

Posture Recognition

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Introduction

POSE ELIMINATION

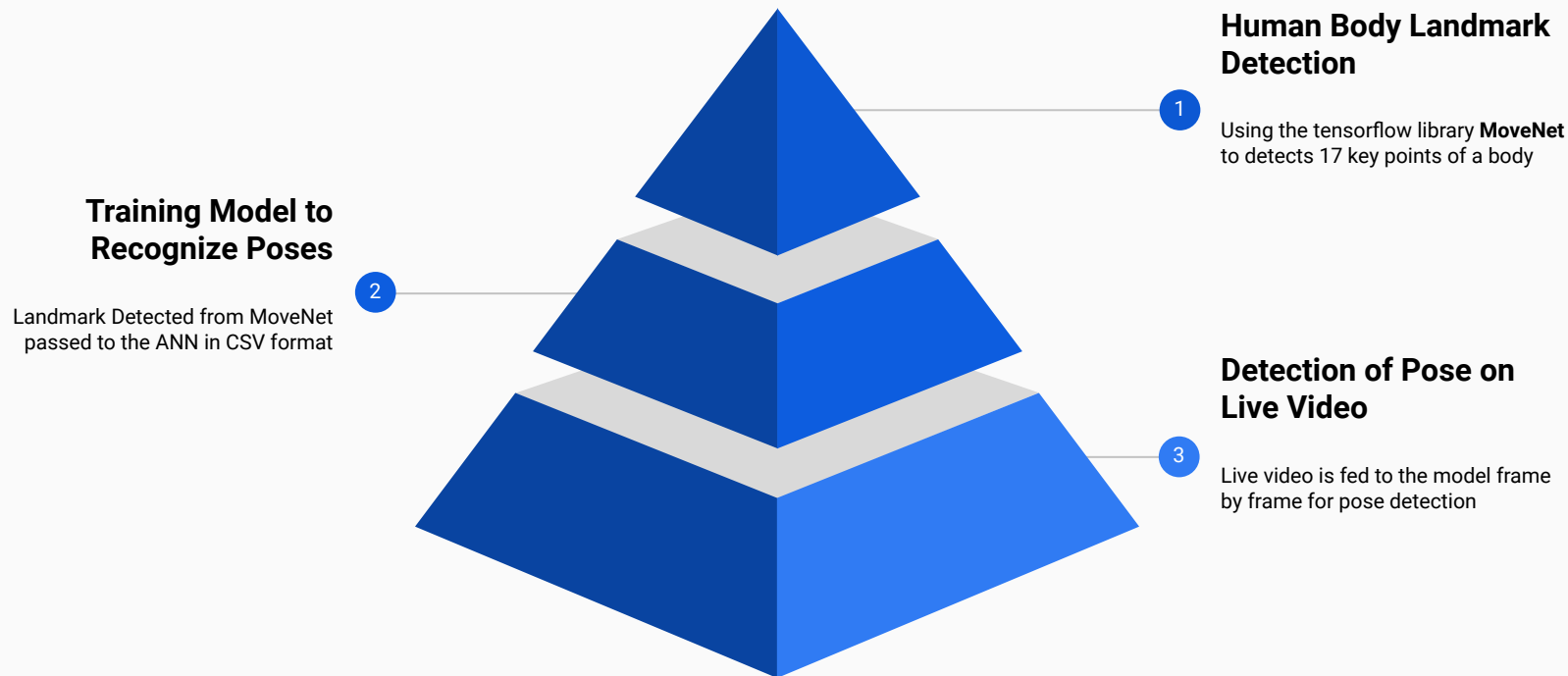
Pose estimation is a computer vision technique to track the movements of a person or an object.

This is usually performed by finding the location of key points for the given objects. Based on these key points we can compare various movements and postures and draw insights.

Pose estimation is actively used in the field of augmented reality, animation, gaming, and robotics.



3 Step Implementation Process



DEMO

MoveNet

MoveNet is an ultra fast and accurate model that detects **17 key points** of a body.

Model run faster than real time (30+ FPS) on most modern desktops, laptops, and phones, which proves crucial for live fitness, health, and wellness applications.



MoveNet - Working



Feature Extraction - Layers of Image

From Image that is input to the model the key features are extracted



Predict 17 Confidence Map

Map representing a particular part of the human pose skeleton.



Predict 38 Part Affinity Fields (PAFs)

Fields represents the degree of association between parts.

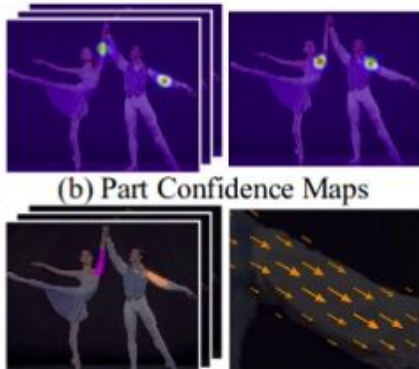


Forming Bipartite Graphs of Parts

Using the part confidence maps the graph is formed



(a) Input Image



(c) Part Affinity Fields



(d) Bipartite Matching

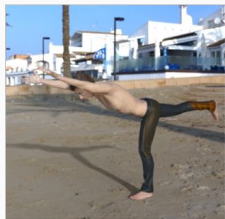


(e) Parsing Results

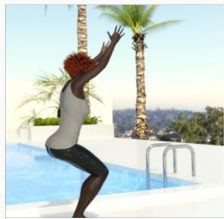
Project Implementation

1. Training & Testing Dataset

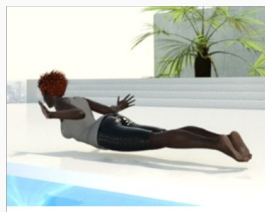
- 8 different classes of yoga poses



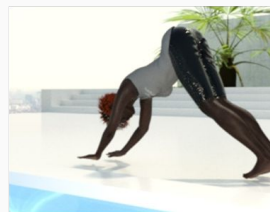
Warrior



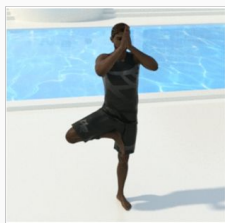
chair



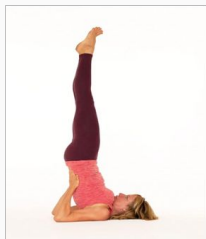
Cobra



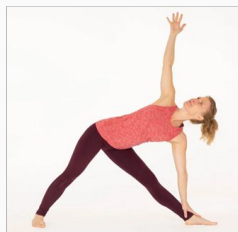
Dog



Tree



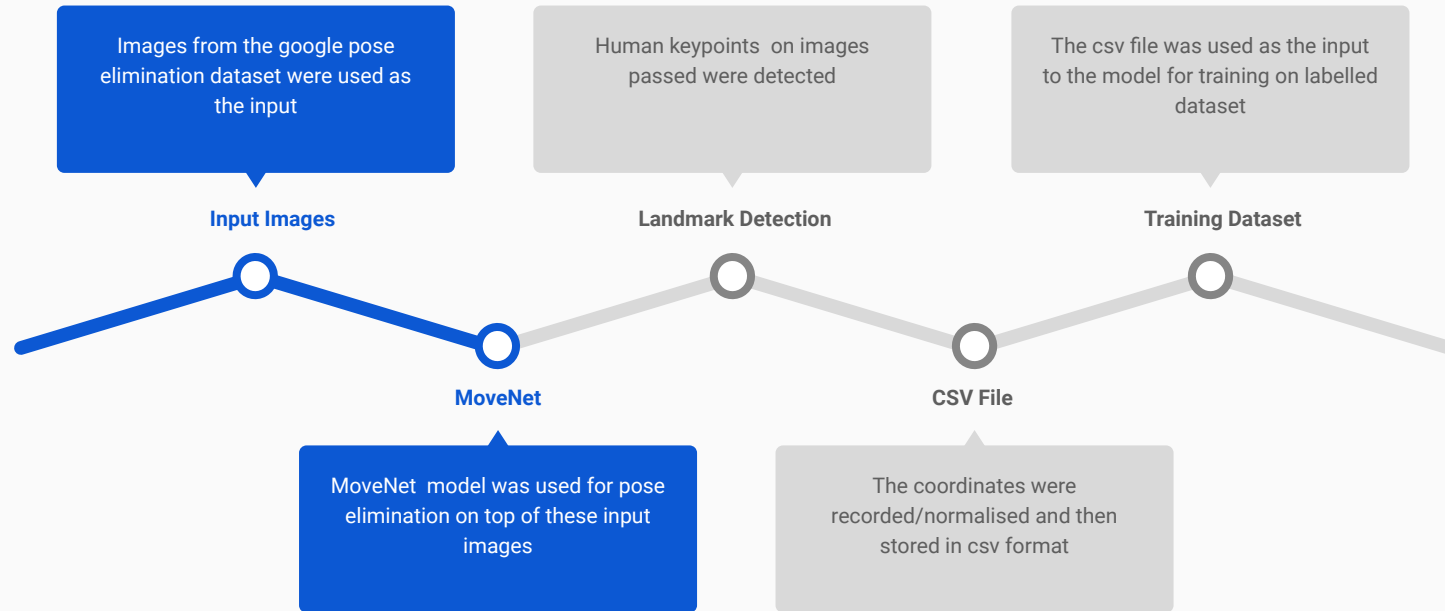
Shoulder stand



Triangle

```
▼ yoga_poses
  > test
  ▼ train
    > chair
    > cobra
    > dog
    > no_pose
    > shoudler_stand
    > traingle
    > tree
  ▼ warrior
    📄 girl1_warrior046_flipped.jpg
    📄 girl1_warrior046.jpg
    📄 girl1_warrior048_flipped.jpg
    📄 girl1_warrior048.jpg
    📄 girl1_warrior049_flipped.jpg
    📄 girl1_warrior049.jpg
    📄 girl1_warrior053_flipped.jpg
    📄 girl1_warrior053.jpg
    📄 girl1_warrior064_flipped.jpg
```









2. Preprocessing Data



Preprocessing Data

```
1 processed_X_train[0]
```

```
<tf.Tensor: shape=(34,), dtype=float32, numpy=
array([-0.36180115, -0.00283766, -0.35612583, -0.01986359, -0.36180115,
       -0.02270125, -0.30221036, -0.03121422, -0.31639865, -0.03688953,
       -0.20856771,  0.00283766, -0.23126896, -0.06242843, -0.05817195,
        0.05107781, -0.131951  , -0.05107781, -0.14897694,  0.13620749,
       -0.20005475,  0.01986359,  0.01276945,  0.02270125, -0.01276945,
       -0.02270125,  0.19154178,  0.01986359,  0.12911335, -0.01702594,
        0.313561  , -0.02837656,  0.29653504, -0.04256484], dtype=float32)>
```

-  chair
-  cobra
-  dog
-  no_pose
-  shouldler_stand
-  traingle
-  tree
-  warrior

[illegible]

2. Model Training

Calculates the center point of the two given landmarks.

Helps in determining the pose and the coordinates in better manner with the links

Center Landmarks

Pose Size

Scaling the pose so that the pose size becomes 1

Torso size multiplied by torso_size_multiplier or the maximum distance from pose center to any pose landmark

Flattening the coordinates into a feature vector

Normalizes the landmarks translation by moving the pose center to (0,0) and scaling it to a constant pose size.

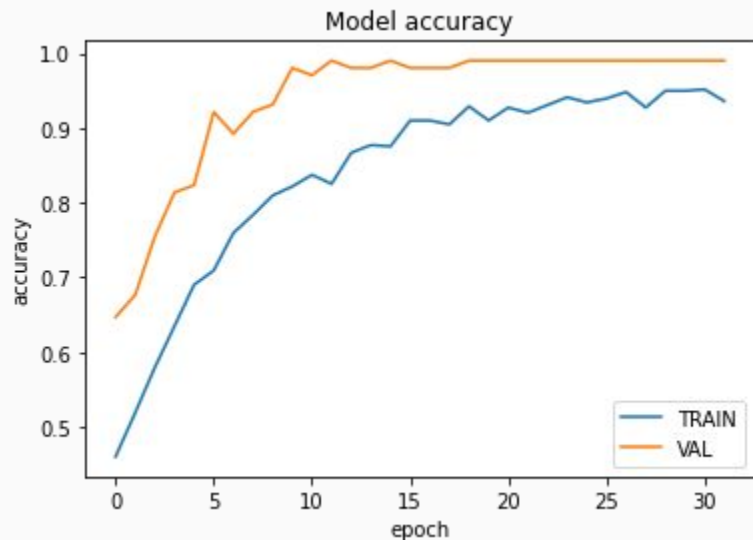
Normalize Landmarks

Pose Embeddings

Feature vector

Convert the pose landmarks to vectors for training the model in Pose Detection

Model Training



```
] 1 # Start training
2 print('-----TRAINING-----')
3 history = model.fit(processed_X_train, y_train,
4                     epochs=2000,
5                     batch_size=16,
6                     validation_data=(processed_X_val, y_val),
7                     callbacks=[checkpoint, earlystopping])
```

-----TRAINING-----

Epoch 1/2000

41/81 [=====>.....] - ETA: 0s - loss: 1.8939 - accuracy: 0.3338

Epoch 1: val_accuracy improved from -inf to 0.51542, saving model to weights.best.hdf5

81/81 [=====] - 1s 3ms/step - loss: 1.6579 - accuracy: 0.4058 - val_loss: 1.2030 - val_accuracy: 0.5154

Epoch 2/2000

80/81 [=====>.....] - ETA: 0s - loss: 1.1163 - accuracy: 0.5781

Epoch 2: val_accuracy improved from 0.51542 to 0.71366, saving model to weights.best.hdf5

81/81 [=====] - 0s 2ms/step - loss: 1.1158 - accuracy: 0.5779 - val_loss: 0.8631 - val_accuracy: 0.7137

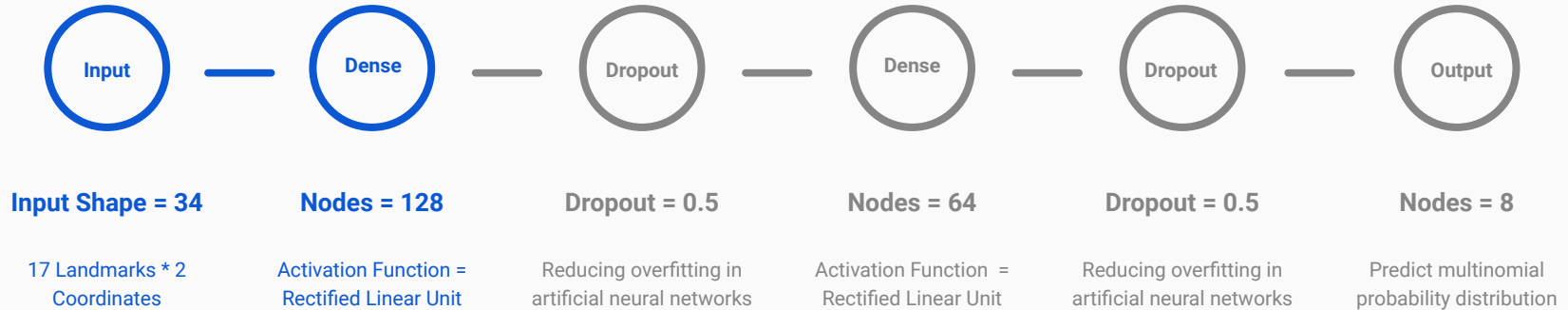
Epoch 3/2000

45/81 [=====>.....] - ETA: 0s - loss: 0.9422 - accuracy: 0.6250

Epoch 3: val_accuracy improved from 0.71366 to 0.77974, saving model to weights.best.hdf5

81/81 [=====] - 0s 2ms/step - loss: 0.9106 - accuracy: 0.6449 - val_loss: 0.7218 - val_accuracy: 0.7797

3. Artificial Neural Network



Model Creation

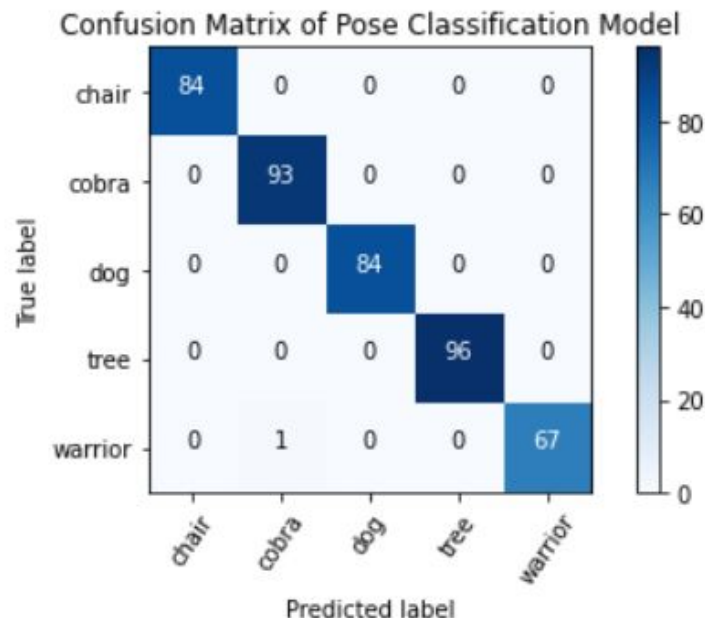
```
In [24]: 1 X, y, class_names = load_csv('train_data.csv')
          2 X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.15)
          3 X_test, y_test, _ = load_csv('test_data.csv')
          4
          5
          6 processed_X_train = preprocess_data(X_train)
          7 processed_X_val = preprocess_data(X_val)
          8 processed_X_test = preprocess_data(X_test)
          9
         10 inputs = tf.keras.Input(shape=(34))
         11 layer = keras.layers.Dense(128, activation=tf.nn.relu6)(inputs)
         12 layer = keras.layers.Dropout(0.5)(layer)
         13 layer = keras.layers.Dense(64, activation=tf.nn.relu6)(layer)
         14 layer = keras.layers.Dropout(0.5)(layer)
         15 outputs = keras.layers.Dense(len(class_names), activation="softmax")(layer)
         16
         17 model = keras.Model(inputs, outputs)
```

```
In [25]: 1 model.compile(
          2     optimizer='adam',
          3     loss='categorical_crossentropy',
          4     metrics=['accuracy']
          5 )
```


Model Performance Evaluation

Classification Report:

	precision	recall	f1-score	support
chair	1.00	1.00	1.00	84
cobra	0.99	1.00	0.99	93
dog	1.00	1.00	1.00	84
tree	1.00	1.00	1.00	96
warrior	1.00	0.99	0.99	68
accuracy			1.00	425
macro avg	1.00	1.00	1.00	425
weighted avg	1.00	1.00	1.00	425



-----EVAUATION-----

28/28 [=====] - 0s 995us/step - loss: 0.0059 - accuracy: 0.9977

LOSS: 0.005906759295612574

ACCURACY: 0.9977195262908936

Inspirations & References



Sign Language Detection using ACTION RECOGNITION with Python | LSTM Deep Learning Model

69K views • 8 months ago



Nicholas Renotte

Want to take your sign language model a little further? In this video, you'll learn how to leverage action detection to do so! You'll ...



Real Time AI GESTURE RECOGNITION with Tensorflow.JS + React.JS + Fingerpose


33K views • 1 year ago



Nicholas Renotte

I'm talking deep learning powered computer vision based **gesture recognition**. Using Tensorflow.JS and fingerpose, you're able to ...

Inspirations & References

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Video interpolation


Text-to-video retrieval


TensorFlow > Resources > Hub > Tutorials


Was this helpful? 👍👎

MoveNet: Ultra fast and accurate pose detection model.


 Run in Google Colab

 View on GitHub

 Download notebook

 See TF Hub models

MoveNet is an ultra fast and accurate model that detects 17 keypoints of a body. The model is offered on [TF Hub](#) with two variants, known as Lightning and Thunder. Lightning is intended for latency-critical applications, while Thunder is intended for applications that require high accuracy. Both models run faster than real time (30+ FPS) on most modern desktops, laptops, and phones, which proves crucial for live fitness, health, and wellness applications.



*Images downloaded from Pexels (<https://www.pexels.com/>)

This Colab walks you through the details of how to load MoveNet, and run inference on the input image and video below.

<https://www.tensorflow.org>

Special Thanks



Thanks!

