

Configuration Manual

MSc Research Project MSc. Data Analytics

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MSc Project Submission Sheet



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Configuration Manual

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1 Introduction

This Configuration Manual outlines the comprehensive process involved in realizing the project "Leveraging OpenCV for Precise Yoga Pose Estimation and Reducing Injury Risks ". It details the specific aspects of data sources, system prerequisites, utilized libraries, and the code involved in the implementation and evaluation of the research models.

2 System Prerequisites

The hardware and software version for this project used are given below.

2.1 Hardware Prerequisites

Operating System	Windows 11	
Processor	12 th Gen Intel [®] core [™] i9-12900Mhz, 14 core(s)	
	20 Logical Processor	
Ram	16.0 GB	
System type	X64-based PC	

Table 1: Hardware Prerequisites

2.2 Software Prerequisites

Programming Language used in this project is Python and Jupiter Notebook is used as a programming tool to run the Python code.

- Python 3.9.13
- Jupiter Notebook 6.4.12

All the libraries used in the research to complete the project from start to end is shown in the Figure 1 and Figure 2.

#!pip install mediapipe opencv-python pandas scikit-learn import mediapipe as mp #Meidapipe import cv2 #opencv import csv import numpy as np import os import sys import tadm import random import pandas as pd import pickle # to save a model # Package for visualisation import matplotlib.pyplot as plt import seaborn as sns # Packages for model Implementation and Evaluation from sklearn.metrics import confusion_matrix,classification_report from sklearn import metrics from sklearn.preprocessing import LabelEncoder from sklearn.model selection import train test split, RepeatedStratifiedKFold from sklearn.model_selection import RandomizedSearchCV

Figure 1: Python Libraries used in this Python Project- Part 1

```
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Embedding
from keras.layers import SpatialDropout1D
from keras.layers import InputLayer
from keras.layers import Conv1D
from keras.layers import Flatten
from keras.layers import Dropout
```

Figure 2: Python Libraries used in this Python Project- Part 2

3 Data Collection

This project draws upon a curated yoga image dataset sourced from Kaggle, consisting of diverse yoga poses to classify and detect in real-time. The dataset encompasses five prevalent yoga poses: Asho Mukha Scanasana (320 images), Balasana (261 images), Utkata Konasana (180 images), Virabhadrasana (209 images), and Vrikshasana (334 images). In total, 1304 yoga pose images were meticulously compiled, featuring individuals with varying backgrounds and body types. These poses were systematically organized into distinct folders, each named after the corresponding yoga pose, facilitating structured data management and analysis.

4 Data Preprocessing

In order to transform the yoga image dataset into a CSV file format containing 99 landmark features (33 landmark points * 3 dimensions), several crucial steps were undertaken in research project code. Before proceeding with the data preprocessing phase, it was imperative to install essential libraries such as Mediapipe and OpenCV. Additionally, all the requisite packages, as outlined in Figure 1 and Figure 2 of the project documentation, were imported to facilitate the dataset conversion process. These preparatory steps ensured the seamless execution of the subsequent data preprocessing procedures.

4.1 Feature Extraction

In this part all the images are extracted from the yoga pose folder name and with the help of Mediapipe library all the 33 landmarks in three different direction is extracted. This landmark is then stored in the csv file format.

So, there will be in total 99 features in this csv file format. Refer Figure 3and Figure 4.

```
#Initialising input image path and output csv path
images_in_folder = 'C:\\Users\\jhaan\\Downloads\\Dataset'
#images_out_folder = 'fitness_poses_images_out_basic'
#csv_out_path = 'yoga_poses_landmark_dataset.csv'
#from mediapipe.solutions import drawing_utils as mp_drawing
mp_drawing = mp.solutions.drawing_utils # Drawing helpers
# from mediapipe.solutions import pose as mp_pose
mp_pose= mp.solutions.pose # Blazepose pose estimation model
```

Figure 3: Initialize Path and Load Blazepose model

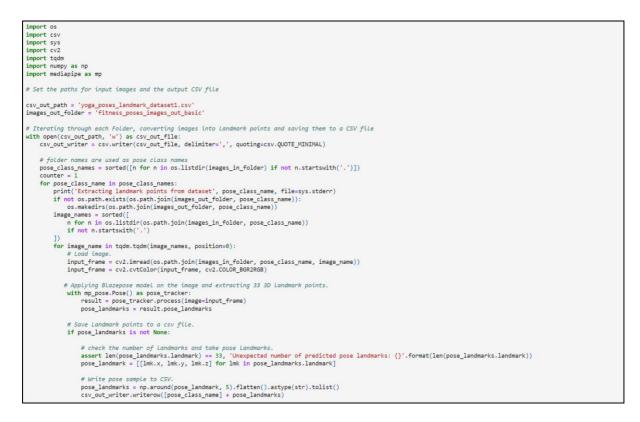


Figure 4: Creating CSV file for landmarks in x,y,z direction

Heading to each column is give as x1, y1, z1, x2, y2, z2 and so on. Refer Figure 5.

```
df_csv = pd.read_csv('./yoga_poses_landmark_dataset1.csv', header=None)
l1=['pose_name']
for i in range(1,34):
    l1.append('x'+str(i))
    l1.append('y'+str(i))
    l1.append('z'+str(i))

df_csv.to_csv('./yoga_poses_landmark_dataset_new11.csv', header=l1, index=False)
df_csv1 = pd.read_csv('./yoga_poses_landmark_dataset_new11.csv')
df_csv1
```

Figure 5: Adding Header to the Dataset

5 Data Transformation

As all the data in sequence order of yoga below code is used to shuffle the dataset, so that there will be no bias in the model. Refer Figure 6.

```
import csv
import random
# Set the path for your CSV file
csv_file_path = './yoga_poses_landmark_dataset_new11.csv'
# Read the CSV file into a list
with open(csv_file_path, 'r') as csv_file:
    csv reader = csv.reader(csv_file)
    rows = list(csv_reader)
# Separate the header (first row) and the data rows
header = rows[0]
data = rows[1:]
# Shuffle the rows randomly
random.shuffle(data)
# Write the shuffled rows back to the CSV file, including the header
with open(csv_file_path, 'w', newline='') as csv_file:
   csv_writer = csv.writer(csv_file)
    csv_writer.writerow(header) # Write the header
    csv_writer.writerows(data) # Write the shuffled data rows
print("CSV file rows shuffled (excluding header) successfully.")
CSV file rows shuffled (excluding header) successfully.
df = pd.read_csv('./yoga_poses_landmark_dataset_new11.csv')
df
```

Figure 6: Shuffling the Dataset

To visualize the distribution of the class Following code is used below, refer to the Figure 7. And Later Label encoding is done in Figure 8.

```
import matplotlib.pyplot as plt
# Assuming 'df' contains your dataset and 'pose_name' is the column representing classes
class_counts = df['pose_name'].value_counts()
# Plotting a bar plot for class distribution
plt.figure(figsize=(8, 6))
class_counts.plot(kind='bar', color='skyblue')
plt.title('Class Distribution')
plt.xlabel('Yoga Poses')
plt.ylabel('Number of Instances')
plt.xticks(rotation=45) # Rotating x-labels for better readability
plt.tight_layout()
plt.show()
```

Figure 7: Class Distribution Graph

```
Feature Encoding
# Encode the response variable into numrical values
from sklearn.preprocessing import LabelEncoder
labelencoder = LabelEncoder()
df['label_enc'] = labelencoder.fit_transform(df['pose_name'])
classes df[['label_enc','pose_name']].drop_duplicates()
classes
```

Figure 8: Feature Encoding

After Feature encoding, to add the pose name to encoded classes use the below code, refer Figure 9.

```
# Adding pose names and encode values to a dictionary for display purposes
classes.set_index('label_enc', inplace= True)
yoga_pose=classes.to_dict()
yoga_pose_dict=yoga_pose['pose_name']
yoga_pose_dict
```

Figure 9: Labelling the Class

Before Training the model, dataset must split into training and test in 70:30. Refer Figure 10

```
Splitting data into train test split - 70-30 ratio
X=df.drop(['pose_name', 'label_enc'], axis=1) # independent variable
y=df['label_enc'] # dependent variable
A=X.columns
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test=train_test_split(X,y,test_size=0.3, random_state=1234,stratify=y)
```

6 Model Implementation and Evaluation

Both deep learning and Machine learning algorithm are used to train the model, to evaluate deep learning Figure 11 and 15) mode accuracy and loss function is used, and graph is drawn for the same (Figure 12,13 and 14). In the case of machine learning evaluation matrix like accuracy, precision, recall and f2 score is used to find the best model. And model is further optimising by using the Hyper parameter.

6.1 Deep learning

```
LSTM Model Implementation
# reshaping the input array before applying to lstm
y_train_re= to_categorical(y_train).astype(int)
y_test_re= to_categorical(y_test).astype(int)
X_train_lstm= np.array(X_train)
X test lstm = np.array(X test)
X_train_lstm=X_train_lstm.reshape(X_train_lstm.shape[0],1,X_train_lstm.shape[1])
X_test_lstm=X_test_lstm.reshape(X_test_lstm.shape[0],1,X_test_lstm.shape[1])
#LSTM Model Implementation
#tf.set_random_seed(122)
model = Sequential()
model.add(LSTM(64, return_sequences=True, activation='relu', dropout=0.2, input_shape=(1,X_train_lstm.shape[2])))
model.add(LSTM(128, return_sequences=True, dropout=0.2, activation='relu'))
model.add(LSTM(64, return_sequences=False, dropout=0.2, activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dense(32, activation='relu'))
model.add(Dense(5, activation='softmax'))
#Compile
model.compile(optimizer='Adam', loss='categorical_crossentropy', metrics=['categorical_accuracy'])
#Fitting LSTM model on train data
history_model_lstm=model.fit(X_train_lstm, y_train_re, epochs=200, validation_data=(X_test_lstm,y_test_re))
```

Figure 11: LSTM model

```
model.evaluate(X_test_lstm,y_test_re)
11/11 [=========================] - 0s 13ms/step - loss: 0.4182 - categorical_accuracy: 0.9020
[0.4181867241859436, 0.9020172953605652]
#Plottina Accuracv and loss Curve
%matplotlib inline
import matplotlib.pyplot as plt
acc= history_model_lstm.history['categorical_accuracy']
val_acc = history_model_lstm.history['val_categorical_accuracy']
loss = history_model_lstm.history['loss']
val_loss = history_model_lstm.history['val_loss']
epochs = range(len(acc))
plt.plot(epochs, acc, 'r', label='Training accuracy')
plt.plot(epochs, val_acc, 'b', label='Testing accuracy')
plt.title('Training and Testing accuracy - LSTM')
plt.legend()
plt.figure()
plt.plot(epochs, loss,'r', label='Training Loss')
plt.plot(epochs,val_loss,'b', label='Testing Loss')
plt.title('Training and Testing loss - LSTM')
plt.legend()
```

```
plt.show()
```

Figure 12: Accuracy and Loss Graph

```
# Confusion report
from sklearn.metrics import confusion_matrix,classification_report
y_predicted = model.predict(X_test_lstm)
y_pred=[]
for i in y_predicted:
    y_pred.append(np.argmax(i))
y_pred1=pd.Series(y_pred)
y_pred1
print(classification_report(y_test,y_pred1))
```

Figure 13: Confusion Report For LSTM

Confusion metric
from sklearn import metrics
import seaborn as sns
cm=metrics.confusion_matrix(y_test,y_pred1)
crete seaborn heatmap with required labels
sns.heatmap(cm,annot =True,cmap='Reds', fmt='g',xticklabels=yoga_pose_dict.values(), yticklabels=yoga_pose_dict.values())

Figure 14: Confusion Matrix for LSTM

To implement and evaluate CNN use below Figure 15.

1D CNN Model Implementation

```
# Reshaping the input array before applying to 1D CNN
X_train_re=np.array(X_train)
X_test_re=np.array(X_test)
sample_size=X_train_re.shape[0]
time_steps=X_test_re.shape[1]
input_dim=1
X_train_re.shape
sample_size1=X_test_re.shape[0]
time_steps1=X_test_re.shape[1]
input_dim1=1
X_test_re=X_test_re.reshape(sample_size1,time_steps1,input_dim1)
X_test_re.shape
```

(347, 99, 1)

1D CNN model Implementation

```
model_cnn = Sequential()
model_cnn.add(Conv1D(128,kernel_size=3,input_shape=(X_train_re.shape[1],1)))
model_cnn.add(Dropout(0.5))
model_cnn.add(Hatten())
model_cnn.add(Flatten())
model_cnn.add(Dense(64, activation='relu'))
model_cnn.add(Dense(5, activation='relu'))
model_cnn.add(Dense(5, activation='relu'))
# Compiling the model
model_cnn.compile(optimizer='Adam',loss='categorical_crossentropy', metrics=['categorical_accuracy'])
# Fitting the model_on_train_data
history_model_cnn.model_cnn.fit(X_train_re, y_train_re, epochs=200,validation_data=(X_test_re,y_test_re))
```

Figure 15: CNN Model

```
#Evaluate the 1DCNN model on test data
model_cnn.evaluate(X_test_re,y_test_re)
[0.3825025260448456, 0.9135446548461914]
# Visualize Loss and Accuracy Plot of the 1D CNN
%matplotlib inline
import matplotlib.pyplot as plt
acc= history_model_cnn.history['categorical_accuracy']
val_acc = history_model_cnn.history['val_categorical_accuracy']
loss = history_model_cnn.history['loss']
val_loss = history_model_cnn.history['val_loss']
epochs = range(len(acc))
plt.plot(epochs, acc, 'r', label='Training accuracy')
plt.plot(epochs, val_acc, 'b', label='Testing accuracy')
plt.title('Training and Testing accuracy - 1D CNN')
plt.legend()
plt.figure()
plt.plot(epochs, loss,'r', label='Training Loss')
plt.plot(epochs,val_loss,'b', label='Testing Loss')
plt.title('Training and Testing loss - 1D CNN')
plt.legend()
```

```
plt.show()
```

Figure 16: CNN Model Evaluation Graph

6.2 Machine learning

To Implement Machine learning model, refer below codes. Figure 17 is implementation for Random Forest Model.

Applying Machine Learning Models on GeneratedLand_Mark dataset

Fitting Generated Landmark datset on Random Forest classifier
import numpy as np
seed = np.random.seed(22)
rng=np.random.RandomStat(3)
from sklearn.model_selection import train_test_split, RepeatedStratifiedKFold
cv:RepeatedStratifiedKFold(_mplites, n_repeate=3, random_state=1)
#RandomizedSearchCV for hyperparameter tuning
from sklearn.model_selection import RandomForestClassifier
parames {'n_estimators':[18,20,30,40,50,60,70,80,90,100], 'max_features': ['log2','sqrt'],'max_depth':[2,4,6,8,10],'min_samples_split':[2,5],'min_samples_leaf':[1,2],'bootstrap':[True,False]}
random_forest.fat(X_train,y_train)

Figure 17: Random Forest Model

Refer Figure 18, 19 for the evaluation matrix.



Figure 18: Evaluation Matrix for Random Forest Model- Part 1

Model Accuracy, how often is the classifier correct?
print("Accuracy-Random forest:",round((metrics.accuracy_score(y_test, y_pred_random))*100,2))
print("Precision-Random Forest:",round((metrics.precision_score(y_test, y_pred_random, average="macro"))*100,2))
print("Recall-Random Forest:", round((metrics.fl_score(y_test, y_pred_random, average="macro"))*100,2))
print("F1 Score -RandomForest:",round((metrics.f1_score(y_test,y_pred_random,average="macro"))*100,2))

Figure 19: Evaluation Matrix for Random Forest Model- Part 2

To implement Xgboost Classifier refer Figure 20,21,22.



Figure 20: XGBoost Classifier Model

```
print(xgboost.best_params_)
print("Accuracy is:", xgboost.score(X_test,y_test))
{'max_depth': 3, 'learning_rate': 0.25, 'alpha': 0.1}
Accuracy is: 0.9164265129682997
from sklearn import metrics
import seaborn as sns
y_pred_xgboost=xgboost.predict(X_test)
cm = metrics.confusion_matrix(y_test,y_pred_xgboost)
# create seaborn heatmap with required Labels
sns.heatmap(cm,annot = True,cmap='Reds',fmt='g',xticklabels=yoga_pose_dict.values(),yticklabels=yoga_pose_dict.values())
```

Figure 21: XGBoost Classifier Evaluation Matrix Part 1

print("Accuracy-xgboost:",round((metrics.accuracy_score(y_test, y_pred_xgboost))*100,2))
print("Precision-xgboost:",round((metrics.precision_score(y_test, y_pred_xgboost, average="macro"))*100,2))
print("Recall-xgboost:", round((metrics.recall_score(y_test, y_pred_xgboost, average="macro"))*100,2))
print("F1 Score -xgboost:",round((metrics.f1_score(y_test,y_pred_xgboost, average="macro"))*100,2))

Figure 22: XGBoost Classifier Evaluation Matrix Part 2

To implement SVM refer Figure 22,23,24.

from sklearn.svm import SVC
from sklearn.model_selection import RandomizedSearchCV
seed=np.random.seed(33)
rng=np.random.RandomState(3)
cv= RepeatedStratifiedKFold(n_splits=5, n_repeats=3, random_state=1)
param_grid={'C':[0.1,1,10,20,50,100], 'kernel':['rbf','poly','sigmoid','linear'],'degree':[1,2,3,4,5,6]}
model_svm=RandomizedSearchCV(SVC(random_state =rng),param_distributions=param_grid,n_iter=5,scoring='accuracy',n_jobs=-1,cv=cv,verbose=3,random_state =rng)
model_svm.fit(X_train,y_train)

Figure 23: SVM Model

print(model_svm.best_params_)
print("Accuracy is:", model_svm.score(X_test,y_test))
{'kernel': 'poly', 'degree': 6, 'C': 1}
Accuracy is: 0.9077809798270894
from sklearn import metrics
import seaborn as sns
y_pred_svm=model_svm.predict(X_test)
svm_cm = metrics.confusion_matrix(y_test,y_pred_svm)
create seaborn heatmap with required Labels
sns.heatmap(svm_cm,annot = True,cmap='Reds',fmt='g',xticklabels=yoga_pose_dict.values(),yticklabels=yoga_pose_dict.values())

Figure 24: SVM Model Evaluation Matrix Part 1

<pre>print(classification_report(y_test,y_pred_svm))</pre>					
	precision	recall	f1-score	support	
0	0.99	0.97	0.98	88	
1	0.92	0.92	0.92	65	
2	0.83	0.83	0.83	52	
3	0.96	0.81	0.88	59	
4	0.84	0.95	0.89	83	
accuracy			0.91	347	
macro avg	0.91	0.90	0.90	347	
weighted avg	0.91	0.91	0.91	347	
<pre>print("Accuracy-svm:",round((metrics.accuracy_score(y_test, y_pred_svm))*100,2)) print("Precision-svm:",round((metrics.precision_score(y_test, y_pred_svm, average="macro"))*100,2)) print("Recall-svm:", round((metrics.recall_score(y_test, y_pred_svm, average="macro"))*100,2)) print("F1 Score -svm:",round((metrics.f1_score(y_test,y_pred_svm,average="macro"))*100,2))</pre>					

Figure 25: SVM Model Evaluation Matrix Part 2

To implement decision model, refer following Figure 26,27,28.

Figure 26: Decision Tree Classifier

```
print(model_decision.best_params_)
print("Accuracy is:", model_decision.score(X_test,y_test))
{'min_samples_split': 2, 'max_features': 'sqrt', 'max_depth': 30}
Accuracy is: 0.8645533141210374
from sklearn import metrics
import seaborn as sns
y_pred_decision=model_decision.predict(X_test)
decision_cm = metrics.confusion_matrix(y_test,y_pred_decision)
# create seaborn hactmap with required LabeLs
sns.heatmap(decision_cm,annot = True,cmap='Reds',fmt='g',xticklabels=yoga_pose_dict.values(),yticklabels=yoga_pose_dict.values())
```

Figure 27: Decision Tree Classifier Evaluation Matrix Part 1

print("Accuracy-decision tree:",round((metrics.accuracy_score(y_test, y_pred_decision))*100,2))
print("Precision-decision tree:",round((metrics.precision_score(y_test, y_pred_decision, average="macro"))*100,2))
print("Recall-decision tree:", round((metrics.recall_score(y_test, y_pred_decision, average="macro"))*100,2))
print("F1 Score -decision tree:",round((metrics.f1_score(y_test,y_pred_decision,average="macro"))*100,2))

Figure 28: Decision Tree Classifier Evaluation Matrix Part2

To Implement KNN Model, refer Figure 29,30.

```
import matplotlib.pyplot as plt
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score
k_values = list(range(1, 20))
accuracy_values = []
for k in k_values:
   knn = KNeighborsClassifier(n_neighbors=k)
   knn.fit(X_train, y_train)
   y_pred = knn.predict(X_test)
   accuracy = accuracy_score(y_test, y_pred)
   accuracy_values.append(accuracy)
plt.plot(k_values, accuracy_values, marker='o')
plt.xlabel('k')
plt.ylabel('Accuracy')
plt.title('Accuracy vs. k Values')
plt.show()
```

Figure 29: KNN Model

```
knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
```

Figure 30: KNN Evaluation Matrix

7 Saving the Optimal Model

Evaluate and save the model with highest accuracy and dump it in pickle file and load it when the system is built for future use.

```
saving the model
import pickle
file_name='xgb-reg_fix2.pkl'
pickle.dump(xgboost,open(file_name,"wb"))
xgb_model_loaded=pickle.load(open("xgb-reg_fix.pkl","rb"))
xgb_model_loaded=pickle.load(open("xgb-reg_fix.pkl","rb"))
```

8 Building Yoga Pose Image Detection System

Refer Below Figure 32 to build the system to identify pose in the given image.

```
def poseclassify(path):
   sample_img=cv2.imread(path)
plt.figure(figsize=[10,10])
plt.title("Sample_image")
    plt.axis("off"
    plt.imshow(sample_img)
    plt.imshow(sample_img[:,:,::-1])
    plt.show()
    # Define pose estimation and skeltal image drawing object
    mp_drawing = mp.solutions.drawing_utils
    mp_pose = mp.solutions.pose
    pose = mp_pose.Pose(static_image_mode=True,model_complexity=2)
   img_copy = sample_img.copy()
#Convert BGR to RGB format and apply the Blazepose pose estimation model
   results = pose.process(cv2.cvtColor(sample_img,cv2.COLOR_BGR2RGB))
   # to draw it in 3D Space
   mp_drawing.plot_landmarks(results.pose_world_landmarks,mp_pose.POSE_CONNECTIONS)
    # Extract the landmark data and pass to xgboost model for prediction
   landmarks = results.pose_landmarks.landmark
    # Flatten Array
    pose_row = list(np.array([[landmark.x, landmark.y,landmark.z] for landmark in landmarks]).flatten())
    X = pd.DataFrame([pose_row])
    # Xgboost prediction
    X.columns = A
    body_language_class = xgb_model_loaded.predict(X)[0]
    body_language_prob = xgb_model_loaded.predict_proba(X)[0]
    print(body_language_class, body_language_prob)
    pose detected= yoga pose dict[body language class]
    prob=(round(body_language_prob[np.argmax(body_language_prob)],2))
    print(" The pose detected is:", pose_detected)
    print("probablity :", prob)
    if results.pose landmarks:
        mp_drawing.draw_landmarks(img_copy, results.pose_landmarks, mp_pose.POSE_CONNECTIONS,
                                  mp_drawing.DrawingSpec(color=((255,127,80)), thickness=1,circle_radius=2),
                                   mp_drawing.DrawingSpec(color=(50,205,50),thickness =1,circle_radius=2)
        fig=plt.figure(figsize=[10,10])
        plt.title("output-image")
        plt.axis("off")
        plt.imshow(img_copy[:,:,::-1])
        plt.show()
```

Figure 32: Yoga Pose Image Detection

To call the system use the code in Figure 33.

poseclassify("C:\\Users\\jhaan\\Desktop\\Anand_01.jpg")

Figure 33: Identify the Yoga Pose

9 Building the Real Time Yoga Pose Detector

To build the final real time yoga pose detector refer the Figure 34, 35, 36. In this Figure 34 has code to add yoga pose benefit and Figure 35 has Audio feedback Function.



Figure 34: Building Yoga Pose Benefit Function







Figure 36: Yoga Pose Detector System- Part 1



Figure 37: Yoga Pose Detector System- Part 2

References

Link for the dataset used in this Project.