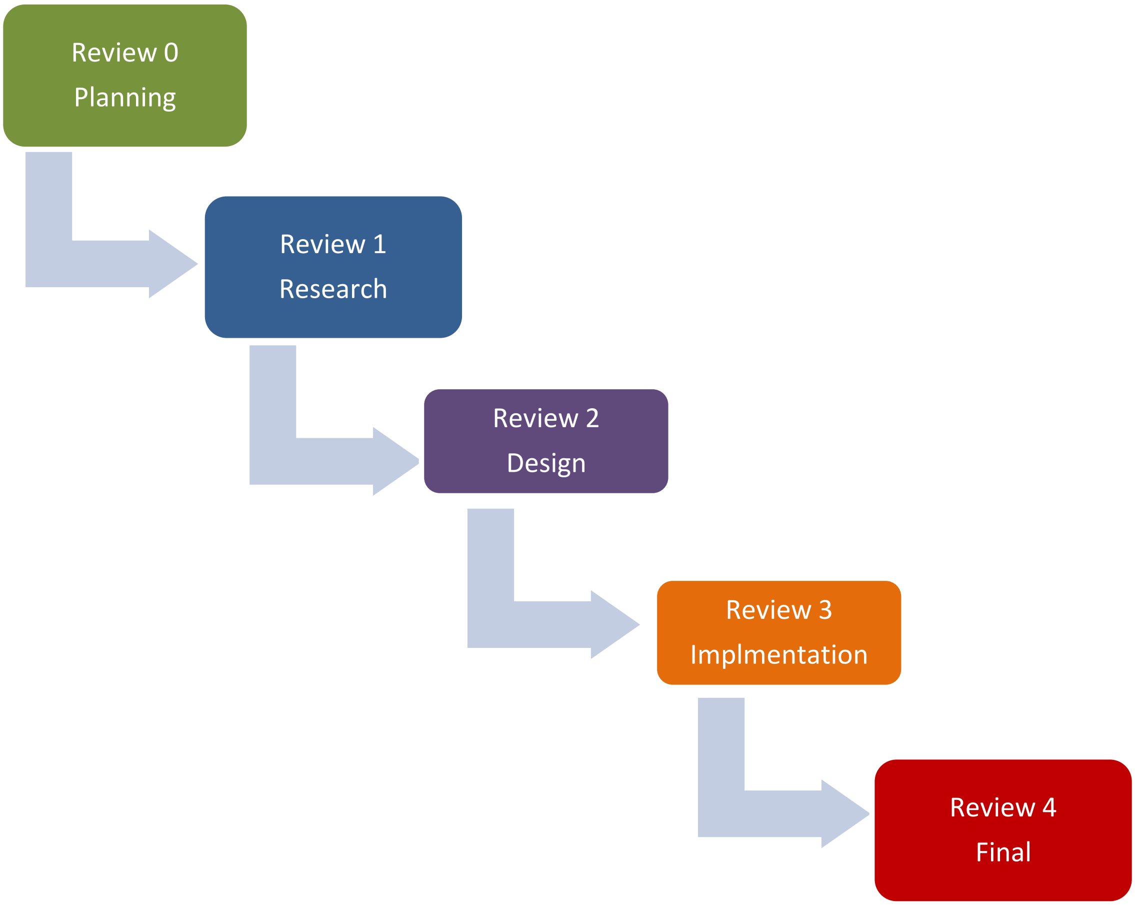
CNN Model I3D is chosen for performing classification. This helps in reducing complexity and showcases rigid classification tasks within the video sequence.

Here, we use UCF101 dataset and hence the model is already trained. However, we fine tune the dataset for adaptability by further initializing pre-trained weights. The use of Kinetics is made as it simplifies the task.

The CNN model is then tested post training on the designated test data.

CHAPTER-7

TIMELINE FOR EXECUTION OF PROJECT



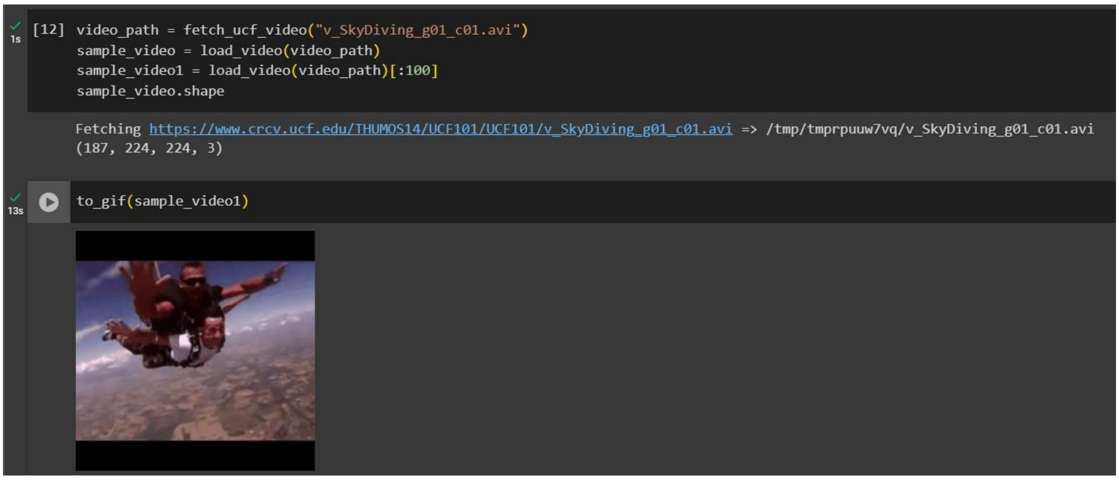
CHAPTER-8

OUTCOMES

- The CNN-based model I3D model yield higher accuracy in recognizing and classifying diverse human activities, contributing to more reliable and precise outcomes, specialized for a 3D environment *i.e.* video clips.
- The utilization of CNN architectures has aided to enhance the adaptability of human activity recognition systems across varied environments, scenarios, and activity types incorporated in UCF101 dataset.
- Optimizing the model for real-time processing efficiency has enabled quicker and more responsive recognition of human activities while enhancing the practical utility of the developed model.
- Successful implementation of CNN models is likely to result in better generalization across a wide spectrum of human activities, ensuring versatility and applicability in different contexts.
- The model demonstrates reduced reliance on manually engineered features while allowing for more automatic and adaptable feature learning directly from raw sensor data,
- The developed CNN demonstrates advancements in accuracy, efficiency, and adaptability compared to existing state-of-the-art methods in human activity recognition, especially with the use of images datasets.

CHAPTER-9

RESULTS AND DISCUSSIONS

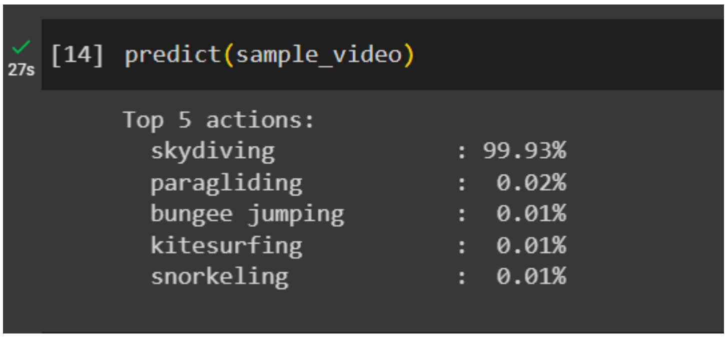


```
[12] video_path = fetch_ucf_video("v_SkyDiving_g01_c01.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_SkyDiving_g01_c01.avi => /tmp/tmprpuuw7vq/v_SkyDiving_g01_c01.avi
     (187, 224, 224, 3)

     to_gif(sample_video1)
```

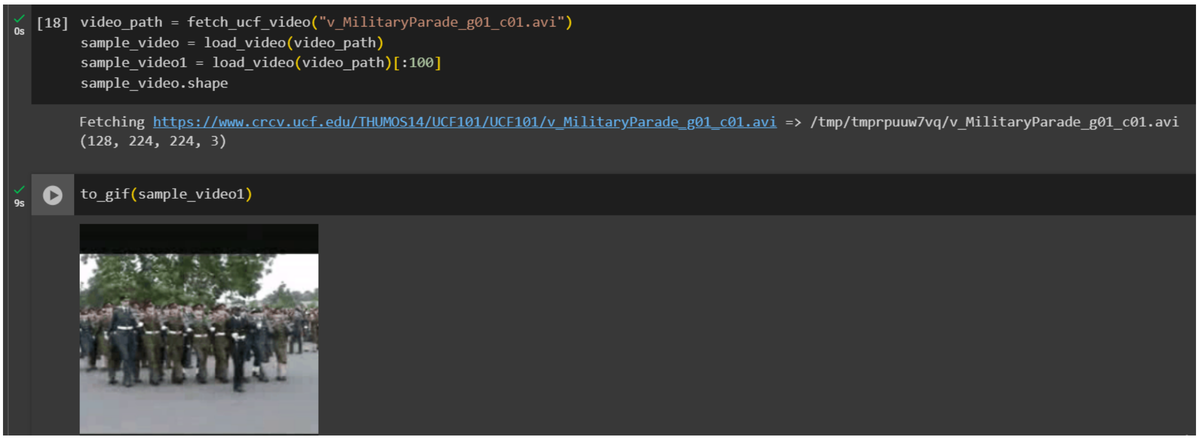
Fig 2.1: Fetching the shape and video of “Skydiving – v1” video clip



```
[14] predict(sample_video)

     Top 5 actions:
       skydiving             : 99.93%
       paragliding           :  0.02%
       bungee jumping        :  0.01%
       kitesurfing           :  0.01%
       snorkeling            :  0.01%
```

Fig 2.2: Prediction percentage for the sample video “Skydiving – v1” is stated above as the output. The output is obtained as skydiving for the sample video entered as the probability of the action “skydiving” is 99.93%. The other 4 actions are probabilistically the closest match after skydiving. However, these are very low.

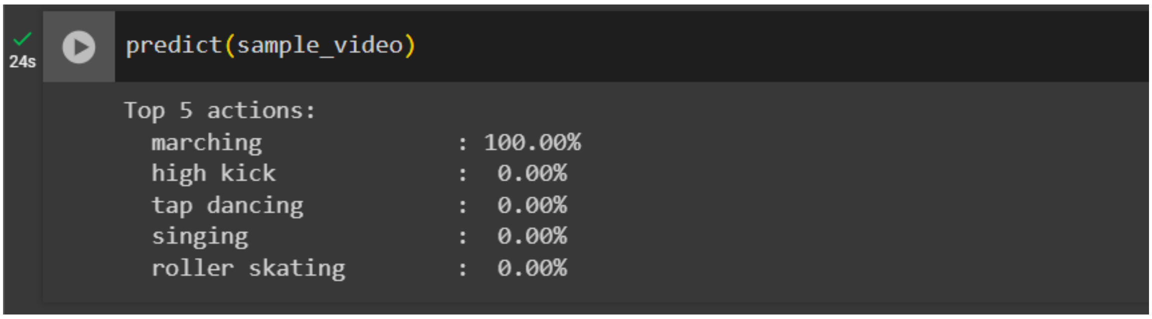


```
[18] video_path = fetch_ucf_video("v_MilitaryParade_g01_c01.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_MilitaryParade_g01_c01.avi => /tmp/tmprpuuw7vq/v_MilitaryParade_g01_c01.avi
     (128, 224, 224, 3)

     to_gif(sample_video1)
```

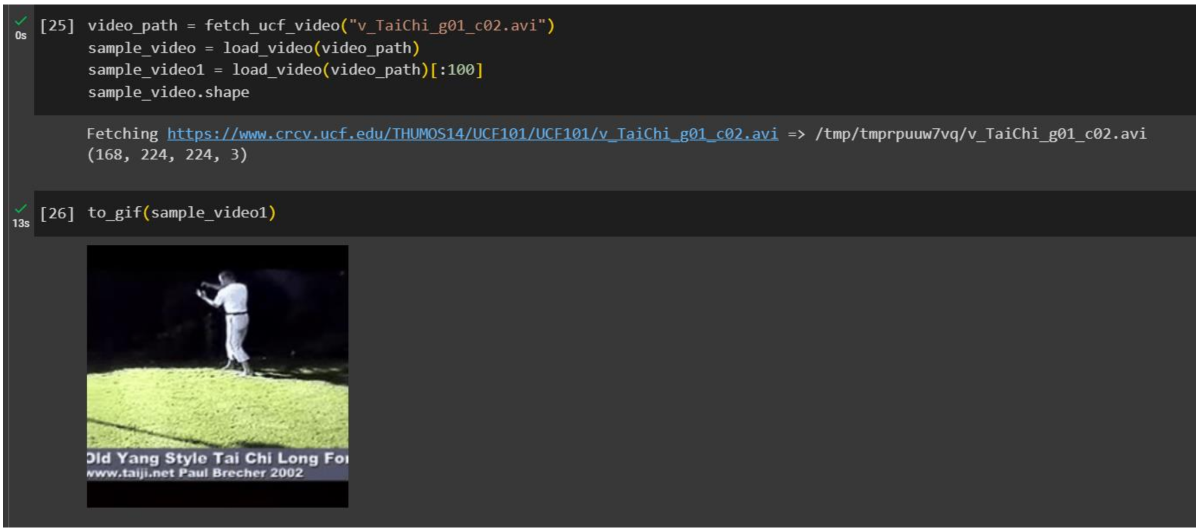
Fig 2.3: Fetching the shape and video of “MilitaryParade – v1” video clip



```
24s  predict(sample_video)

     Top 5 actions:
       marching              : 100.00%
       high kick             :  0.00%
       tap dancing           :  0.00%
       singing               :  0.00%
       roller skating        :  0.00%
```

Fig 2.4: Prediction percentage for the sample video "MilitaryParade – v1" is as stated above. The output is obtained as marching for the sample video entered as the probability of the action "marching" is a straight 100%.



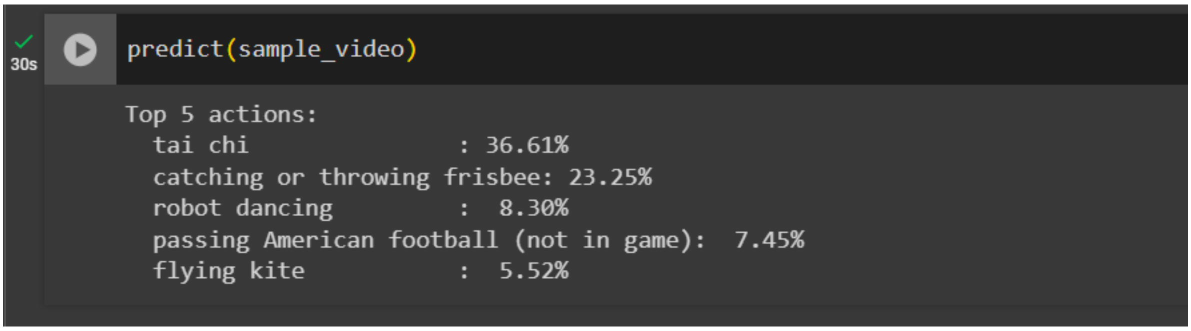
```
0s  [25] video_path = fetch_ucf_video("v_TaiChi_g01_c02.avi")
         sample_video = load_video(video_path)
         sample_video1 = load_video(video_path)[:100]
         sample_video.shape

         Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_TaiChi_g01_c02.avi => /tmp/tmprpuuw7vq/v_TaiChi_g01_c02.avi
         (168, 224, 224, 3)

13s [26] to_gif(sample_video1)
```

Old Yang Style Tai Chi Long For
www.taiji.net Paul Brecher 2002

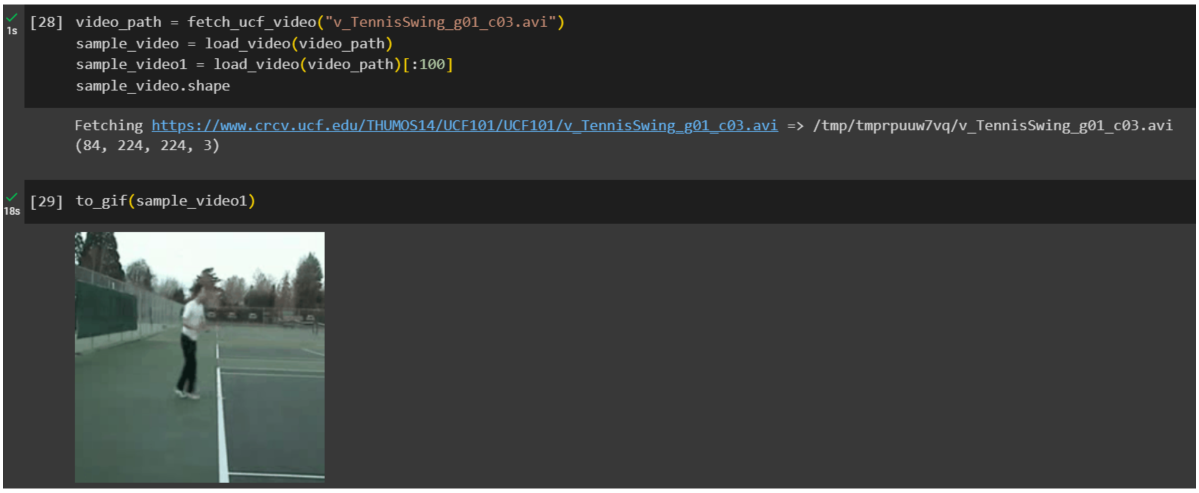
Fig 2.5: Fetching the shape and video of "Taichi – v2" video clip



```
30s  predict(sample_video)

     Top 5 actions:
       tai chi               : 36.61%
       catching or throwing frisbee: 23.25%
       robot dancing         :  8.30%
       passing American football (not in game):  7.45%
       flying kite           :  5.52%
```

Fig 2.6: Prediction percentage for the sample video "Taichi – v2" is as stated above.. The output is obtained as taichi for the sample video entered as the probability of the action "tai chi" is at a cutting edge of 36.61%. When compared, this testing data shows a positive prospect towards the model trained and helps one in probabilistically analyzing the activities which may seem familiar in sight.

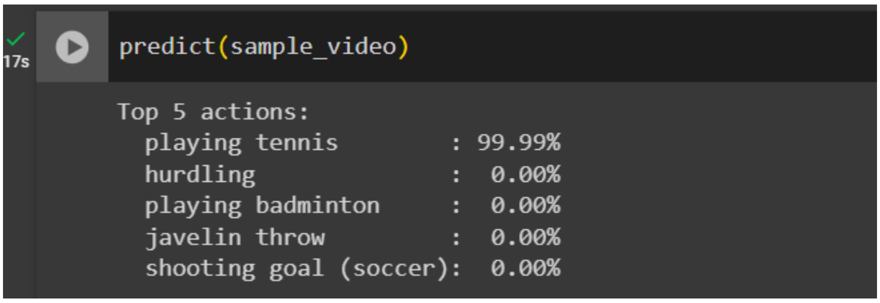


```
[28] video_path = fetch_ucf_video("v_TennisSwing_g01_c03.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_TennisSwing_g01_c03.avi => /tmp/tmprpuuw7vq/v_TennisSwing_g01_c03.avi
     (84, 224, 224, 3)

[29] to_gif(sample_video1)
```

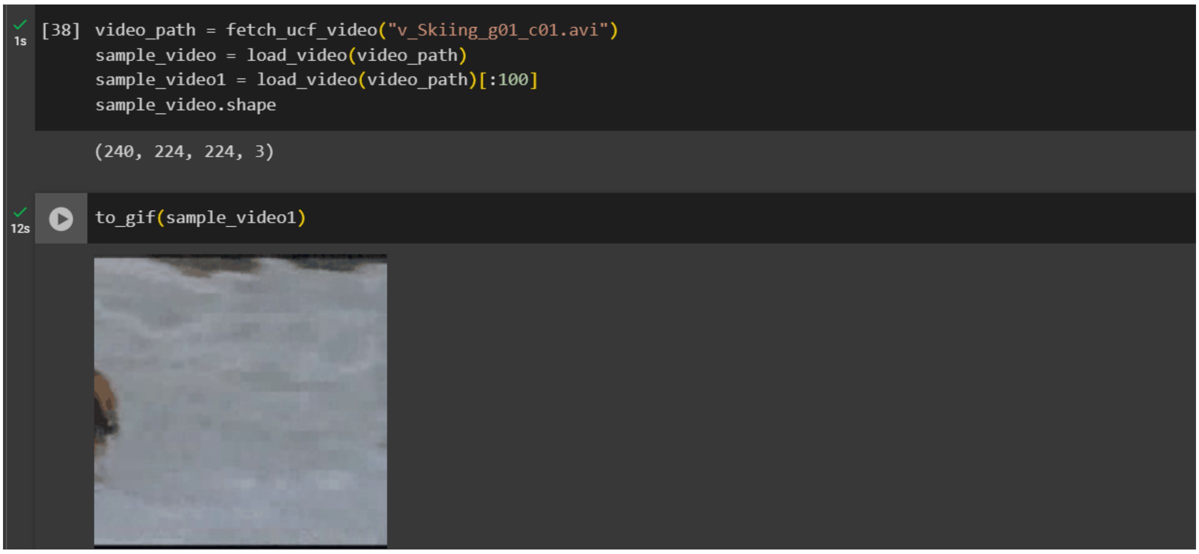
Fig 2.7: Fetching the shape and video of “TennisSwing – v3” video clip



```
predict(sample_video)

Top 5 actions:
  playing tennis         : 99.99%
  hurdling               :  0.00%
  playing badminton      :  0.00%
  javelin throw          :  0.00%
  shooting goal (soccer):  0.00%
```

Fig 2.8: Prediction percentage for the sample video “TennisSwing – v3” is as stated above. The output is obtained as “playing tennis” with a clear probability of 99.99%. This shows that the model is highly accurate in extreme cases wherein tennis swing can easily be misinterpreted as playing badminton.

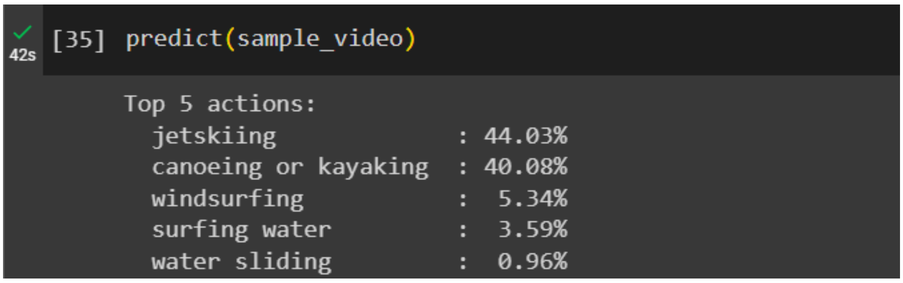


```
[38] video_path = fetch_ucf_video("v_Skiing_g01_c01.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     (240, 224, 224, 3)

to_gif(sample_video1)
```

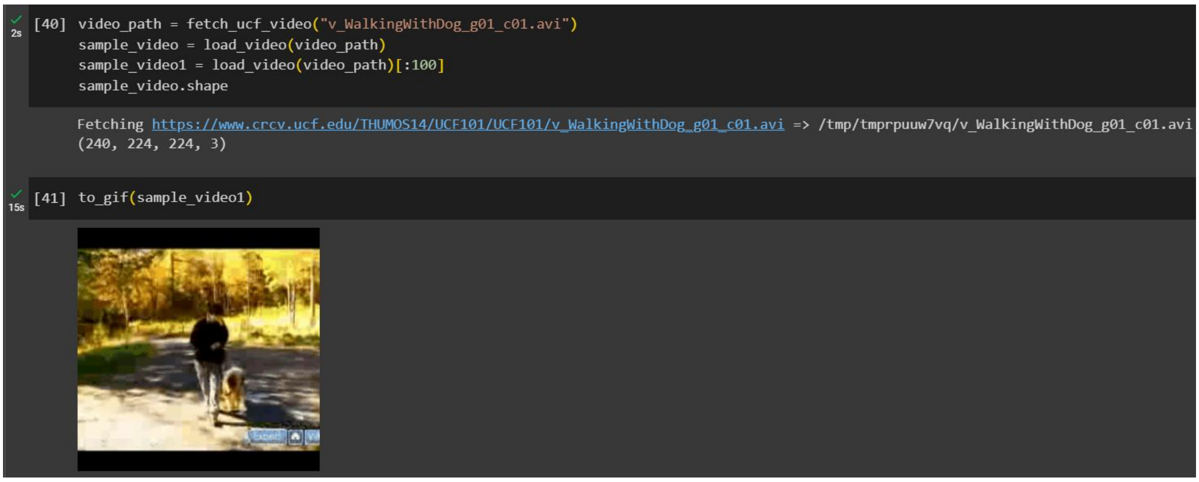
Fig 2.9: Fetching the shape and video of “Skiing –v1” video clip



```
[35] predict(sample_video)

     Top 5 actions:
       jetskiing              : 44.03%
       canoeing or kayaking   : 40.08%
       windsurfing            :  5.34%
       surfing water          :  3.59%
       water sliding          :  0.96%
```

Fig 2.10: Prediction percentage for the sample video "Skiing – v1" is as stated above. The output is obtained as "jetskiing" with a relatively close probability of 44.03% when compared to "canoeing" that has a probability of 40.08%. Other water sports such as water gliding and surfing water is also enlisted as the background of the video plays a pivotal role in the training of the model for the dataset.

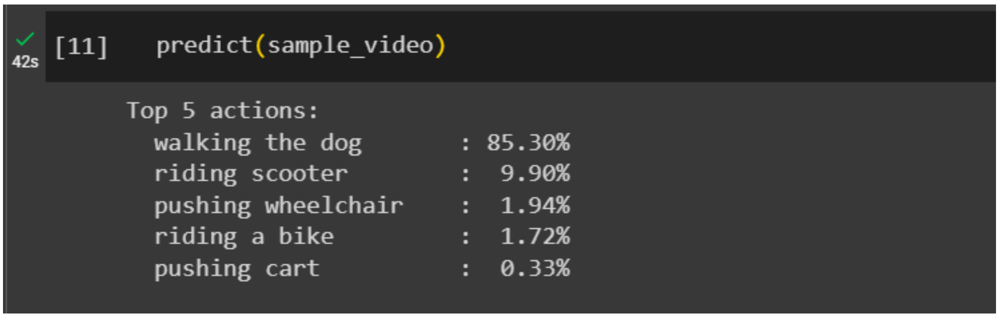


```
[40] video_path = fetch_ucf_video("v_WalkingWithDog_g01_c01.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_WalkingWithDog_g01_c01.avi => /tmp/tmprpuuw7vq/v_WalkingWithDog_g01_c01.avi
     (240, 224, 224, 3)

[41] to_gif(sample_video1)
```

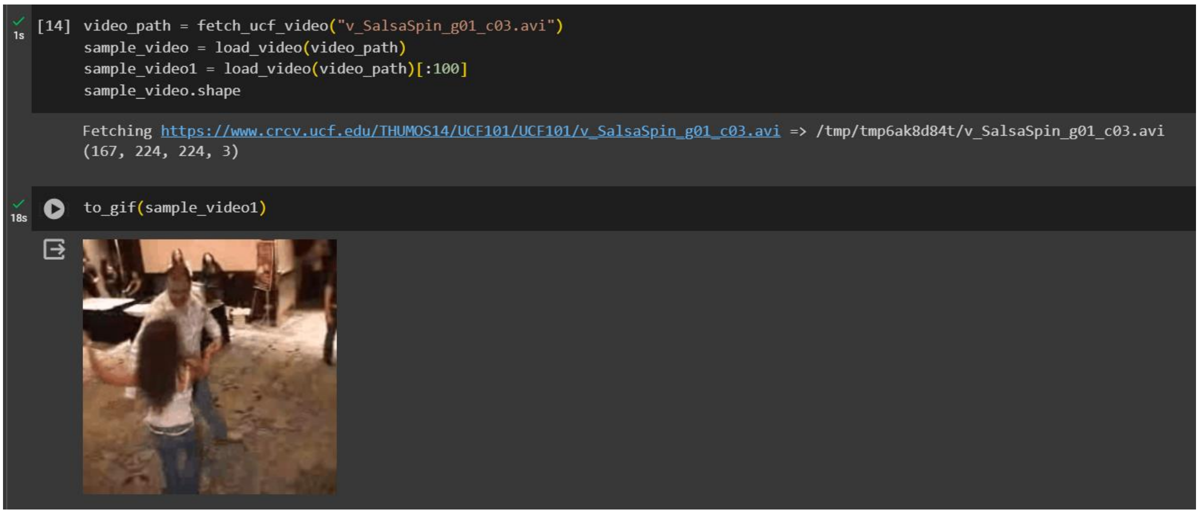
Fig 2.11: Fetching the shape and video of "WalkingWithDog –v1" video clip



```
[11]   predict(sample_video)

       Top 5 actions:
         walking the dog      : 85.30%
         riding scooter       :  9.90%
         pushing wheelchair   :  1.94%
         riding a bike        :  1.72%
         pushing cart         :  0.33%
```

Fig 2.12: Herein, the prediction percentage for the sample video "WalkingWithDog – v1" is as stated above where the output is obtained as "walking the dog" with a distinct probability of 85.30%. Other activities enlisted when observed are all associated with an additional entity.

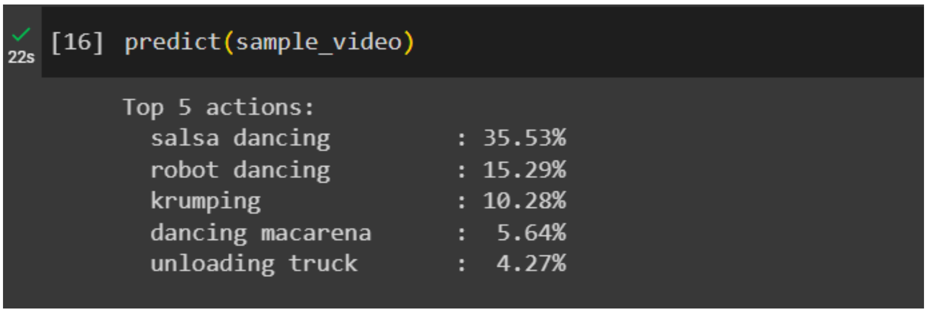


```
[14] video_path = fetch_ucf_video("v_SalsaSpin_g01_c03.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_SalsaSpin_g01_c03.avi => /tmp/tmp6ak8d84t/v_SalsaSpin_g01_c03.avi
     (167, 224, 224, 3)

     to_gif(sample_video1)
```

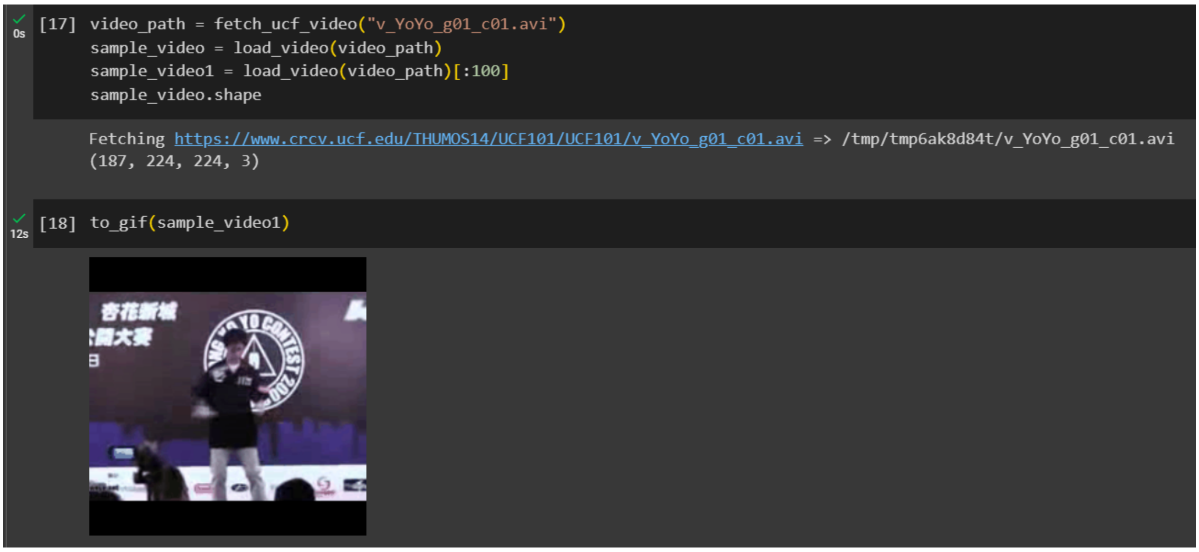
Fig 2.13: Fetching the shape and video of “SalsaSpin –v1” video clip



```
[16] predict(sample_video)

     Top 5 actions:
       salsa dancing          : 35.53%
       robot dancing          : 15.29%
       krumping               : 10.28%
       dancing macarena       :  5.64%
       unloading truck        :  4.27%
```

Fig 2.14: The prediction percentage for the video clip “SalsaSpin – v1” is stated above. The output is obtained are not very distinct when compared. However, the result of the same is “salsa dancing” as it holds the highest probability amongst all the activities predicted for the video clip.

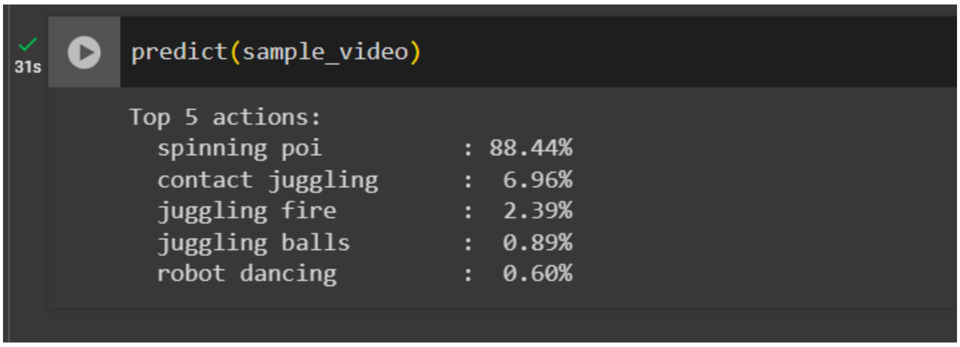


```
[17] video_path = fetch_ucf_video("v_YoYo_g01_c01.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_YoYo_g01_c01.avi => /tmp/tmp6ak8d84t/v_YoYo_g01_c01.avi
     (187, 224, 224, 3)

[18] to_gif(sample_video1)
```

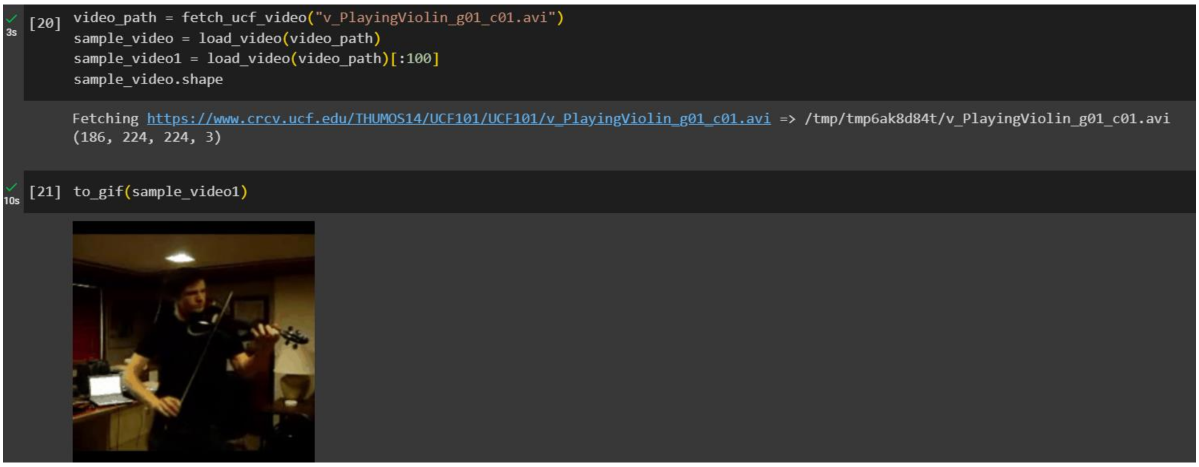
Fig 2.15: Fetching the shape and video of “YoYo –v1” video clip



```
predict(sample_video)

Top 5 actions:
  spinning poi           : 88.44%
  contact juggling       :  6.96%
  juggling fire          :  2.39%
  juggling balls         :  0.89%
  robot dancing          :  0.60%
```

Fig 2.16: Herein, the prediction percentage for the sample video “YoYo – v1” is as stated above where the output is obtained as “spinning poi” with a distinct probability of 88.44%. Other activities enlisted when observed are all associated with an additional entity that may have similar entities.

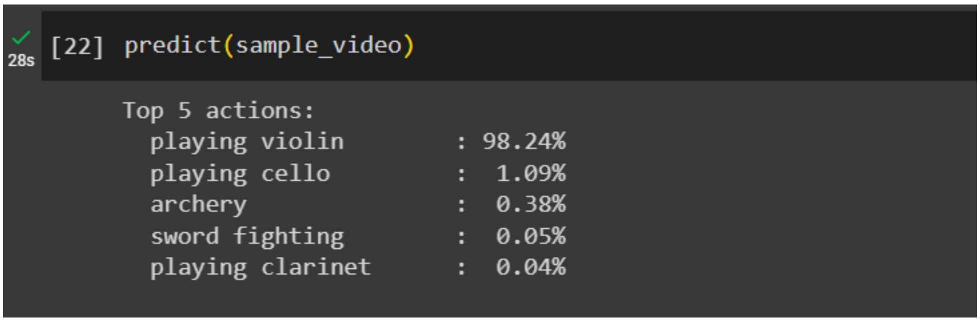


```
[20] video_path = fetch_ucf_video("v_PlayingViolin_g01_c01.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_PlayingViolin_g01_c01.avi => /tmp/tmp6ak8d84t/v_PlayingViolin_g01_c01.avi
     (186, 224, 224, 3)

[21] to_gif(sample_video1)
```

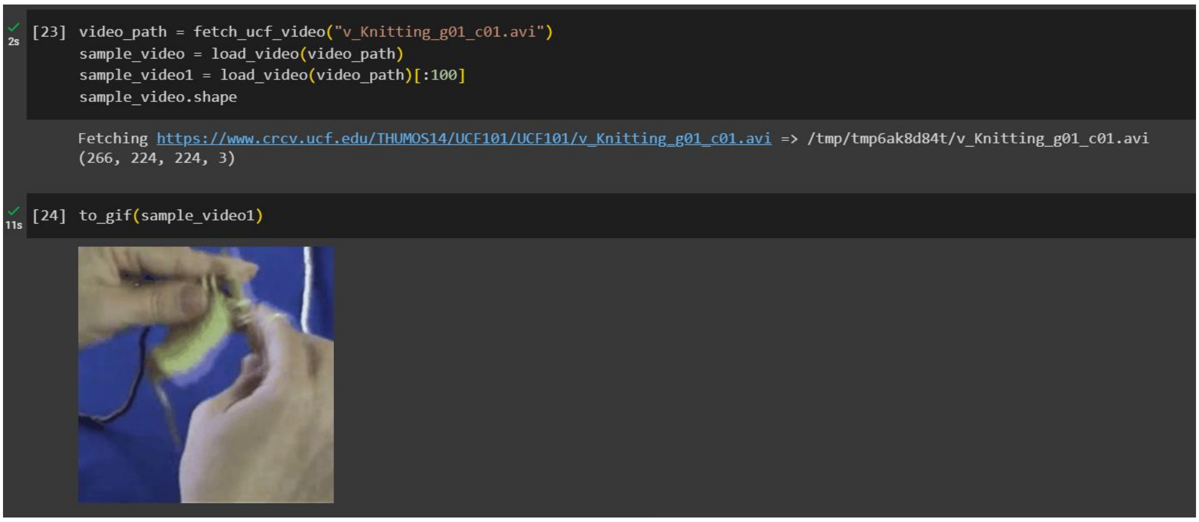
Fig 2.17: Fetching the shape and video of “PlayingViolin –v1” video clip



```
[22] predict(sample_video)

     Top 5 actions:
       playing violin         : 98.24%
       playing cello          :  1.09%
       archery                :  0.38%
       sword fighting         :  0.05%
       playing clarinet       :  0.04%
```

Fig 2.18: The prediction percentage for the sample video “PlayingViolin – v1” is as stated above where the output is obtained as “playing violin” with a distinct probability of 98.24%. Other activities enlisted are mostly those with other instruments which share similarity with that of a violin.

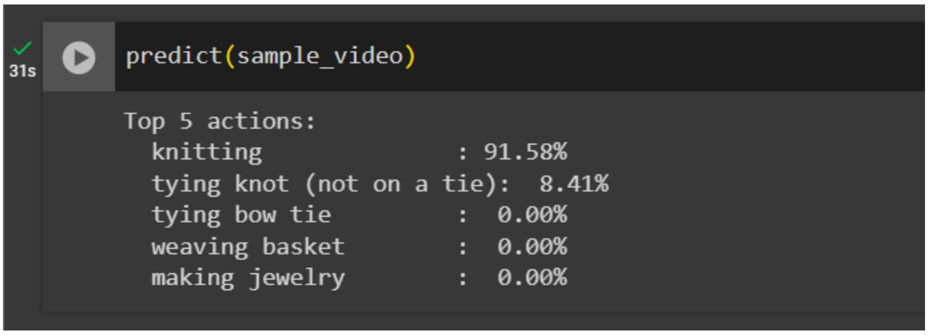


```
[23] video_path = fetch_ucf_video("v_Knitting_g01_c01.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_Knitting_g01_c01.avi => /tmp/tmp6ak8d84t/v_Knitting_g01_c01.avi
     (266, 224, 224, 3)

[24] to_gif(sample_video1)
```

Fig 2.19: Fetching the shape and video of “Knitting –v1” video clip



```
predict(sample_video)

Top 5 actions:
  knitting              : 91.58%
  tying knot (not on a tie):  8.41%
  tying bow tie         :  0.00%
  weaving basket        :  0.00%
  making jewelry        :  0.00%
```

Fig 2.20: The prediction percentage for the sample video “Knitting – v1” which also yields the output as “knitting” with a probability of 91.58%.

CHAPTER-10
CONCLUSION

In conclusion, the implementation of Convolutional Neural Networks (CNNs) into Human Activity Recognition (HAR) is an important advancement towards more accurate, versatile, and real-time activity recognition. The findings of this study highlight the potential of CNN architectures to boost recognition accuracy, encapsulate temporal dynamics, and minimize emphasis on handcrafted attributes. The proposed model is more resistant to environmental alterations and have a greater ability to generalize over a broad spectrum of human activities. Furthermore, research into multimodal sensor fusion and an emphasis on interpretability contribute to the overall progress of HAR with CNNs.

As the model is adaptable, users and researchers can obtain useful insights into how the model makes its predictions, increasing transparency and confidence in the system's decision-making process, which is especially crucial for applications requiring human trust.

The implementation of transfer learning enhances the ability of the model to adapt to the intricate nature of UCF101's activity classes by utilizing pre-trained weights. Post-processing techniques, such as temporal smoothing, help to refine predictions on video sequences, and the optional research of multimodal sensor fusion offers prospective pathways for increasing resilience. As the developed HAR system demonstrates its efficacy in recognizing actions in real-world video data, the results contribute not only to the field of activity recognition, but also to practical applications spanning security, healthcare, and human-computer interaction.

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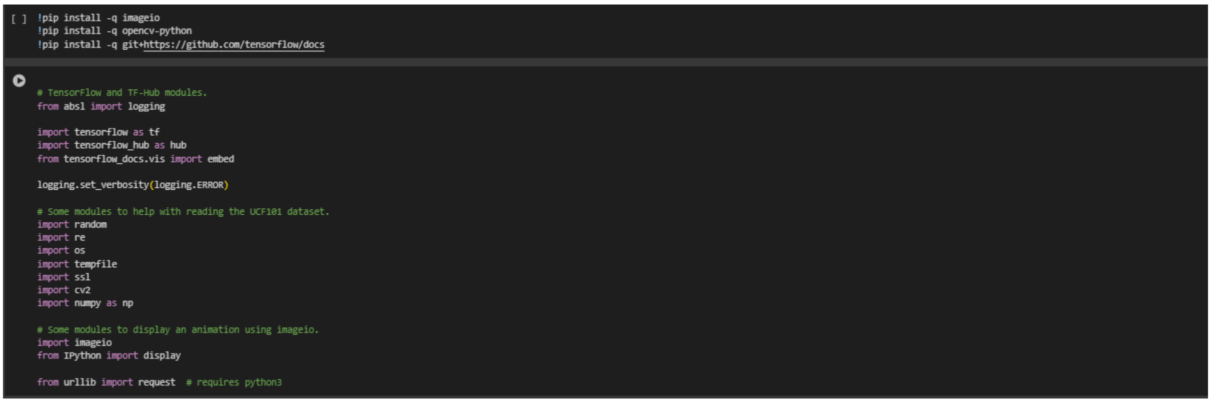
APPENDIX-A

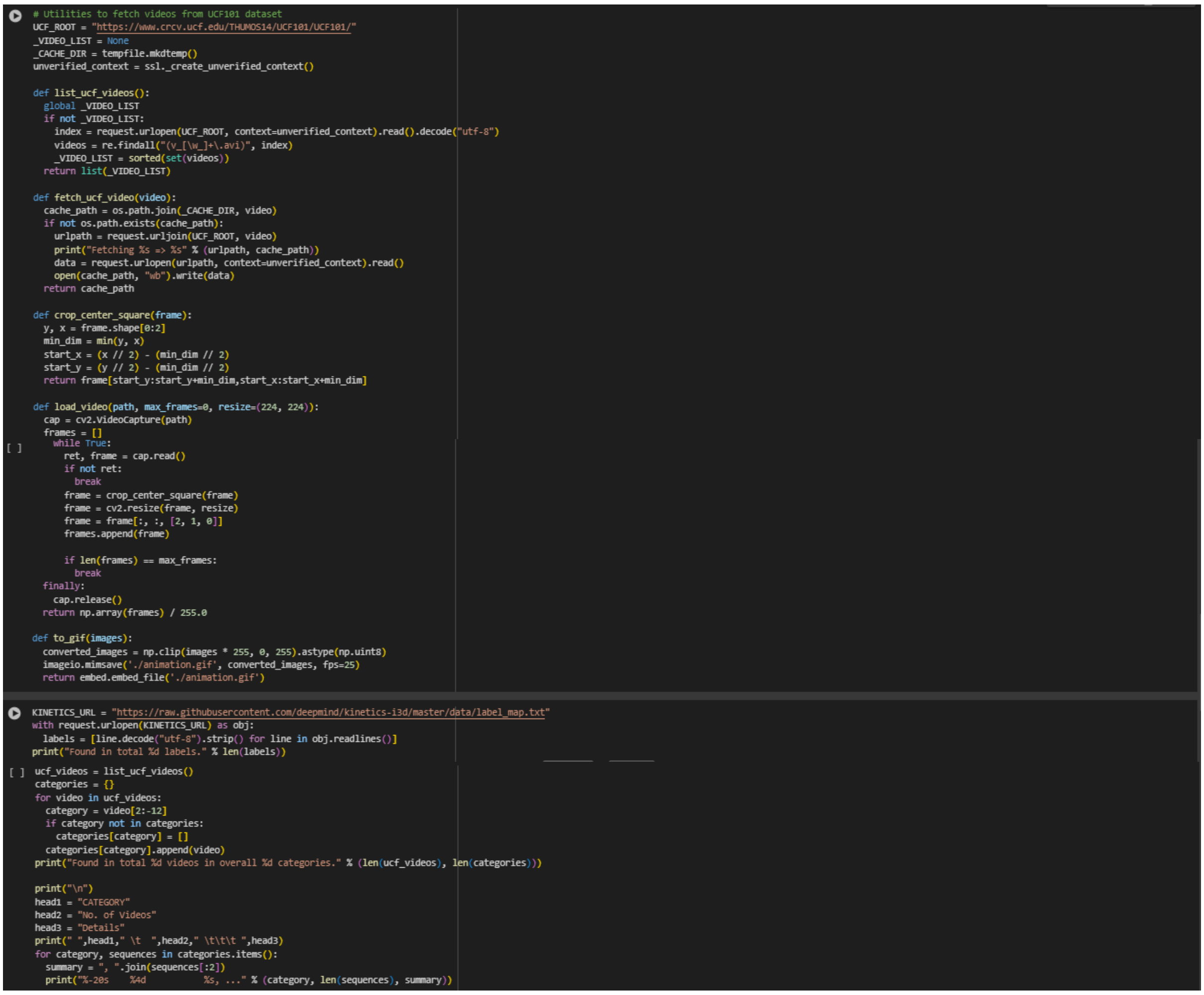
PSUEDOCODE



```
!pip install -q imageio
!pip install -q opencv-python
!pip install -q git+https://github.com/tensorflow/docs
```

```
# TensorFlow and TF-Hub modules.
from absl import logging

import tensorflow as tf
import tensorflow_hub as hub
from tensorflow_docs.vis import embed

logging.set_verbosity(logging.ERROR)

# Some modules to help with reading the UCF101 dataset.
import random
import re
import os
import tempfile
import ssl
import cv2
import numpy as np

# Some modules to display an animation using imageio.
import imageio
from IPython import display

from urllib import request  # requires python3
```

Fig 3.1: Installing and importing necessary modules and libraries

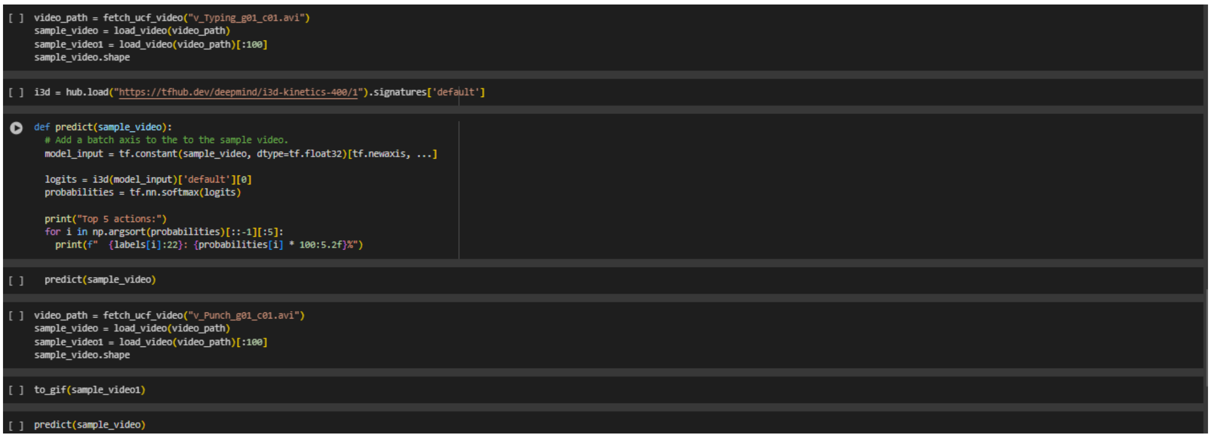


```
# Utilities to fetch videos from UCF101 dataset
UCF_ROOT = "https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/"
_VIDEO_LIST = None
_CACHE_DIR = tempfile.mkdtemp()
unverified_context = ssl._create_unverified_context()

def list_ucf_videos():
  global _VIDEO_LIST
  if not _VIDEO_LIST:
    index = request.urlopen(UCF_ROOT, context=unverified_context).read().decode("utf-8")
    videos = re.findall("(v_[\w_]+\.avi)", index)
    _VIDEO_LIST = sorted(set(videos))
  return list(_VIDEO_LIST)

def fetch_ucf_video(video):
  cache_path = os.path.join(_CACHE_DIR, video)
  if not os.path.exists(cache_path):
    urlpath = request.urljoin(UCF_ROOT, video)
    print("Fetching %s => %s" % (urlpath, cache_path))
    data = request.urlopen(urlpath, context=unverified_context).read()
    open(cache_path, "wb").write(data)
  return cache_path

def crop_center_square(frame):
  y, x = frame.shape[0:2]
  min_dim = min(y, x)
  start_x = (x // 2) - (min_dim // 2)
  start_y = (y // 2) - (min_dim // 2)
  return frame[start_y:start_y+min_dim,start_x:start_x+min_dim]

def load_video(path, max_frames=0, resize=(224, 224)):
  cap = cv2.VideoCapture(path)
  frames = []
    while True:
      ret, frame = cap.read()
      if not ret:
        break
      frame = crop_center_square(frame)
      frame = cv2.resize(frame, resize)
      frame = frame[:, :, [2, 1, 0]]
      frames.append(frame)

      if len(frames) == max_frames:
        break
  finally:
    cap.release()
  return np.array(frames) / 255.0

def to_gif(images):
  converted_images = np.clip(images * 255, 0, 255).astype(np.uint8)
  imageio.mimsave('./animation.gif', converted_images, fps=25)
  return embed.embed_file('./animation.gif')
```

```
KINETICS_URL = "https://raw.githubusercontent.com/deepmind/kinetics-i3d/master/data/label_map.txt"
with request.urlopen(KINETICS_URL) as obj:
  labels = [line.decode("utf-8").strip() for line in obj.readlines()]
print("Found in total %d labels." % len(labels))
```

```
ucf_videos = list_ucf_videos()
categories = {}
for video in ucf_videos:
  category = video[2:-12]
  if category not in categories:
    categories[category] = []
  categories[category].append(video)
print("Found in total %d videos in overall %d categories." % (len(ucf_videos), len(categories)))

print("\n")
head1 = "CATEGORY"
head2 = "No. of Videos"
head3 = "Details"
print(" ",head1," \t  ",head2," \t\t\t ",head3)
for category, sequences in categories.items():
  summary = ", ".join(sequences[:2])
  print("%-20s    %4d          %s, ..." % (category, len(sequences), summary))
```

Fig 3.2: Implication and main body of the code wherein the model is trained using Machine Learning Techniques - CNN

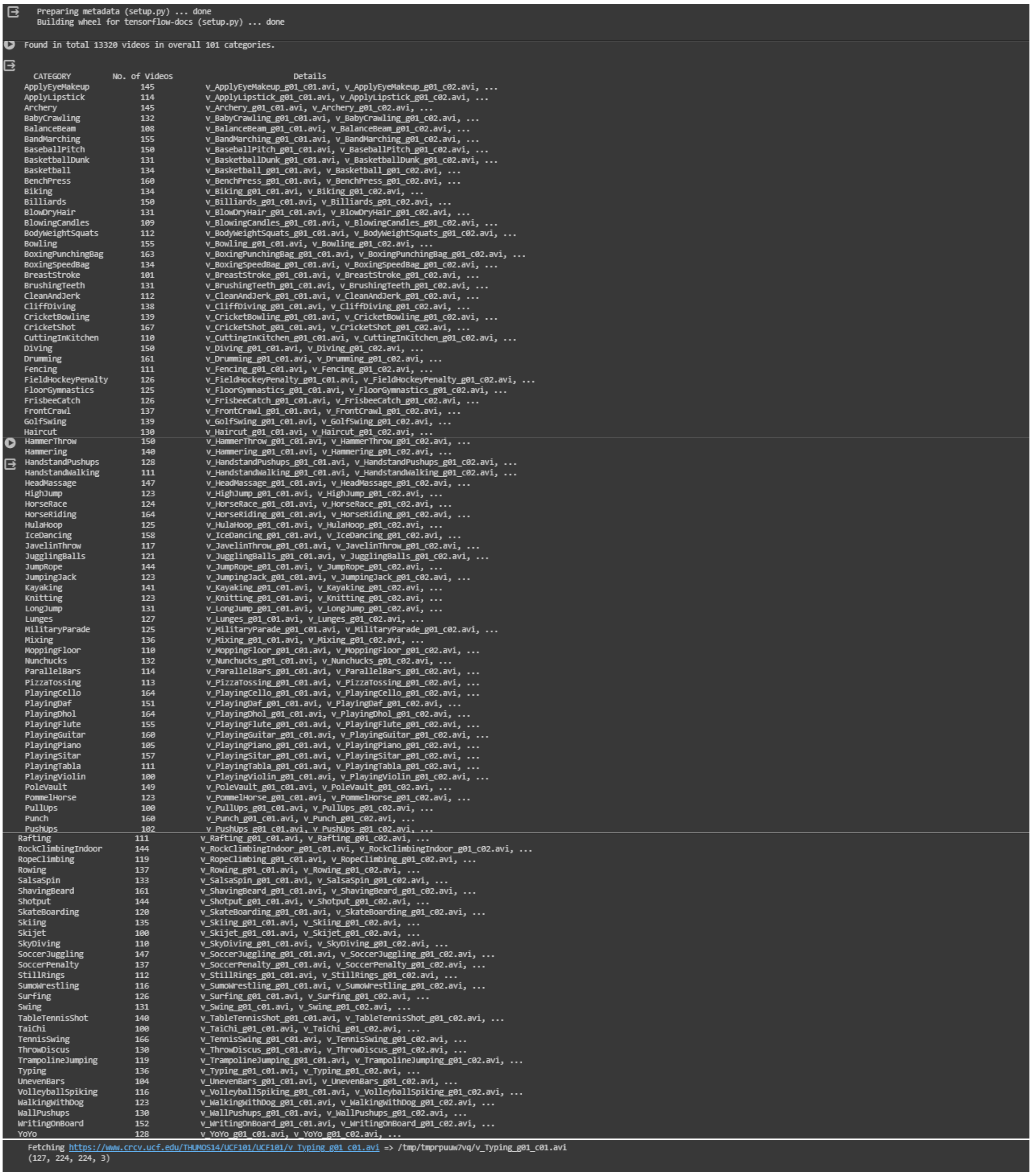


```
[ ] video_path = fetch_ucf_video("v_Typing_g01_c01.avi")
    sample_video = load_video(video_path)
    sample_video1 = load_video(video_path)[:100]
    sample_video.shape

[ ] i3d = hub.load("https://tfhub.dev/deepmind/i3d-kinetics-400/1").signatures['default']

    def predict(sample_video):
      # Add a batch axis to the to the sample video.
      model_input = tf.constant(sample_video, dtype=tf.float32)[tf.newaxis, ...]

      logits = i3d(model_input)['default'][0]
      probabilities = tf.nn.softmax(logits)

      print("Top 5 actions:")
      for i in np.argsort(probabilities)[::-1][:5]:
        print(f"  {labels[i]:22}: {probabilities[i] * 100:5.2f}%")

[ ]   predict(sample_video)

[ ] video_path = fetch_ucf_video("v_Punch_g01_c01.avi")
    sample_video = load_video(video_path)
    sample_video1 = load_video(video_path)[:100]
    sample_video.shape

[ ] to_gif(sample_video1)

[ ] predict(sample_video)
```

Fig 3.3: Testing the model on specific data retrieved from the UCF101 dataset

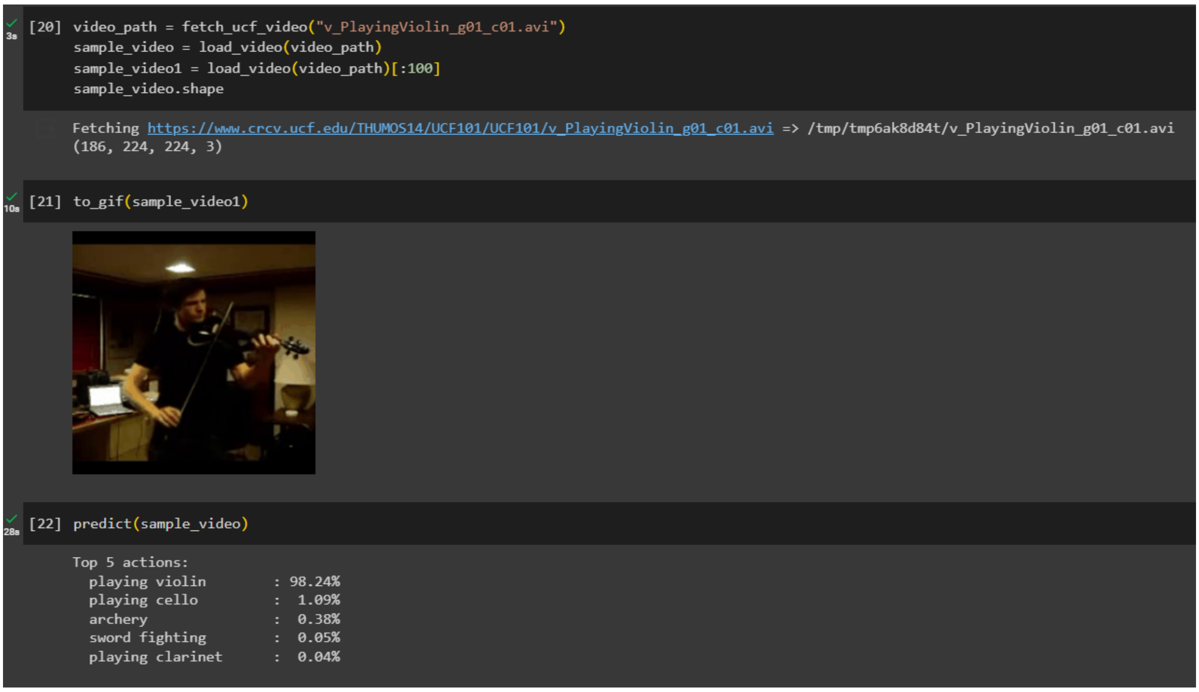
APPENDIX-B
SCREENSHOTS

Outputs and Results:



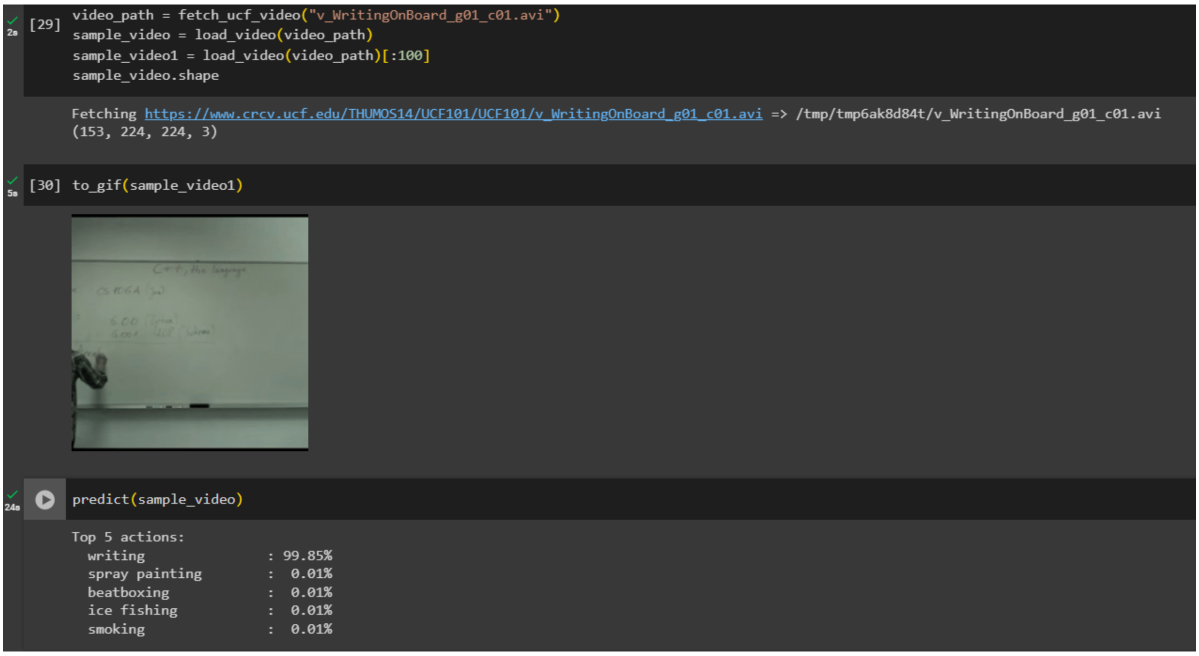
```
Preparing metadata (setup.py) ... done
Building wheel for tensorflow-docs (setup.py) ... done

Found in total 13320 videos in overall 101 categories.

  CATEGORY            No. of Videos                    Details
ApplyEyeMakeup             145          v_ApplyEyeMakeup_g01_c01.avi, v_ApplyEyeMakeup_g01_c02.avi, ...
ApplyLipstick              114          v_ApplyLipstick_g01_c01.avi, v_ApplyLipstick_g01_c02.avi, ...
Archery                    145          v_Archery_g01_c01.avi, v_Archery_g01_c02.avi, ...
BabyCrawling               132          v_BabyCrawling_g01_c01.avi, v_BabyCrawling_g01_c02.avi, ...
BalanceBeam                108          v_BalanceBeam_g01_c01.avi, v_BalanceBeam_g01_c02.avi, ...
BandMarching               155          v_BandMarching_g01_c01.avi, v_BandMarching_g01_c02.avi, ...
BaseballPitch              150          v_BaseballPitch_g01_c01.avi, v_BaseballPitch_g01_c02.avi, ...
BasketballDunk             131          v_BasketballDunk_g01_c01.avi, v_BasketballDunk_g01_c02.avi, ...
Basketball                 134          v_Basketball_g01_c01.avi, v_Basketball_g01_c02.avi, ...
BenchPress                 160          v_BenchPress_g01_c01.avi, v_BenchPress_g01_c02.avi, ...
Biking                     134          v_Biking_g01_c01.avi, v_Biking_g01_c02.avi, ...
Billiards                  150          v_Billiards_g01_c01.avi, v_Billiards_g01_c02.avi, ...
BlowDryHair                131          v_BlowDryHair_g01_c01.avi, v_BlowDryHair_g01_c02.avi, ...
BlowingCandles             109          v_BlowingCandles_g01_c01.avi, v_BlowingCandles_g01_c02.avi, ...
BodyWeightSquats           112          v_BodyWeightSquats_g01_c01.avi, v_BodyWeightSquats_g01_c02.avi, ...
Bowling                    155          v_Bowling_g01_c01.avi, v_Bowling_g01_c02.avi, ...
BoxingPunchingBag          163          v_BoxingPunchingBag_g01_c01.avi, v_BoxingPunchingBag_g01_c02.avi, ...
BoxingSpeedBag             134          v_BoxingSpeedBag_g01_c01.avi, v_BoxingSpeedBag_g01_c02.avi, ...
BreastStroke               101          v_BreastStroke_g01_c01.avi, v_BreastStroke_g01_c02.avi, ...
BrushingTeeth              131          v_BrushingTeeth_g01_c01.avi, v_BrushingTeeth_g01_c02.avi, ...
CleanAndJerk               112          v_CleanAndJerk_g01_c01.avi, v_CleanAndJerk_g01_c02.avi, ...
CliffDiving                138          v_CliffDiving_g01_c01.avi, v_CliffDiving_g01_c02.avi, ...
CricketBowling             139          v_CricketBowling_g01_c01.avi, v_CricketBowling_g01_c02.avi, ...
CricketShot                167          v_CricketShot_g01_c01.avi, v_CricketShot_g01_c02.avi, ...
CuttingInKitchen           110          v_CuttingInKitchen_g01_c01.avi, v_CuttingInKitchen_g01_c02.avi, ...
Diving                     150          v_Diving_g01_c01.avi, v_Diving_g01_c02.avi, ...
Drumming                   161          v_Drumming_g01_c01.avi, v_Drumming_g01_c02.avi, ...
Fencing                    111          v_Fencing_g01_c01.avi, v_Fencing_g01_c02.avi, ...
FieldHockeyPenalty         126          v_FieldHockeyPenalty_g01_c01.avi, v_FieldHockeyPenalty_g01_c02.avi, ...
FloorGymnastics            125          v_FloorGymnastics_g01_c01.avi, v_FloorGymnastics_g01_c02.avi, ...
FrisbeeCatch               126          v_FrisbeeCatch_g01_c01.avi, v_FrisbeeCatch_g01_c02.avi, ...
FrontCrawl                 137          v_FrontCrawl_g01_c01.avi, v_FrontCrawl_g01_c02.avi, ...
GolfSwing                  139          v_GolfSwing_g01_c01.avi, v_GolfSwing_g01_c02.avi, ...
Haircut                    130          v_Haircut_g01_c01.avi, v_Haircut_g01_c02.avi, ...
HammerThrow                150          v_HammerThrow_g01_c01.avi, v_HammerThrow_g01_c02.avi, ...
Hammering                  140          v_Hammering_g01_c01.avi, v_Hammering_g01_c02.avi, ...
HandstandPushups           128          v_HandstandPushups_g01_c01.avi, v_HandstandPushups_g01_c02.avi, ...
HandstandWalking           111          v_HandstandWalking_g01_c01.avi, v_HandstandWalking_g01_c02.avi, ...
HeadMassage                147          v_HeadMassage_g01_c01.avi, v_HeadMassage_g01_c02.avi, ...
HighJump                   123          v_HighJump_g01_c01.avi, v_HighJump_g01_c02.avi, ...
HorseRace                  124          v_HorseRace_g01_c01.avi, v_HorseRace_g01_c02.avi, ...
HorseRiding                164          v_HorseRiding_g01_c01.avi, v_HorseRiding_g01_c02.avi, ...
HulaHoop                   125          v_HulaHoop_g01_c01.avi, v_HulaHoop_g01_c02.avi, ...
IceDancing                 158          v_IceDancing_g01_c01.avi, v_IceDancing_g01_c02.avi, ...
JavelinThrow               117          v_JavelinThrow_g01_c01.avi, v_JavelinThrow_g01_c02.avi, ...
JugglingBalls              121          v_JugglingBalls_g01_c01.avi, v_JugglingBalls_g01_c02.avi, ...
JumpRope                   144          v_JumpRope_g01_c01.avi, v_JumpRope_g01_c02.avi, ...
JumpingJack                123          v_JumpingJack_g01_c01.avi, v_JumpingJack_g01_c02.avi, ...
Kayaking                   141          v_Kayaking_g01_c01.avi, v_Kayaking_g01_c02.avi, ...
Knitting                   123          v_Knitting_g01_c01.avi, v_Knitting_g01_c02.avi, ...
LongJump                   131          v_LongJump_g01_c01.avi, v_LongJump_g01_c02.avi, ...
Lunges                     127          v_Lunges_g01_c01.avi, v_Lunges_g01_c02.avi, ...
MilitaryParade             125          v_MilitaryParade_g01_c01.avi, v_MilitaryParade_g01_c02.avi, ...
Mixing                     136          v_Mixing_g01_c01.avi, v_Mixing_g01_c02.avi, ...
MoppingFloor               110          v_MoppingFloor_g01_c01.avi, v_MoppingFloor_g01_c02.avi, ...
Nunchucks                  132          v_Nunchucks_g01_c01.avi, v_Nunchucks_g01_c02.avi, ...
ParallelBars               114          v_ParallelBars_g01_c01.avi, v_ParallelBars_g01_c02.avi, ...
PizzaTossing               113          v_PizzaTossing_g01_c01.avi, v_PizzaTossing_g01_c02.avi, ...
PlayingCello               164          v_PlayingCello_g01_c01.avi, v_PlayingCello_g01_c02.avi, ...
PlayingDaf                 151          v_PlayingDaf_g01_c01.avi, v_PlayingDaf_g01_c02.avi, ...
PlayingDhol                164          v_PlayingDhol_g01_c01.avi, v_PlayingDhol_g01_c02.avi, ...
PlayingFlute               155          v_PlayingFlute_g01_c01.avi, v_PlayingFlute_g01_c02.avi, ...
PlayingGuitar              160          v_PlayingGuitar_g01_c01.avi, v_PlayingGuitar_g01_c02.avi, ...
PlayingPiano               105          v_PlayingPiano_g01_c01.avi, v_PlayingPiano_g01_c02.avi, ...
PlayingSitar               157          v_PlayingSitar_g01_c01.avi, v_PlayingSitar_g01_c02.avi, ...
PlayingTabla               111          v_PlayingTabla_g01_c01.avi, v_PlayingTabla_g01_c02.avi, ...
PlayingViolin              100          v_PlayingViolin_g01_c01.avi, v_PlayingViolin_g01_c02.avi, ...
PoleVault                  149          v_PoleVault_g01_c01.avi, v_PoleVault_g01_c02.avi, ...
PommelHorse                123          v_PommelHorse_g01_c01.avi, v_PommelHorse_g01_c02.avi, ...
PullUps                    100          v_PullUps_g01_c01.avi, v_PullUps_g01_c02.avi, ...
Punch                      160          v_Punch_g01_c01.avi, v_Punch_g01_c02.avi, ...
PushUps                    102          v_PushUps_g01_c01.avi, v_PushUps_g01_c02.avi, ...
Rafting                    111          v_Rafting_g01_c01.avi, v_Rafting_g01_c02.avi, ...
RockClimbingIndoor         144          v_RockClimbingIndoor_g01_c01.avi, v_RockClimbingIndoor_g01_c02.avi, ...
RopeClimbing               119          v_RopeClimbing_g01_c01.avi, v_RopeClimbing_g01_c02.avi, ...
Rowing                     137          v_Rowing_g01_c01.avi, v_Rowing_g01_c02.avi, ...
SalsaSpin                  133          v_SalsaSpin_g01_c01.avi, v_SalsaSpin_g01_c02.avi, ...
ShavingBeard               161          v_ShavingBeard_g01_c01.avi, v_ShavingBeard_g01_c02.avi, ...
Shotput                    144          v_Shotput_g01_c01.avi, v_Shotput_g01_c02.avi, ...
SkateBoarding              120          v_SkateBoarding_g01_c01.avi, v_SkateBoarding_g01_c02.avi, ...
Skiing                     135          v_Skiing_g01_c01.avi, v_Skiing_g01_c02.avi, ...
Skijet                     100          v_Skijet_g01_c01.avi, v_Skijet_g01_c02.avi, ...
SkyDiving                  110          v_SkyDiving_g01_c01.avi, v_SkyDiving_g01_c02.avi, ...
SoccerJuggling             147          v_SoccerJuggling_g01_c01.avi, v_SoccerJuggling_g01_c02.avi, ...
SoccerPenalty              137          v_SoccerPenalty_g01_c01.avi, v_SoccerPenalty_g01_c02.avi, ...
StillRings                 112          v_StillRings_g01_c01.avi, v_StillRings_g01_c02.avi, ...
SumoWrestling              116          v_SumoWrestling_g01_c01.avi, v_SumoWrestling_g01_c02.avi, ...
Surfing                    126          v_Surfing_g01_c01.avi, v_Surfing_g01_c02.avi, ...
Swing                      131          v_Swing_g01_c01.avi, v_Swing_g01_c02.avi, ...
TableTennisShot            140          v_TableTennisShot_g01_c01.avi, v_TableTennisShot_g01_c02.avi, ...
TaiChi                     100          v_TaiChi_g01_c01.avi, v_TaiChi_g01_c02.avi, ...
TennisSwing                166          v_TennisSwing_g01_c01.avi, v_TennisSwing_g01_c02.avi, ...
ThrowDiscus                130          v_ThrowDiscus_g01_c01.avi, v_ThrowDiscus_g01_c02.avi, ...
TrampolineJumping          119          v_TrampolineJumping_g01_c01.avi, v_TrampolineJumping_g01_c02.avi, ...
Typing                     136          v_Typing_g01_c01.avi, v_Typing_g01_c02.avi, ...
UnevenBars                 104          v_UnevenBars_g01_c01.avi, v_UnevenBars_g01_c02.avi, ...
VolleyballSpiking          116          v_VolleyballSpiking_g01_c01.avi, v_VolleyballSpiking_g01_c02.avi, ...
WalkingWithDog             123          v_WalkingWithDog_g01_c01.avi, v_WalkingWithDog_g01_c02.avi, ...
WallPushups                130          v_WallPushups_g01_c01.avi, v_WallPushups_g01_c02.avi, ...
WritingOnBoard             152          v_WritingOnBoard_g01_c01.avi, v_WritingOnBoard_g01_c02.avi, ...
YoYo                       128          v_YoYo_g01_c01.avi, v_YoYo_g01_c02.avi, ...

Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_Typing_g01_c01.avi => /tmp/tmprpuuw7vq/v_Typing_g01_c01.avi
(127, 224, 224, 3)
```

Fig 4.1: Printing all the labels present in the UCF101 dataset



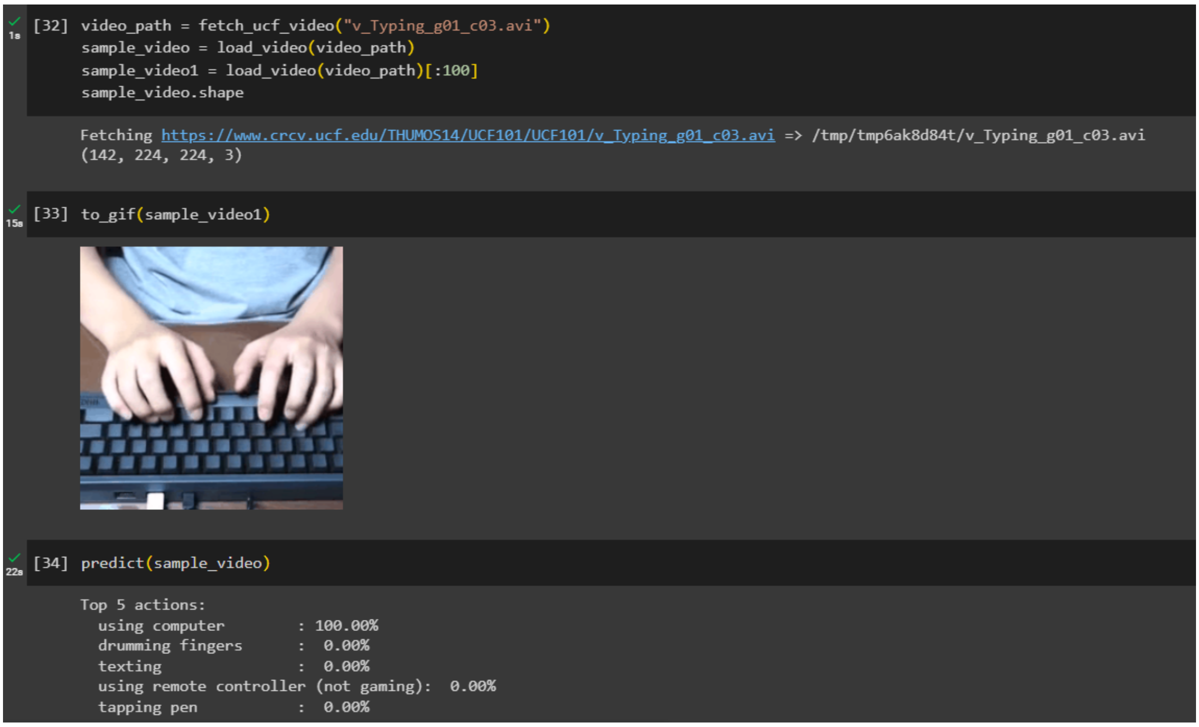
```
[20] video_path = fetch_ucf_video("v_PlayingViolin_g01_c01.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_PlayingViolin_g01_c01.avi => /tmp/tmp6ak8d84t/v_PlayingViolin_g01_c01.avi
     (186, 224, 224, 3)

[21] to_gif(sample_video1)

[22] predict(sample_video)

     Top 5 actions:
       playing violin        : 98.24%
       playing cello         :  1.09%
       archery               :  0.38%
       sword fighting        :  0.05%
       playing clarinet      :  0.04%
```

Fig 4.2: Testing the model for “Playing Violin” from UCF101 dataset. Result is satisfactory.



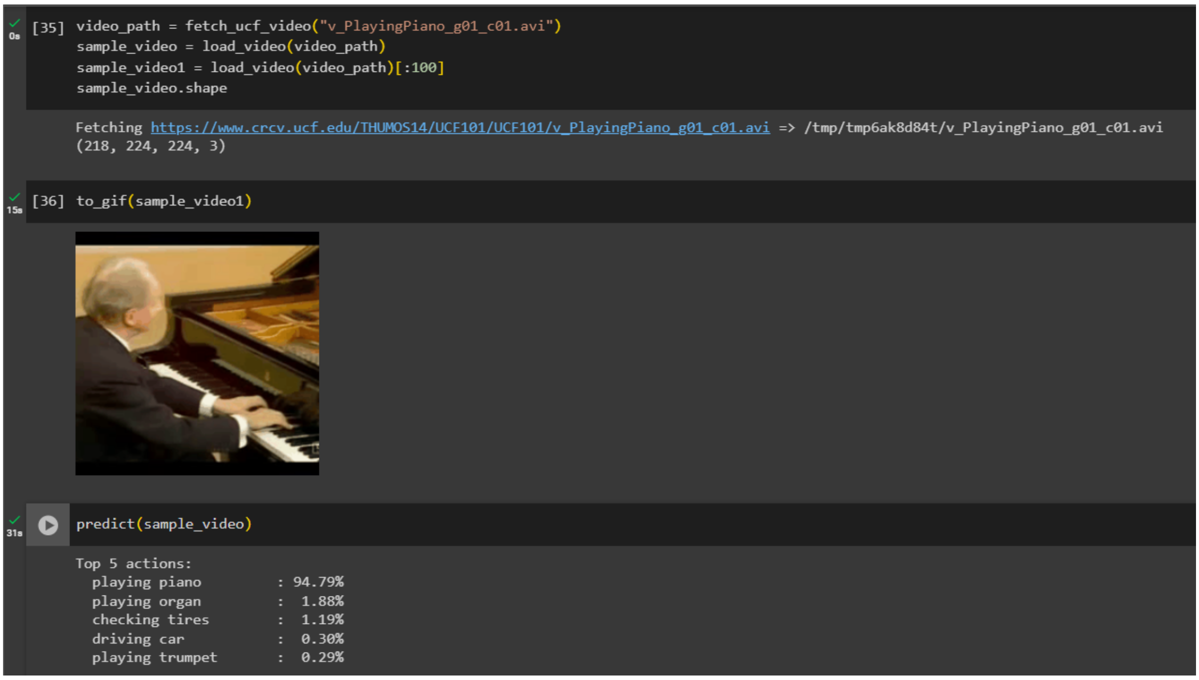
```
[29] video_path = fetch_ucf_video("v_WritingOnBoard_g01_c01.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_WritingOnBoard_g01_c01.avi => /tmp/tmp6ak8d84t/v_WritingOnBoard_g01_c01.avi
     (153, 224, 224, 3)

[30] to_gif(sample_video1)

     predict(sample_video)

     Top 5 actions:
       writing              : 99.85%
       spray painting       :  0.01%
       beatboxing           :  0.01%
       ice fishing          :  0.01%
       smoking              :  0.01%
```

Fig 4.3: Testing the model for “Writing on Board” from UCF101 dataset. Result is satisfactory.



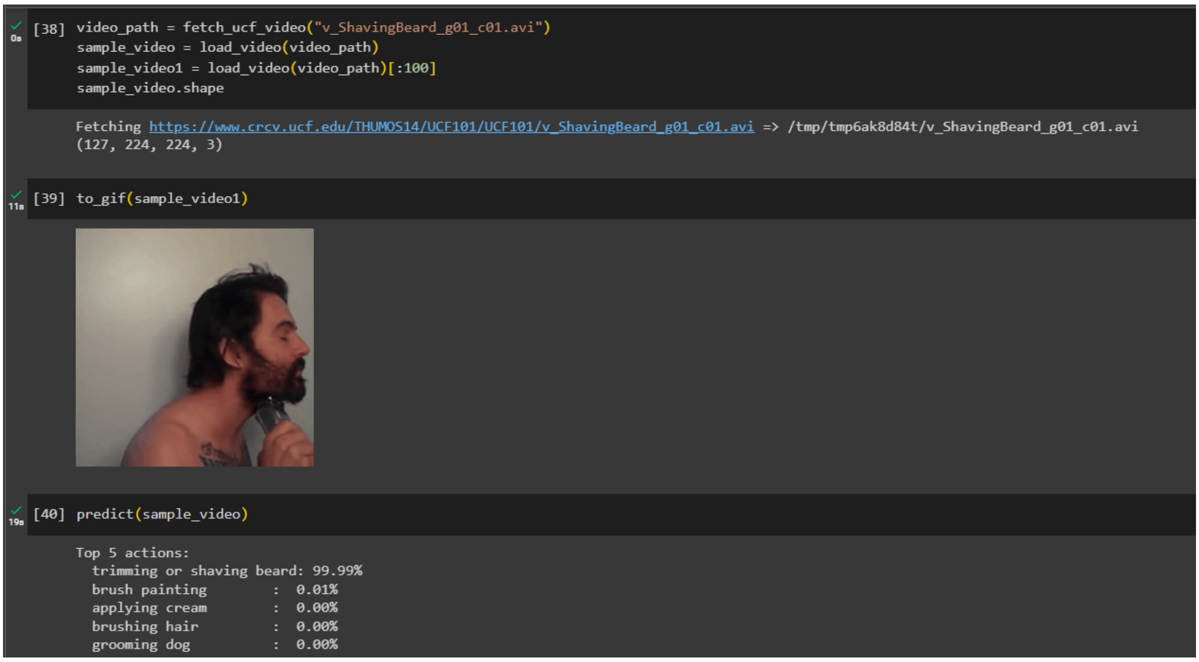
```
[32] video_path = fetch_ucf_video("v_Typing_g01_c03.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_Typing_g01_c03.avi => /tmp/tmp6ak8d84t/v_Typing_g01_c03.avi
     (142, 224, 224, 3)

[33] to_gif(sample_video1)

[34] predict(sample_video)

     Top 5 actions:
       using computer        : 100.00%
       drumming fingers      :  0.00%
       texting               :  0.00%
       using remote controller (not gaming):  0.00%
       tapping pen           :  0.00%
```

Fig 4.4: Testing the model for “Typing” from UCF101 dataset. Result is satisfactory.



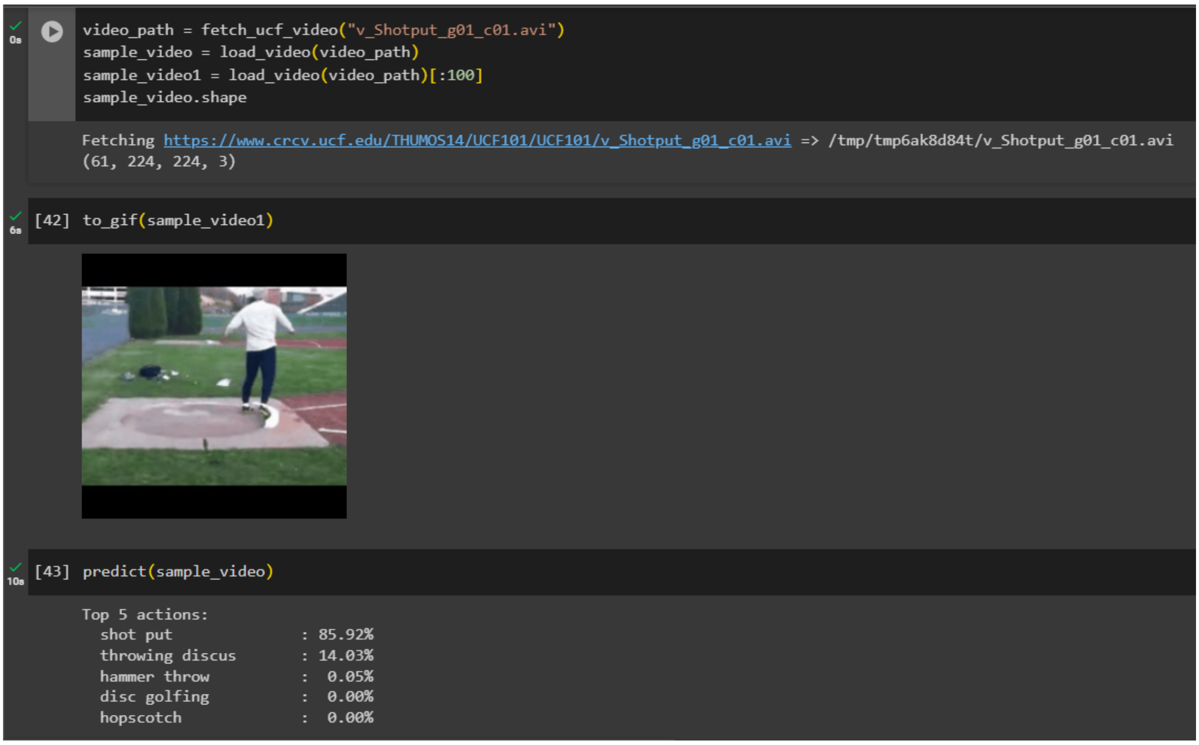
```
[35] video_path = fetch_ucf_video("v_PlayingPiano_g01_c01.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_PlayingPiano_g01_c01.avi => /tmp/tmp6ak8d84t/v_PlayingPiano_g01_c01.avi
     (218, 224, 224, 3)

[36] to_gif(sample_video1)

     predict(sample_video)

     Top 5 actions:
       playing piano         : 94.79%
       playing organ         :  1.88%
       checking tires        :  1.19%
       driving car           :  0.30%
       playing trumpet       :  0.29%
```

Fig 4.5: Testing the model for “Playing Piano” from UCF101 dataset. Result is satisfactory.



```
[38] video_path = fetch_ucf_video("v_ShavingBeard_g01_c01.avi")
     sample_video = load_video(video_path)
     sample_video1 = load_video(video_path)[:100]
     sample_video.shape

     Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_ShavingBeard_g01_c01.avi => /tmp/tmp6ak8d84t/v_ShavingBeard_g01_c01.avi
     (127, 224, 224, 3)

[39] to_gif(sample_video1)

[40] predict(sample_video)

     Top 5 actions:
       trimming or shaving beard: 99.99%
       brush painting           :  0.01%
       applying cream           :  0.00%
       brushing hair            :  0.00%
       grooming dog             :  0.00%
```

Fig 4.6: Testing the model for “Trimming Beard” from UCF101 dataset. Result is satisfactory.

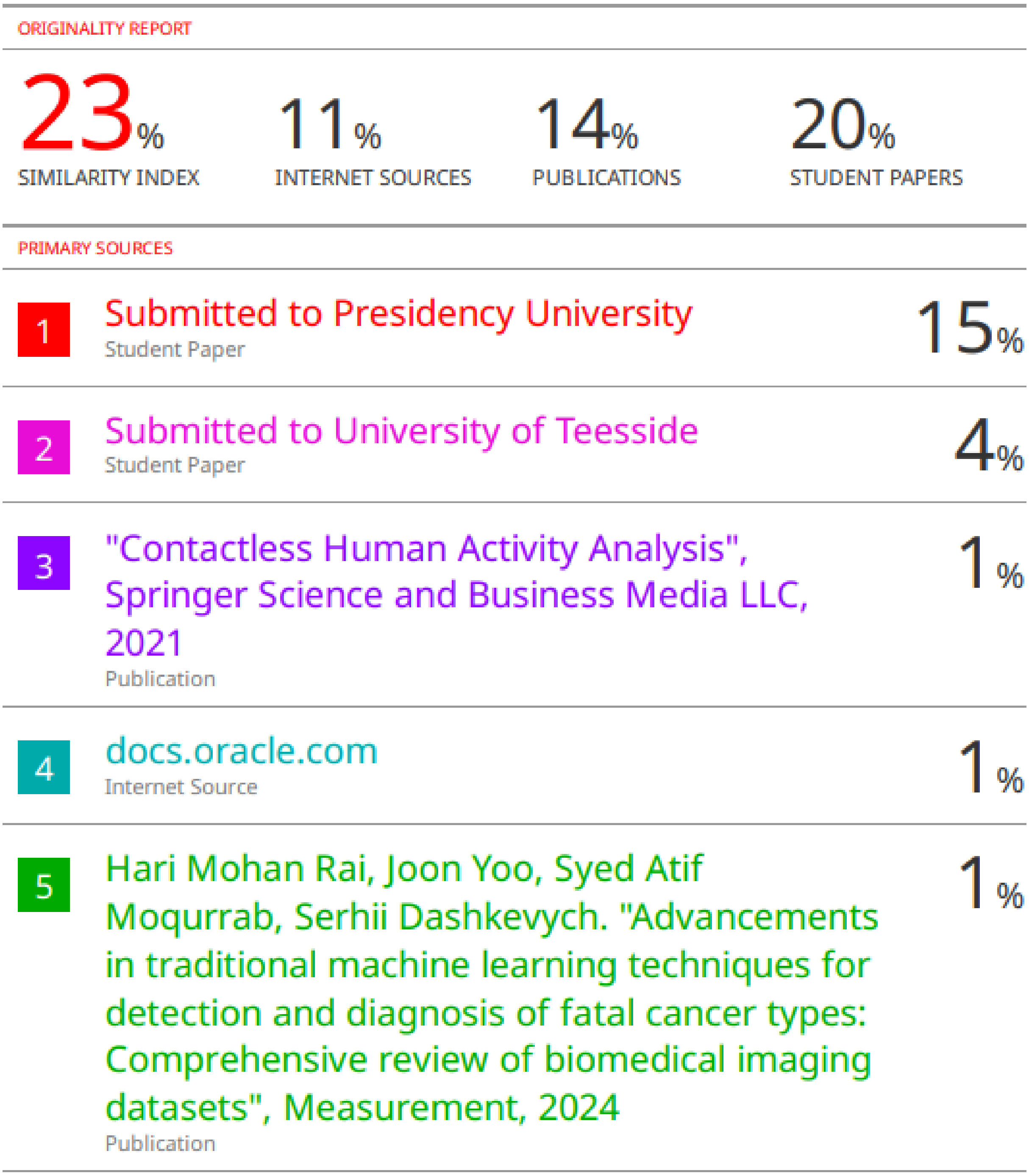


```
video_path = fetch_ucf_video("v_Shotput_g01_c01.avi")
sample_video = load_video(video_path)
sample_video1 = load_video(video_path)[:100]
sample_video.shape

Fetching https://www.crcv.ucf.edu/THUMOS14/UCF101/UCF101/v_Shotput_g01_c01.avi => /tmp/tmp6ak8d84t/v_Shotput_g01_c01.avi
(61, 224, 224, 3)

[42] to_gif(sample_video1)

[43] predict(sample_video)

     Top 5 actions:
       shot put                : 85.92%
       throwing discus         : 14.03%
       hammer throw            :  0.05%
       disc golfing            :  0.00%
       hopscotch               :  0.00%
```

Fig 4.7: Testing the model for “Shotput” from UCF101 dataset. Result is satisfactory

APPENDIX-C

PLAGIARISM REPORT



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5	Hari Mohan Rai, Joon Yoo, Syed Atif Moqurrab, Serhii Dashkevych. "Advancements in traditional machine learning techniques for detection and diagnosis of fatal cancer types: Comprehensive review of biomedical imaging datasets", Measurement, 2024 Publication	1%

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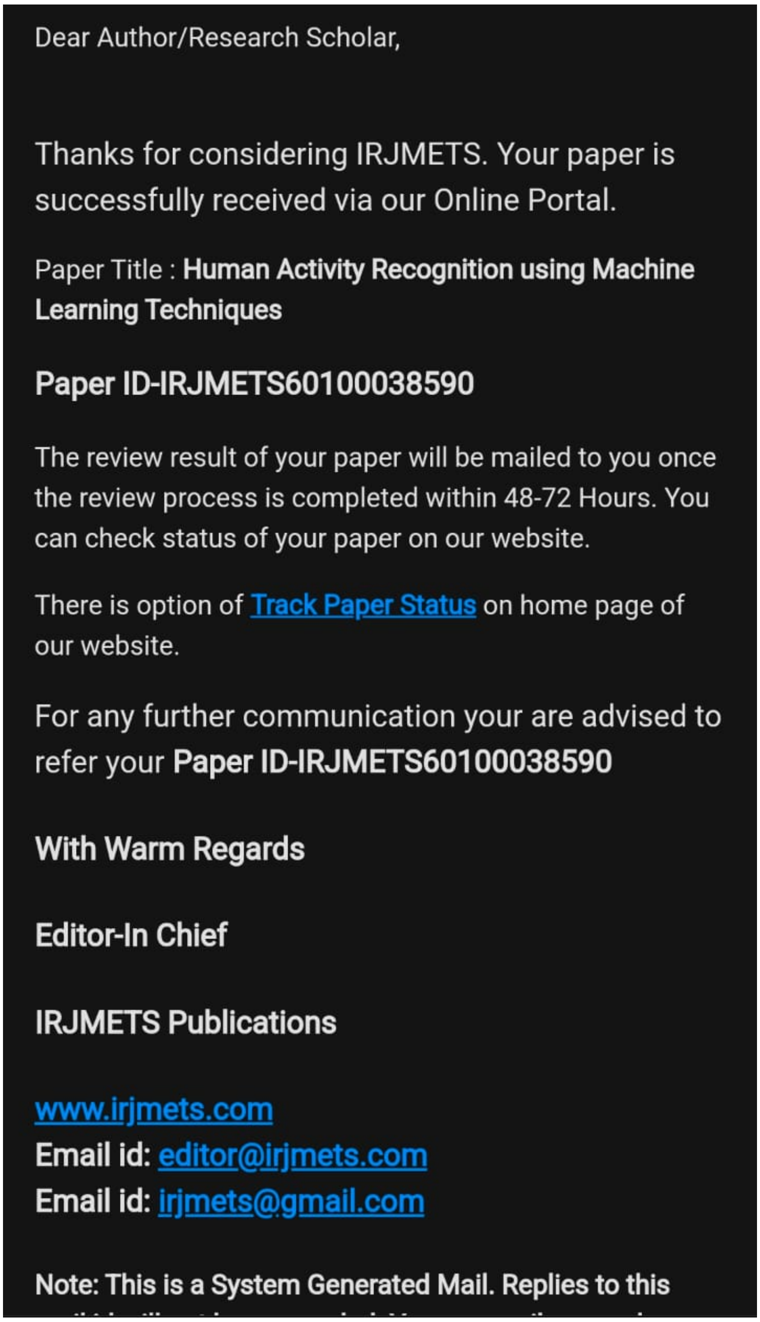

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SDG GOALS

SUSTAINABLE DEVELOPMENT GOALS
17 GOALS TO TRANSFORM OUR WORLD
1 NO POVERTY
2 ZERO HUNGER
3 GOOD HEALTH AND WELL-BEING
4 QUALITY EDUCATION
5 GENDER EQUALITY
6 CLEAN WATER AND SANITATION
7 AFFORDABLE AND CLEAN ENERGY
8 DECENT WORK AND ECONOMIC GROWTH
9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
10 REDUCED INEQUALITIES
11 SUSTAINABLE CITIES AND COMMUNITIES
12 RESPONSIBLE CONSUMPTION AND PRODUCTION
13 CLIMATE ACTION
14 LIFE BELOW WATER
15 LIFE ON LAND
16 PEACE, JUSTICE AND STRONG INSTITUTIONS
17 PARTNERSHIPS FOR THE GOALS
SUSTAINABLE DEVELOPMENT GOALS

Fig: Sustainable Development Goals (SDG)

This paper serves as a resourceful application in multiple domains with several SDG goals.

1. SDG 3: Good Health and Well-being – Applications such as remote health monitoring and rehabilitation support. It has the potential to assist in the early detection of abnormal activity patterns, promoting preventive healthcare and enhancing overall well-being.
2. SDG 9: Industry, Innovation, and Infrastructure – Implementation of CNN contributes to the development of advanced technological infrastructure for applications in healthcare, smart cities, and human-computer interaction.
3. SDG 11: Sustainable Cities and Communities - Applications include traffic management, public safety, and efficient resource utilization based on human activity patterns.
4. SDG 17: Partnerships for the Goals - Partnerships amongst researchers, technology developers and policymakers can foster the sharing of knowledge, resources, and expertise to address challenges and maximize the positive impact of this technology.