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A Minor Project Report

on

REAL TIME POSE DETECTION USING PYTHON

Submitted in partial fulfillment of requirements for the award of the

Degree of

BACHELOR OF ENGINEERING

in

ELECTRONICS AND COMMUNICATION ENGINEERING

Under the guidance of

Mrs. P.SAKTHI

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BONAFIDE CERTIFICATE

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PO 7: Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need forsustainable development.

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PSO2: Able to solve complex problems in Electronics and Communication Engineering with analytical and managerial skills either independently or in team using latest hardware and softwaretools to fulfill the industrial.

MAPPING OF PROJECT WITH POs AND PSO

Abstract	Matching with POs , PSOs
USING OF PYTHON LANGUAGE TO SOLVE THE PROBLEM,USAGE OF MEDIAPIPE LIBRARIES	PO1,PO5,PSO2

ABSTRACT

Yoga is a practice that has been around for millennia and is used by athletes, patients, and physiotherapists. The key to getting the most out of yoga is having the proper posture and technique. Therefore, creating a model to accurately categorize yoga poses is a contemporary research issue. In order to categorize numerous yoga poses, the study provides a revolutionary architecture. Using ML, the media pipe library function in python method estimates yoga poses. The photos are skeletonized in the proposed design before being input into the model. The Media Pipe library is used for body key point identification throughout the skeletonization process .The ever-expanding new range of applications (e.g., human-robot interaction, gaming, and sports performance monitoring) enabled by contemporary technological breakthroughs are the main drivers of this movement. The Multi-view Matching Module chooses the 2D poses of the same person among all 2D poses and groups them

Keywords: Media Pipe - Convolutional neural networks-Deep learning-Computer vision Classification - Skeletonization

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CHAPTER-1

INTRODUCTION

Yoga is a practice that has its roots in ancient India. It improves one's physical well-being and purifies one's body, mind, and spirit. Numerous ailments can be cured by yoga without the need of medications. Only with the introduction of Covid-19, people realized that health is more important than anything else. Anything else in this world, and everyone is in a really terrible circumstance since there is constant bad news. Yoga serves as a fantastic remedy for this in a world where everyone’s mental peace is disturbed. Any system that detects yoga positions must estimate human poses. Some major work is done in the yoga poses detection using the human pose estimation field. Sruthi Kothari worked on a method that uses deep learning mainly convolutional neural networks for classifying yoga.

1.1 SIGNIFICANCE OF YOGA

Yoga derived from the Sanskrit root Yuj, which means to yoke, join or attach, and it is considered as any ‘ practices’ that help facilitate a union between self and the Divine. “There are four Yoga’s, viz., Karma Yoga, Bhakti Yoga, Raja Yoga and Jnana Yoga”. "Yoga is based on the philosophy that is practical and useful for our daily lives. Yoga constructs desirable physiological alterations and has sound scientific foundations". It’s important first to understand the characteristics of modern life to explain the significance of yoga in modern life. Soewondo pointed out the characteristics of modern life in terms of work life, eating style and family life in the following way. In terms of a busy life the people of the city have much work to do; as a result, they leave early in the morning and come back home late, the time they have for rest is very short because they are driving in a very stressful traffic jam. The modern man is involved not in a single activity but in diversities of

Activities for earning their life, and involved in strong business activities driven by technologies which makes the activities faster.

1.2 MEDIAPIPE POSE ESTIMATION

This is a pose estimation method developed by researchers of Google and operates on the blaze fast model for the pose detection method. It is a fast model and performs at a 24FPS rate.

Figure 1.1Yoga pose

1.3 FITNESS APPLICATION

This is one of the most modern use cases of pose detection and the fitness industry is boosted by the same.

1.4 CAMERA SURVEILLANCE

As thieves are getting smarter day by day it’s time for us to make smart cameras with the help of pose detection and detect each moment of them.

CHAPTER-2

RELATED WORK

Robotics and computer engineering are just two areas where human activity recognition has been used. Media pipe are used in references to identify human activity using Reference makes use of concealed Markov models and identified body parts for identifying human activities. A technique is used to identify Yoga activities; this had a 97.16 percent accuracy rate. It is a way used for monitoring services in smart homes. It employs background noise in the environment for human activity and the location of wearable sound-detecting sensors used, which had a 96.9 percent accuracy rate. A lot of effort has been put into building automated systems that assess Human pose as well as yoga.

2.1 COMPUTER VISION

Computer vision helps scholars to analyze images and video to necessary information, Understand information on events or description, and scenic patterns. From a 2D posture and a single-person pose estimation to a 3D pose and multiple-person position estimation. Pose estimation algorithms typically find the body's important points, connect those points, and output them. The model may under fit training dataif there are few hidden layers, and it may over fit if there are more hidden layers. MLPis a fully connected neural network, meaning that every node is linked to every other node in the neural network's subsequent layers.

CHAPTER-3

PROJECT METHODOLOGY

In this research, a deep learning-based methodology for estimating yoga poses is proposed in algorithm 1 to identify right yoga postures and offer comments to help the yoga the suggested strategy has been tested on MEDIA PIPE .It is divided into three primary steps.

3.1. REAL-TIME MULTI PERSON POSE ESTIMATION

One of the key difficulties in computer vision is human pose estimate, which has advanced significantly in recent years. From a 2D posture and a single-person pose estimation to a 3D pose and multiple-person position estimation. Pose estimation algorithms typically find the body's important points, connect those points, and output them. These essential points include the x and y coordinates of everybody point, which is helpful for a variety of computer vision issues, including activity detection, sports analysis, pose analysis in the gym, and surveillance-assisted living. 18 body key points are extracted using +is posture estimation, and each point is made up of the x and y coordinates of a body point.

3.2 DEEP POSE

Deep Pose was the first major paper [1], published in CVPR 2014 that applied Deep Learning to Human pose estimation. It achieved SOTA performance and beat existing models back in the year 2014. The model has an Alex Net backend and estimated pose in a holistic fashion, i.e. certain poses can be estimated even if some joints are hidden when the pose is reasoned holistically. The paper applies Deep Learning (CNN) to pose estimation and kicks off research in this direction. The model used regression for XY locations for certain regions. This added complexity and weakened generalization hence performing poorly. Since the earliest stage of computer vision, the concept of representing articulated objects—and the human pose in particular—as a graph of

Parts has been advocated [16]. This referred to as Pictorial Strictures (PSs), a Fishler invention and Elschlager [8] became tractable and practical thanks to employing the distance transform method as Felzenszwalb and Hutten ocher [6].

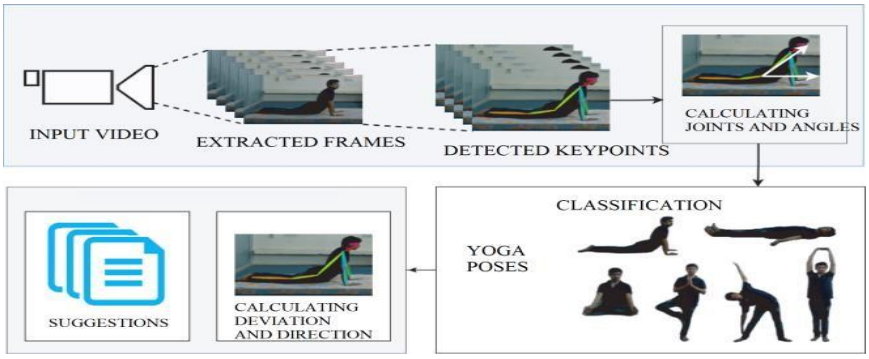


Figure 3.2: A schematic diagram of the proposed approach for correct yoga pose estimation and feedback generations for incorrect posture.

3.3. FEATURE EXTRACTION

Media pipe pose estimation is used to extract important points for pose estimation [7, 8]. Every movie is subjected to a +is posture estimation process, during which frames are retrieved every 2 seconds and poses are computed for 5 consecutive frames of each video, yielding 350 examples for 70 videos. Each pose generates an array of 18 key points, each of which includes an x and y coordinate .due to differences in distance.

```
importmath
import cv2
import numpy as np
from time import time
import mediapipe as mp
import matplotlib.pyplot as plt
```

A

B

C

Figure.3.3: A, B, C represents different yoga poses

CHAPTER-4

RESULTS

Input layer, hidden layer, and output layer are the three types of layers used in the construction of neural networks (MLP). Depending on the complexity of the training data, there may be any number of hidden layers. The model may under fit training data if there are few hidden layers, and it may over fit if there are more hidden layers. MLP is a fully connected neural network, meaning that every node is linked to every other node in the neural network's subsequent layers. These networks are typically used for supervised training, where each input set of data has an associated output label or class.

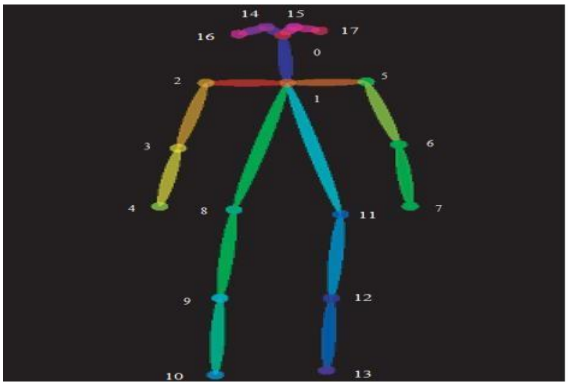
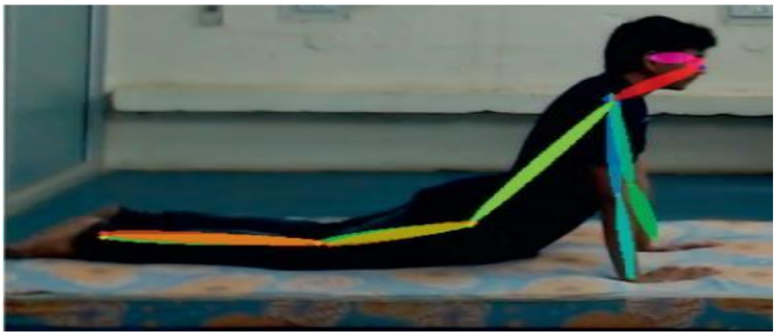


Figure.4.1: extracted key points from a frame by pose estimation method.

Angles between important points have been calculated and supplied as MLP input in this article. The project's input data length is 12, and the project's output layer length is 6, because there are six classes to classify these labels. Figure 8 shows the input layer size as 12, the first and second hidden layers as 10, and the output layer as 6. There are 350 instances in total, 320 of which are utilized for training, and 5 instances are used for validating each position. The training batch size is 20, and there are 10,000 epochs. Up until the 6900 epoch, the accuracy of both the training and validation datasets went through several ups and downs before reaching an accuracy of 0.9958.

The loss of training and validation rapidly decreased from 6900 to 10000 epochs, which led to the training model classifying with high confidence. The loss of validation and training datasets significantly decreased from epoch 0 to epoch 10000. The model is not over fitting, according to the training and validation accuracy results. Since the research is categorizing input features into one of the 6 labels, categorical cross-entropy is the loss function that is employed .Up until the 6900 epoch, the accuracy of both the training and validation datasets went through several ups and downs before reaching an accuracy of 0.9958. The loss of training and validation rapidly decreased from 6900 to 10000 epochs, which led to the training model classifying with high confidence. The loss of validation and training datasets significantly decreased from epoch 0 to epoch 10000. The model is not over fitting, according to the training and validation accuracy results. Since the research is categorizing input features into one of the 6 labels, categorical cross-entropy is the loss function that is employed.

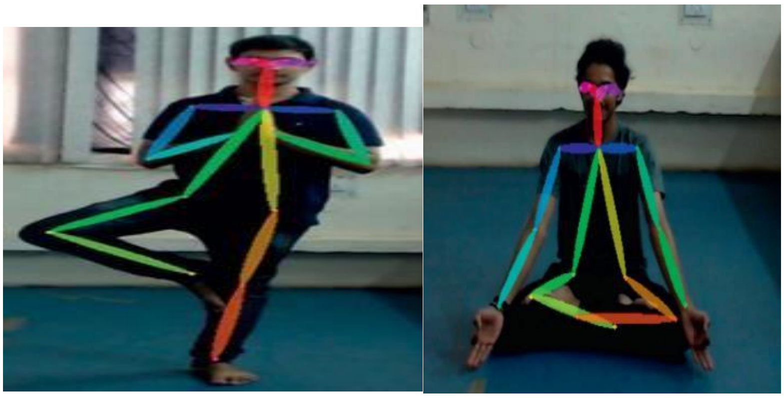
SVM obtained accuracy results of 0.9319, CNN obtained accuracy results of 0.9858, and CNN + LSTM achieved accuracy results of 0.9938. Table 1 shows the accuracy result of the experimental models. Although the MLP power in the system is far lower than CNN and CNN + LSTM, it nevertheless managed to achieve an accuracy of 0.9958 using altered characteristics. SVM obtained accuracy results of 0.9319, CNN obtained accuracy results of 0.9858, and CNN + LSTM achieved accuracy results of 0.9938. Table 2 shows the accuracy result of the experimental models. Although the MLP power in the system is far lower than CNN and CNN + LSTM The outcome evaluation has a 6 6 confusion matrix since the study's confusion matrix includes six labels. The suggested data's projected class is represented by the jth column, whereas the ith row represents the actual class. The confusion matrices of the training, validation, and testing datasets are shown in Figure 9. The total number of instances in the confusion matrix for the training, validation, and training datasets are 320, 30, and 30, respectively. It can be seen that every sample is properly predicted, with an overall accuracy of 0.9958. Figure 10 shows the plot for various competing models.



A

B

C **D**



E **F**

Figure 4.2: Demonstration of key points extraction on all 6 yoga poses: (A) Cobra pose, (B) Corpse pose, (C) Mountain pose, (D) Triangle pose, (E) Tree pose, and (F) Lotus pose

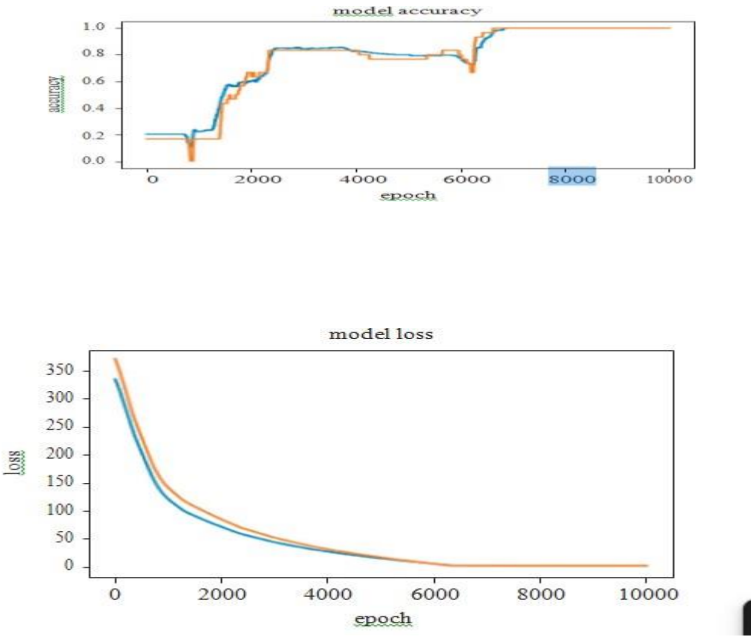
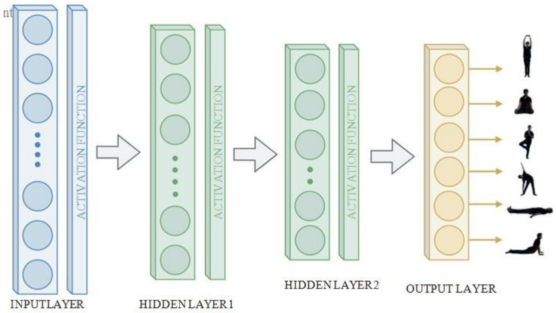


Figure 4.3: Graphs of accuracy and loss for training and validation datasets.



Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 12)]	0
dense (Dense)	(None, 10)	130
dense_1 (Dense)	(None, 8)	88
dense_2 (Dense)	(None, 6)	54

Total params: 272
Trainable params: 272
Non-trainable params: 0

Figure 4.4: Neural network model architecture.

CHAPTER-5

RUNTIME ANALYSIS

The methods described in this study rely on deep learning to identify improper yoga posture and give the user advice on how to straighten up. The computation of vectors for each joint, the extraction of key points using a pose estimation technique, and the angle between the vectors for adjacent joints are all characterized as features in this study.

Table 1: Table represents the accuracy result of the experimented models.

Model	Accuracy	
	Training	Testing
SVM	0.9532	0.9319
CNN	0.9934	0.9858
CNN + LSTM	0.9987	0.9938
MLP	0.9962	0.9958

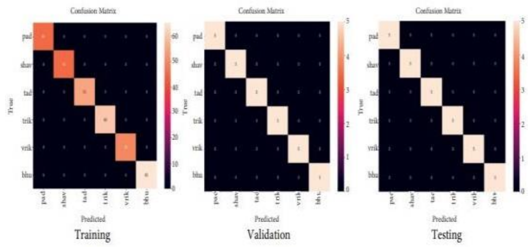


Figure 5.11: Confusion matrices of training, validation, and testing datasets. (a) Training, (b) validation, and (c) testing

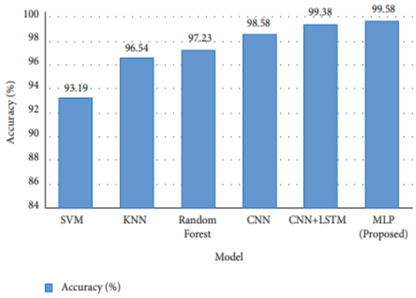


Figure 5.1: The graph illustrates the plot of different competitive models

Evaluation of proposed work runtime in milliseconds with various techniques running. Mean (F.E.+C) demonstrates the mean average runtime per frame for extraction and computation of features with yoga pose classification. Mean (F.G.) is the mean average runtime per frame for feedback generation.

The classification approaches were then given these features, and later feedback regarding the accuracy of the yoga pose was generated. As a result, the runtime is split into three sections: (1) time spent on feature extraction and computation for each frame; (2) time spent on classification; and (3) time spent on creating feedback for each frame's classification of a yoga posture. For each approach, the runtime for feature extraction and computation stays the same.On the Xeon(R) CPU E3-1240 v5 and NVIDIA GeForce GTX-1080, runtime analysis is done.

The experimental methodology's mean average run time per frame and standard deviation are shown in Table 2. Milliseconds are used to display time in +e. It combines the amount of time spent on feature extraction and categorization every frame with the creation of feedback. methodology. Milliseconds are used to display time in +e. It combines the amount of time spent on feature extraction and categorization every frame with the creation of feedback.

CHAPTER-6

CONCLUSION

This study offered a transfer learning-based yoga self-coaching method. Using a standard RGB webcam, the yoga posture dataset was first collected for this study. Next, data augmentation methods were used. Investigated was the transfer learning method, which was trained on the Mobile Net model. In the previous stage, we built an AI yoga system that used a prediction model for inference in real-time.

In previous studies, SVM had a test accuracy of 0.9319, CNN had a test accuracy of 0.9858, and CNN + LSTM had a test accuracy of 0.9938. MLP power in the system is significantly smaller than CNN and CNN + LSTM, but it still managed to reach an accuracy of 0.9958 with altered characteristics. The experimental results reveal promising results when compared to current methods. The suggested method keeps the computational complexity low, may be used in a person's busy life for self-yoga instruction, and can identify bad yoga posture to prevent recurring issues.

In conclusion, the system for classifying yoga postures produced a performance. 98.43% accuracy was achieved by incorporating this into our yoga self-coaching system. The purpose of the yoga self-coaching system is to the yoga poses in accordance with the chosen yoga posture guide, output the anticipated outcome, and provide real-time counseling for improper postures. The recognition is based on the predicted angle of the joints, which is done by utilizing the Media pipe algorithm for key point estimation.

In conclusion, we created a system for self-coaching yoga that can predict posture and confirm feedback from instruction in real time. Since Covid-19 began, there has been an increase in home training, which, in our opinion, is supported by the method we built. The right yoga posture is identified using the yoga self-coaching system, which also provides on-the-fly guidance.

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