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# YOGA POSE ESTIMATION, DETECTION, AND PHYSIOTHERAPY

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**ABSTRACT:** Imagine using technology to make yoga even better! With yoga pose estimation and detection, computers can now watch and understand how we do different yoga poses. It meansthe computer can give us instant tips on how to do the poses better and avoid hurting ourselves. It's like having a personal yoga coach! This technology also keeps track of how well we're doing and can give us goals to improve. It's like a fitness tracker but for yoga. In short, this new tech makes yoga easier, personalized just for us, and more helpful for everyone, no matterif you're a beginner or an expert. Using smart technology in physiotherapy can make a big difference! Here we talk about how machine learning and visual recognition can be super useful for physiotherapy exercises. They can help analyze how patients move, figure out the best personalized treatment plans, and even monitor progress from a distance. They give physiotherapists really helpful data to improve treatments. As physiotherapy keeps getting better, machine learning and visual recognition are becoming key players in making treatments more effective and changing how rehab services work.

## INTRODUCTION

MediaPipe, Keras, TensorFlow, NumPy, and OpenCV-Python help estimate and recognize yoga poses. We estimate and identify yoga poses using these techniques. MediaPipe is great at real-time body tracking, letting computers detect stances and positions. Smart yoga position identification computer models are created via Keras and TensorFlow. NumPy handles data efficiently, while OpenCV-Python processes pictures. These tools make yoga more accessible for all ability levels when combined. This is only the beginning of how these innovative technologies can make yoga healthier and smarter.

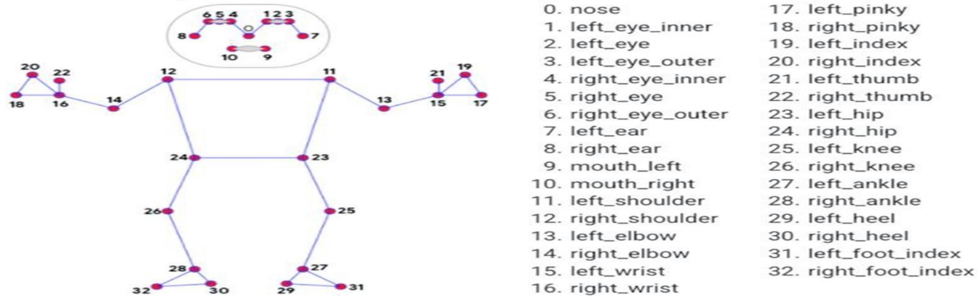



***Figure 1.1:*** *Key Points for Body*

Physiotherapy and machine learning and image recognition are revolutionizing patient treatment. Muscle and nerve patients benefit greatly from physiotherapy. Explainable AI (XAI) is now key to this transformation. XAI is a unique AI that aims to comprehend and explain clever computer models. We use our AI to recognize positions and guide patients on physiotherapy activities.


***Figure 1.2:*** *Physiotherapy Exercise*

Modern work is fast-paced, so people are hooked on their routines. Most people have serious health issues due to their hectic lives. Yoga is an ancient Indian practice that empowers the mind, body, and soul. Mental health is important throughout life, from birth to maturity. Mental health is frequently disregarded despite its significance. Mental illness affects about 870 million people globally. Fitness apps have boomed since 2016, with usage rising over 50% in six months. Fitness Apps are growing 85% faster than other App categories. Wearable technology's capacity to measure fitness regimens has helped yoga fitness apps gain popularity.

Human posture categorization identifies behaviors. Understanding human appearance and associated attributes is essential for assessing people and discovering their environmental connections, which are crucial for industrial applications. Technology has made smartphones and other mobile gadgets more handy, making them more crucial in people's everyday lives. International predictions are 7.33 billion users by 2023, up from 6.8 billion in 2018.

Smartphone users spend 90% of their time on mobile apps. A recent systematic evaluation found that yoga improves muscular strength, flexibility, balance, and quality of life.

The review cannot apply to all patients due to physiological differences. Because of this, we conducted a systematic review to compare yoga intervention to other exercise programs and inactive controls in increasing health-related fitness and quality of life. Posture, attitude, and gesture are key. Content that ICTs and apps diminish the requirement for conventional transportation and physical space for real jobs. Yoga, like any other activity, must be done correctly to avoid injury.

Calculate the instructor-user body angle difference. If it exceeds the threshold, the method suggests repair. This allows yoga to be practiced anywhere, even at home. Thus, everyone may practice yoga, regardless of age or condition. For precise and rapid yoga practice, stance identification must be automated.

Several technological models have been built using extensive literature study. This section summarizes. Innovative human posture detecting methods are related. Existing performance assessment systems employ simulators, sensors, and other devices to compare instructor actions to human body movements. The system's capacity to handle varied self-taught situations and use Kinect for real-time body area recording is unknown. Thus, it cannot distinguish yoga positions. The researchers disclosed their method for detecting yoga positions but did not educate users how to correct them. As a consequence, it requires proper handling. The research developed an automated system-based yoga training technique that used feature points based on skeletons, outlines, and dominant axes to analyze practitioners' postures. Postural data facilitates feature point recognition and axis creation. It compares Microsoft Kinect with the open framework, using an RGB camera, and a depth sensor to estimate/track articulate stance to construct yoga body skeletons.

Poor body map segmentation creates inconsistent instructions. Kinect is used to build a computer. The Adaboost interface system for training identified six yoga postures using an algorithm that tracks depth, color, and body. The smart system also recognizes wheelchair-bound sitting users. After gathering data from a network of sensors using the neighborhood rule, the k-nearest neighbor approach balances it and principal component analysis reduces its dimensions. The k-nearest neighbor method is used to pre-processed and balanced data.

## LITERATURE SURVEY

Robotics and computer engineering use human activity recognition. References detect human activity using sensors using randomized trees (random forests). Reference recognizes human activity using hidden Markov models and body components. This approach recognized 6 home activities with 97.16 percent accuracy. Smart houses monitor services using this way. Wearable sensors that monitor ambient background noises can recognize human activities with 96.9% accuracy.

Developing automated tools to assess yoga, basketball, and cycling has been extensive. Speeded Up Robust Features (SURF) algorithms employing contour information may not be enough for an automated system to compare novice yoga to professional yoga films. A kinetic sensor and AdaBoost classifier yoga stance identification project was 94.8% accurate. Another method presenting 3 yoga positions was 82.84% accurate. The algorithm classified yoga positions using deep learning. Traditional machine learning requires engineering and extracted features, whereas deep learning understands data and extracts features. A self-instructed yoga position system using star skeleton computation. Kinect extracts the body contour from the user's body map with 99.33% accuracy. Hash-based learning extracted human posture from pressure sensor. The suggested method uses no sensors since they may not always be portable.

OpenPose's posture estimation employed the CNN-LSTM hybrid model to categorize yoga poses using feature extraction. Furthermore, it contrasted simple CNN models with a hybrid model and machine learning models with deep learning models. Confusion matrix and classification score are evaluated. SM had 0.9319 test accuracy, CNN 0.9858, and CNN with LSTM 0.9938. OpenPose, PoseNet, and PifPaf are important point detection algorithms. OpenPose, created at CMU, uses CNN-based architecture to find critical spots. OpenPose extracts picture characteristics using VGG-19. The first branch (early layers) found 18 confidence maps. The second branch predicts body part associations.

PoseNet can extract human stance like OpenPose. All significant points are categorized by confidence level, 1 being highest and 0 lowest. The posture is retrieved by PoseNet regardless of picture size. Encoder creates encoding vector, localizer translates to localization feature vector, and regressor regresses final posture. PifPaf pulls human poses from the bottom up. The full body position is created by combining a Part Intensity Field for localization and a Part Association Field for association. The architecture is ResNet.

These models employ 18 key points with 36 x and y coordinates. Extracting features from these important places improves model training accuracy. The project extracts 12 joint angles to feed models. Human activities and angle motion sequences are linked by previous approaches that employed joint angles. Scalable angle features have more information than key points. Reference shows that elbow, shoulder, knee, and crotch angles improve 3D human activity detection. Hip bone angle pairs are added, and right knee, left knee, and elbow information is given for standing and walking.

References scale features using joint angles. In reference, hip and knee angles dominate. Hip angles are created by the shoulders and knees, while knee angles are made by the hips and ankles. These characteristics are more insightful than key points since their angles are constant regardless of camera distance, unlike key points, which are not scaled. A reference key point in 3D space is used to determine angles. These traits are rotation invariant in both circumstances. Proposed system considers x-axis (ground) angles. All 12 joints link two important locations, hence 12 angles are present. The angle between joint ab and the x-axis is a feature if a and b are important points.

## PROPOSED SYSTEM

A suggested yoga stance estimate, detection, and treatment system uses modern technology and new methods to overcome restrictions. This technology uses cutting-edge computer vision algorithms to recognize and monitor yoga positions in real time, giving users exact alignment, posture, and movement feedback. Wearable gadgets with sensors and smart fabrics improve motion-tracking, providing tailored yoga practice insights. User-friendly mobile apps let practitioners access guided yoga exercises, get interactive feedback, and track their progress. Additionally, VR and AR technologies enable users to adjust postures with visual assistance and feedback in immersive situations. AI algorithms analyse user motions to offer posture and physiotherapy routines that maximise benefits. The suggested system combines technical advancements with a holistic approach to yoga practice and rehabilitation to help people reach their health objectives with accuracy, effectiveness, and awareness.

Figure 3.1 graphically depicts the suggested strategy, and the following sections explain each step.

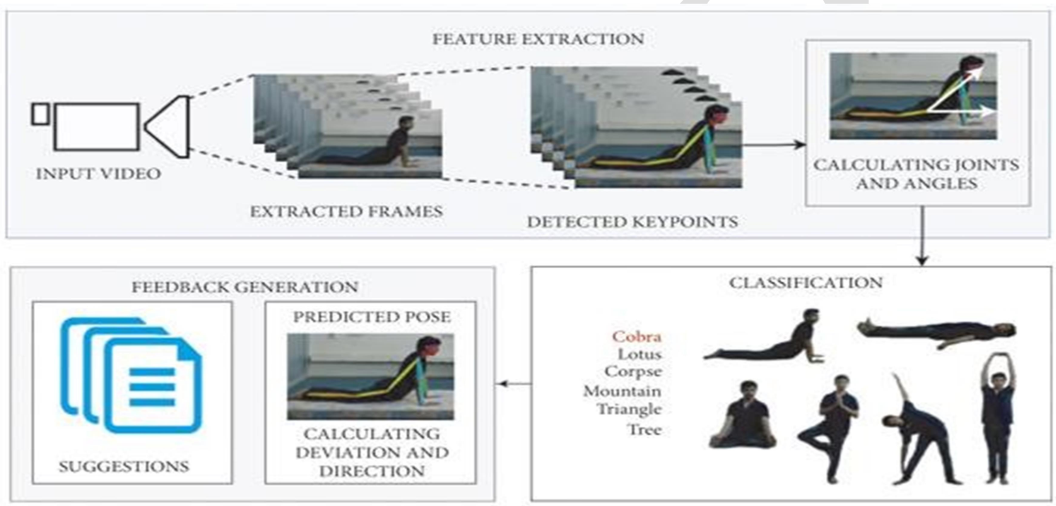



***Figure 3.1:*** *A schematic diagram of the proposed approach for correct yoga poseestimation and feedback generations for incorrect posture.*

The suggested system used MediaPipe and MoveNet-based deep learning to automatically recognize yoga positions. Raw yoga position photographs are used in the study. The raw photos are scaled using bicubic interpolation. Bicubic interpolation calculates new pixel values from neighboring pixels to resize pictures without affecting quality. Images are normalized after resizing. Typically, normalization scales pixel values to a predefined range (e.g., 0 to 1) for consistent model input. The MediaPipe method skeletonizes the pictures utilizing key points. Google's MediaPipe framework is for perception applications including hand tracking, face recognition, and position estimation. MediaPipe then finds landmarks in yoga posture photographs. Key points are bodily markers that establish the pose's structure and direction. The MoveNet model uses key-point-skeletonized pictures. Human posture estimation is done using deep-learning model MoveNet. The model may detect and categorize yoga positions by key points. The MoveNet model classifies yoga postures. The essential points simplify each posture, making it simpler for the model to learn and distinguish.

**SYSTEM ARCHITECTURE**

Yoga stance estimation, detection, and treatment system design uses multiple linked components to deliver accurate analysis and feedback to practitioners. Data gathering modules collect input data, such as yoga positions in photos or videos. Preprocessing improves quality and reduces noise, guaranteeing excellent data for analysis. Pose estimation methods like OpenPose and PoseNet use preprocessed data to identify body landmarks and infer postures. Wearable sensors or smart clothes may contribute motion-tracking data to posture estimation. These components are integrated to provide practitioners with tailored feedback in the form of visual signals, written instructions, or auditory prompts via a mobile app or online platform. The system customizes feedback depending on individual features and objectives using machine learning techniques. To aid recuperation, physiotherapy integration uses the system's information to create customised workouts and rehabilitation routines. User data is protected by strong privacy and security safeguards. Continuous testing, validation, and iterative improvement maintain the system's accuracy, dependability, and usability across varied contexts and user demographics, helping practitioners to improve their yoga practice and reach holistic health objectives.

## HUMAN BODY MODELING

Human body modeling is essential to estimate a human pose by locating the joints in thebody skeleton from an image. Most methods use kinematic models where the body's kinematicstructure and shape information are represented by its joints and limbs.[7] Different types of human body modeling are shown in the following figure.

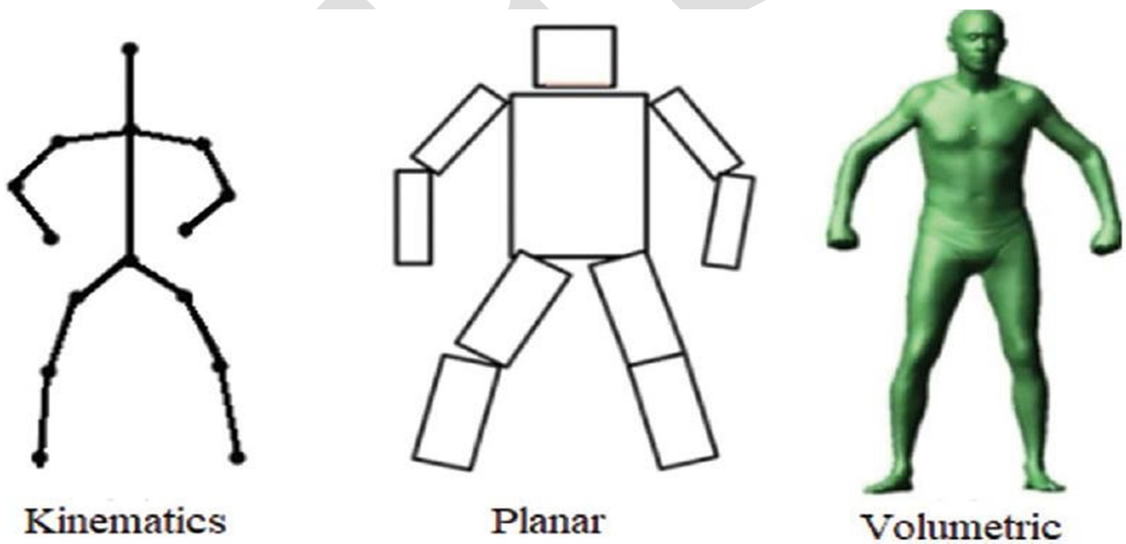



***Figure 5.1:*** *Human Body Modeling*

## IMPLEMENTATION

### DATASET INFORMATION

The proposed methodology is examined on a publicly available, online, open-source collection dataset.

This dataset includes 6 yoga poses, namely, Cobra (Bhuj), Tree (Vriksh), Mountain (Tada), Lotus (Padam), Triangle (Trik), and Corpse (Shav). The total number of videos of the 6 poses is 70, and the total instances combining the 6 poses are 350. These videosare recorded in a room using the camera from a distance of 4 meters; the frame per second rateis 30. To have robustly trained models, individuals performed these poses with few variations. Table 1 summarizes the statistics of the dataset in terms of video count, duration ofeach activity class in seconds, and the number of persons for each yoga pose separately, and some sample frame of every pose is depicted in the following figure.

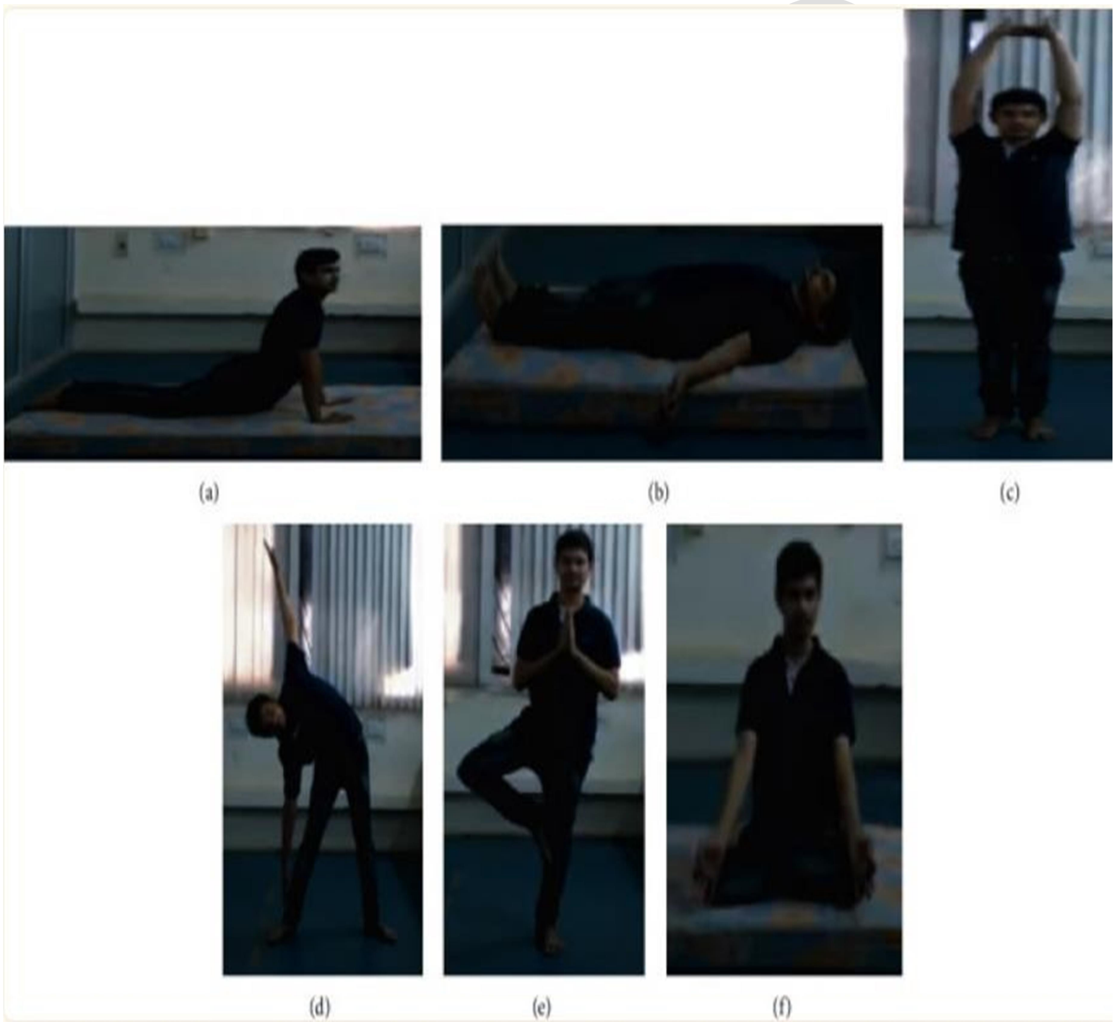



***Figure 6.1:*** Sample frames of every yoga pose: (a) Cobra, (b) Corpse, (c) Mountain, (d) Triangle, (e) Tree, and (f) Lotus pose.

| Yoga pose | Time (s) | Persons | Videos |
|---|---|---|---|
| Cobra pose | 615 | 15 | 14 |
| Lotus pose | 495 | 15 | 10 |
| Corpse pose | 450 | 15 | 10 |
| Mountain pose | 585 | 15 | 12 |
| Triangle pose | 540 | 15 | 13 |
| Tree pose | 500 | 15 | 11 |
| Total | | | 70 |

***Figure 6.2:*** Summarization of statistics of the dataset for each yoga pose.

A large and diversified yoga (LDY) dataset comprising five yoga courses was used to assess the suggested technique. The yoga dataset utilized in this study is at https://www.kaggle.com/datasets/lakshmanarajak/yoga-dataset. Five yoga classes—Downdog, Goddess, Plank, Tree, and Warrior—make up the dataset. It has 2000 yoga class main posture photos. Separate key posture photos are used for training and assessment. The following Figure shows LDY dataset yoga positions.

This research tested the suggested model using the large and diverse yoga (LDY) dataset. Training and test datasets are segregated in the database. The picture is a 300x300 pixel jpg file. We also apply contrast histogram equalization (CLAHE) to increase picture pixel intensity and contact. Training and testing photos are shown in the table below.


***Figure 6.3:*** *Different yoga poses images from the used LDY dataset.*

| Yoga Class | Training Image | Test Image | Validation Image | Total |
|---|---|---|---|---|
| Downdog | 300 | 100 | 28 | 428 |
| Goddess | 306 | 70 | 26 | 402 |
| Plank | 314 | 100 | 28 | 442 |
| Tree | 220 | 50 | 20 | 290 |
| Warrior | 321 | 90 | 27 | 438 |
| **Total** | **1461** | **410** | **129** | **2000** |

***Figure 6.4:*** *Large and diverse yoga (LDY) dataset of five classes*

**OUTPUT SCREENS**

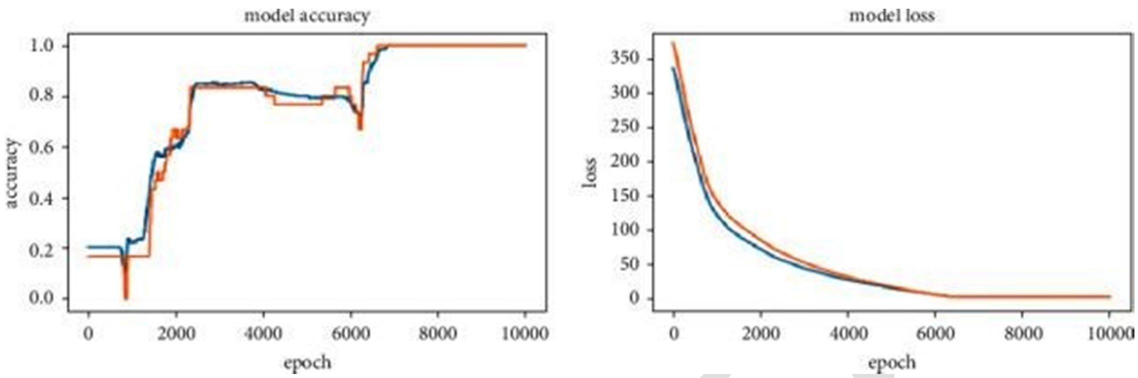



***Figure 7.1:*** Graphs of accuracy and loss for training and validation datasets.

| 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 7.2:*** The Table represents the accuracy result of the experimented models.

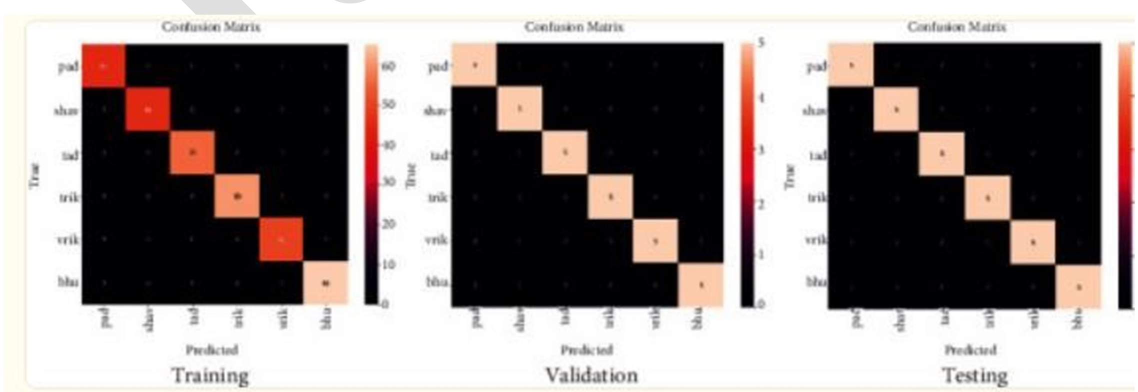


***Figure 7.3:*** Confusion matrices of training, validation, and testing datasets. (a) Training, (b) validation, and (c) testing.

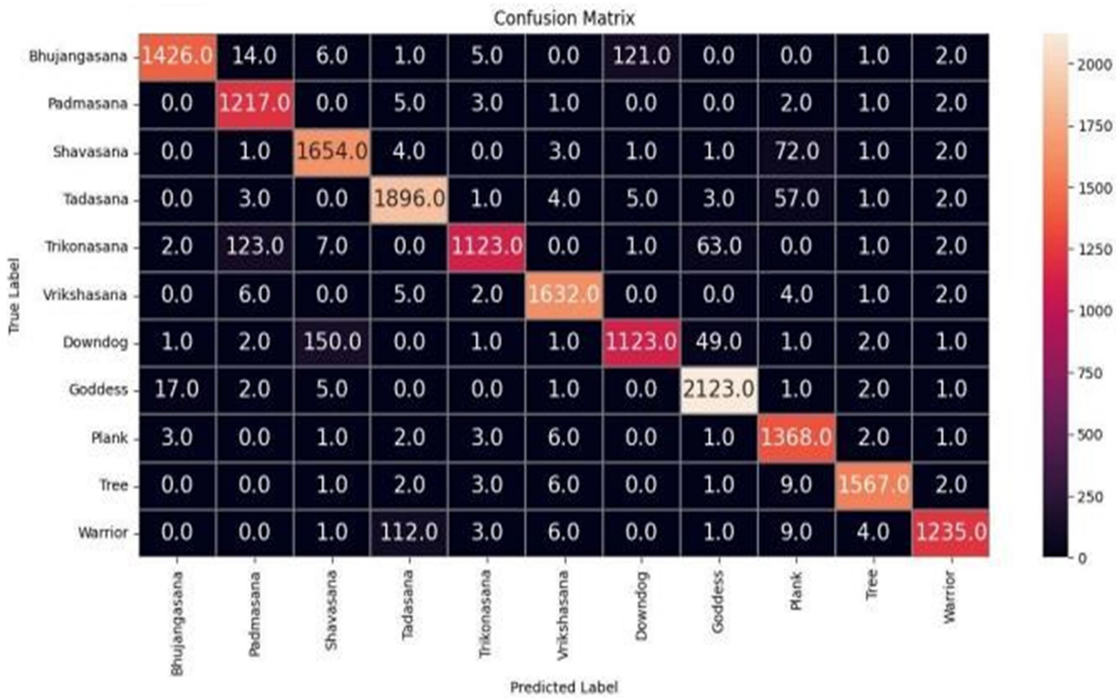



***Figure 7.4:*** *Confusion matrix for Yoga*

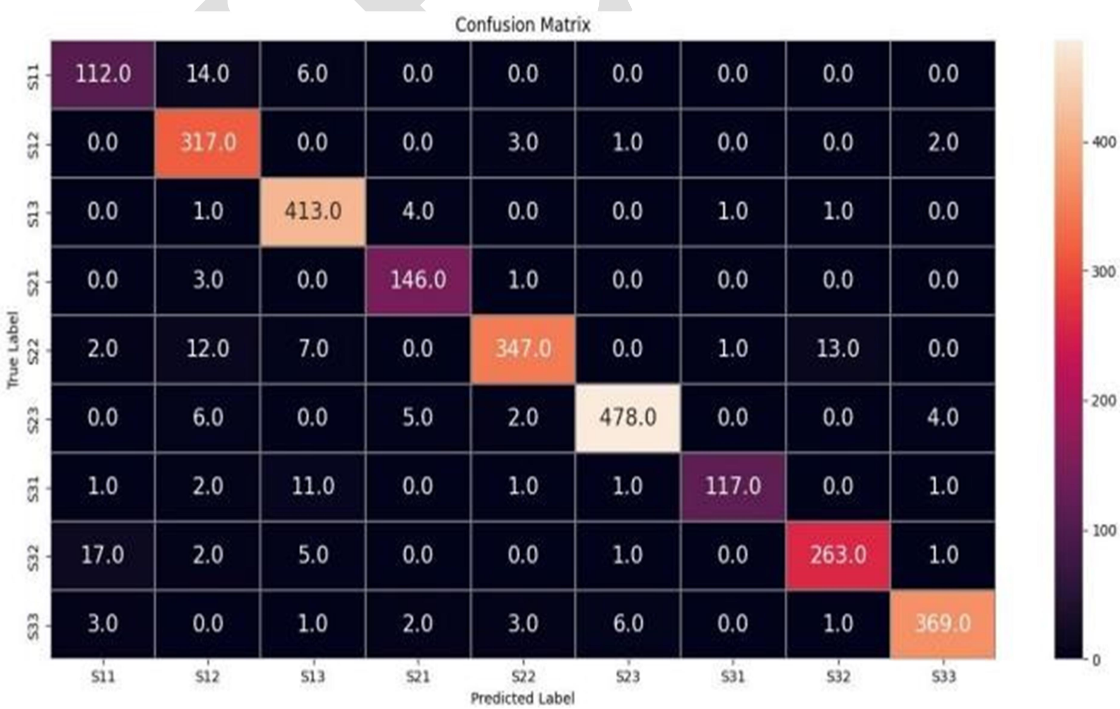



***Figure 7.5:*** Confusion matrix for physiotherapy

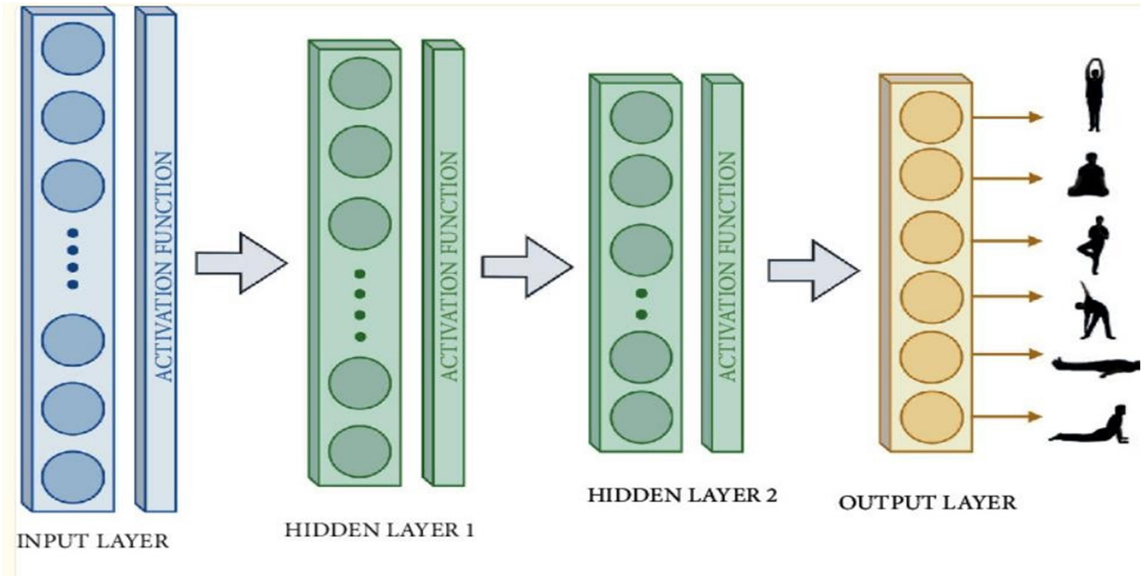



***Figure 7.6:*** Neural network model architecture.

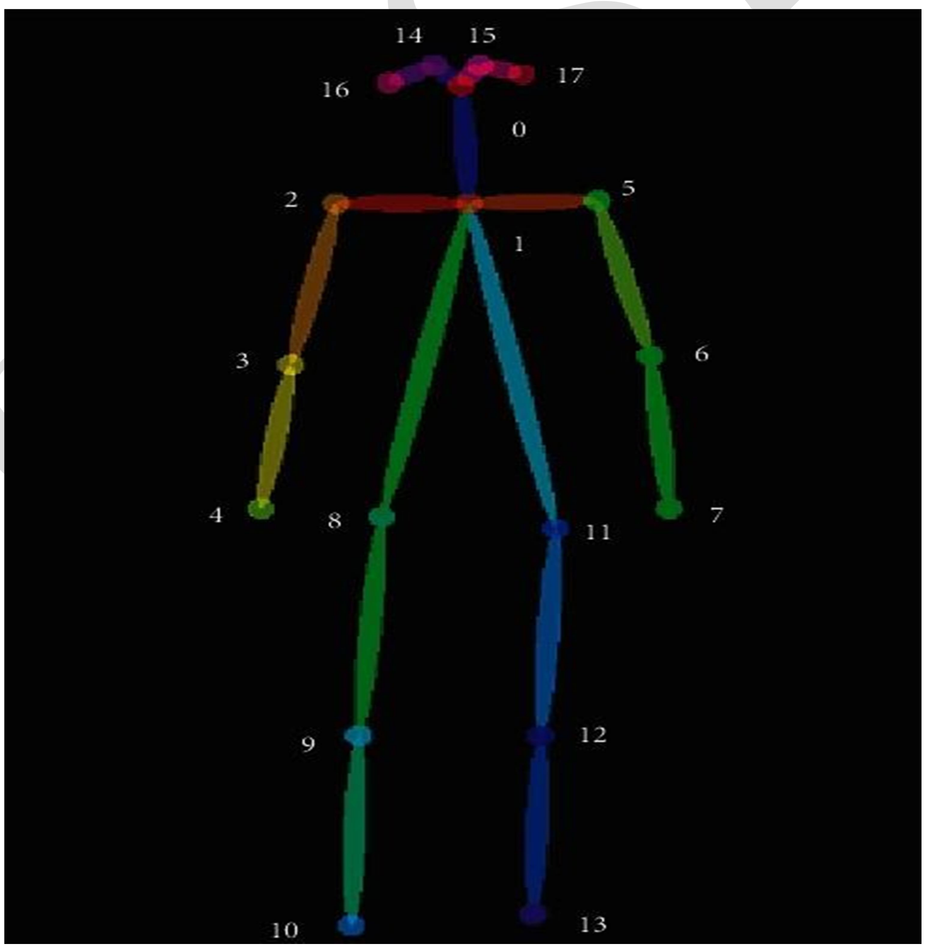
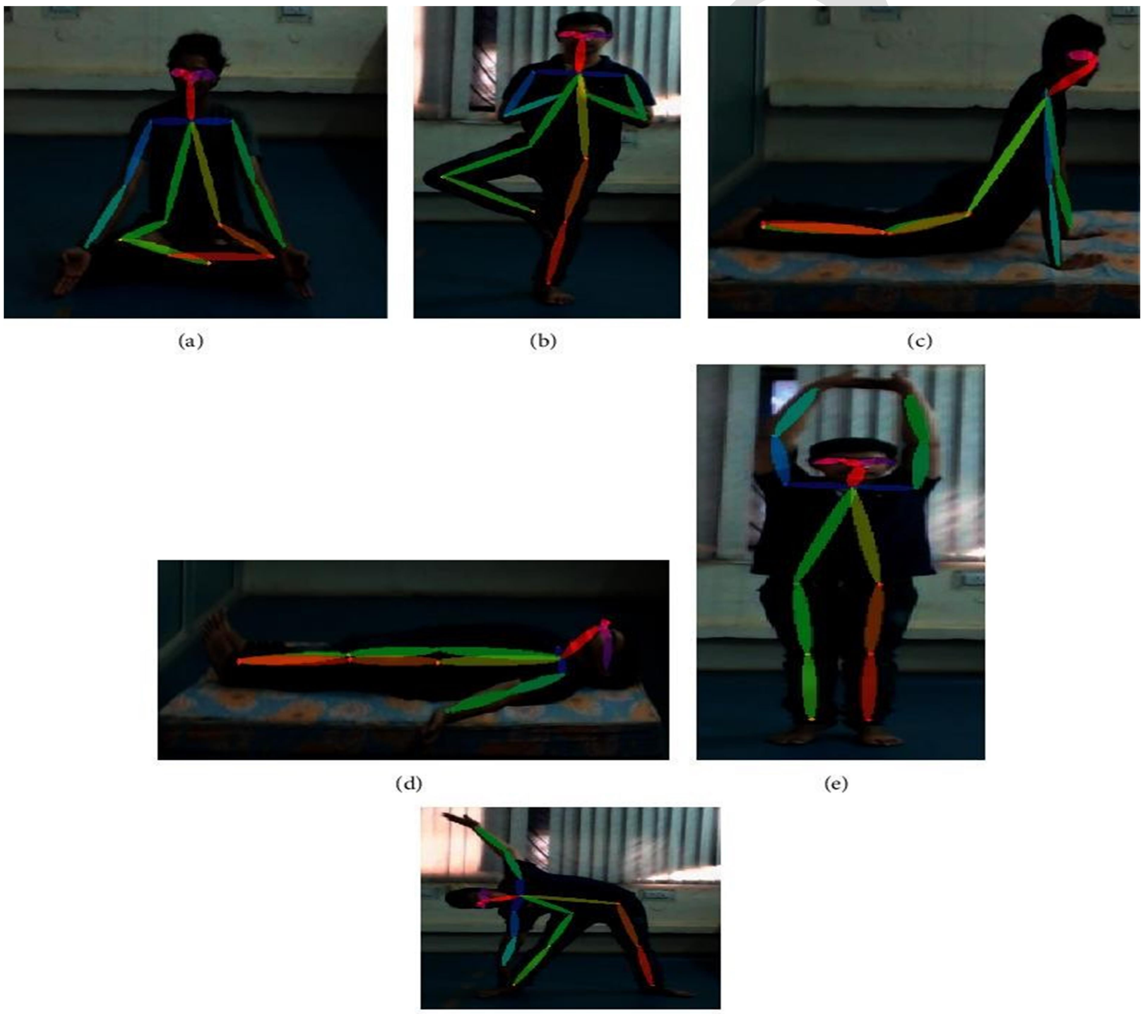



***Figure 7.7:*** Extracted key points from a frame by the pose estimation.

***Figure 7.8***: Person pose estimation for the Bhuj pose with different confidence levels.




(f)

***Figure 7.9:*** Demonstration of key points extraction on all 6 yoga poses: (a) Lotus pose, (b) Tree pose, (c) Cobra pose, (d) Corpse pose, (f) Triangle pose, and (e) Mountain pose.

CONCLUSION

We use MediaPipe and a MoveNet-based deep learning model to automate yoga posture identification in this Project. The suggested model uses MediaPipe for key point-based skeletonization. Processing yoga photos using MediaPipe yields individuals' main points and skeletons. Next, the MoveNet model receives normalized and skeletonized pictures to accurately recognize yoga positions. The LDY yoga dataset was utilized to assess the proposed model. We obtained 99.50% accuracy using MoveNet's deep learning architecture. Four models were used to verify the method's resilience. The MoveNet and MediaPipe technique outperforms other yoga posture identification systems. The suggested technique excelled yoga position identification in accuracy when compared to current methods. position recognition improves alignment and participation in yoga practice via tailored virtual yoga teaching, real-time position correction, and progress monitoring.

Yoga position estimate works well in health and fitness. Fitness position estimate is difficult because to the huge range of poses with significant degrees of freedom, occlusions as the body or other objects occlude limbs as viewed from the camera, and looks or clothes. This study measures posture accuracy and compares it to four designs. According to the analysis, MediaPipe architecture has the greatest estimate accuracy.

## FUTURE ENHANCEMENT

In future, we are planning to work on transfer learning and convert the yoga pose estimation and detection model to dancing steps training. We are also planning to in physiotherapy to convert our model for 3D working features.

The proposed model currently identifies only 3 yoga asanas. As there are a huge number of yoga asanas, it is a huge challenge to create a pose estimation model that accurately identifiesall the poses. In case of overlapping between humans or body parts, the OpenPose library will face challenges in detecting accurately. So, a 3D approach was made which has a scope of improvisation. Using this approach, Human Pose Estimation can be used in various fields suchas Sports, Medical Management, security, etc. There is still a lot of scope for research in this incredible field of Pose Estimation. To improve the model further, a depth camera can be used to detect the Human body/ image. The depth camera will be able to identify multiple bodies, which may solve the problem of multi-person pose estimation. Using the above ideas, we willcreate an AI Trainer, which will act as a substitute for a trainer. This AI trainer will not only recognize the Yoga pose but will also rectify the incorrect posture (if any).

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