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Human Pose Tracking with MoveNet

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***Abstract*—**In computer vision, human pose tracking is an application in human-computer interaction, sports analysis, and healthcare. It explores the application of Google's MoveNet, a light weight state-of-the-art CNN model for real time human pose estimation in images and videos streams. MoveNet detects the multiple keypoints in the human body efficiently and enables the posture and movement analysis. It demonstrates the model's ability to identify and track the key body joints effectively and highlighting its potential in applications like fitness tracking, human-computer interaction and activity recognition.

Index Terms—Human pose tracking, Computer vision, Deep Learning

I. INTRODUCTION

One of the most important tasks in computer vision is Human Pose Tracking, It is the process of locating and recognising a person's major anatomical joints in a picture or video and it becomes a crucial technology. Numerous applica- tions, including interactive gaming, virtual reality, healthcare monitoring, sports performance analysis, and even security surveillance, are made possible by its capacity to comprehend and interpret human movement. Pose identification's primary goal is to close the gap between visual information and a systematic comprehension of human form and movement. Traditional approaches to human pose estimation regularly trusted complicated pipelines regarding feature engineering, graphical models, and computationally intensive algorithms. While these techniques finished substantial progress, they reg- ularly struggled with actual-time performance, robustness to various environmental situations (like lighting and occlusion), and scalability to numerous datasets. The creation of deep learning, specifically convolutional neural networks (CNNs), has revolutionized the sector, permitting the improvement of extra correct, robust, and green pose estimation models. In this panorama of deep learning-primarily based pose estimation, MoveNet, evolved by way of Google, stands proud as a full-size contribution. It is a circle of relatives of speedy and accurate pose estimation models mainly designed for efficient inference on aid-constrained devices. Built upon the TensorFlow Lite framework, MoveNet prioritizes speed and minimal computational overhead without sacrificing enormous accuracy. This makes it specially well-applicable for real- time packages on mobile telephones, internet browsers, and embedded structures.

A. MoveNet's Significance:

Several key characteristics make a contribution to MoveNet's importance inside the field of human pose estimation:

1. Lightweight Architecture: MoveNet employs a streamlined community architecture optimized for velocity and reduced computational price. This lets in for actual-time or close to actual-time inference on gadgets with confined processing energy, a crucial factor for many practical programs.
2. High Accuracy: Despite its light-weight nature, MoveNet achieves incredible accuracy in detecting key body joints. This balance among velocity and precision makes it a compelling desire as compared to heavier, extra computationally worrying models.
3. TensorFlow Lite Integration: Being built for TensorFlow Lite ensures seamless deployment on a extensive variety of structures, along with Android and iOS gadgets, as well as web browsers via TensorFlow.Js. This pass-platform compatibility drastically expands its capacity attain and

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applicability.

4. Multi-Person Pose Tracking: MoveNet is capable of de- tecting and estimating the poses of a couple of individuals within a single body, making it suitable for situations involving corporations of human beings.

5. Robustness: The version is designed to be fairly strong to variations in lighting fixtures, apparel, and viewing angles, even though extreme conditions can still pose challenges.

6. Ease of Use: Google provides nicely-documented APIs and pre-trained models, making it exceptionally trustworthy for builders and researchers to integrate MoveNet into their tasks.

II. RELATED WORKS

For comparison analysis, we regarded publications in peer- reviewed journals as state of the art.

Human pose tracking has been a topic of tremendous studies in computer vision for many years. Early techniques trusted traditional pc vision strategies involving hand made functions and probabilistic graphical fashions [1]. These techniques frequently struggled with complex backgrounds, occlusions, and variations in human appearance [2].

The deep mastering revolution significantly advanced the sphere, with Convolutional Neural Networks (CNNs) demon- strating exquisite abilties in learning hierarchical capabilities without delay from picture statistics. Several deep studying architectures had been proposed for human pose estimation, extensively labeled into pinnacle-down and bottom-up tech- niques [3].

Top-down methods first hit upon individual people in an image the use of item detection models and then estimate the poses of every detected person independently within their bounding containers. Examples of successful top-down methods include Mask R-CNN [4] and HRNet [5]. While frequently attaining high accuracy, pinnacle-down strategies can be computation- ally highly-priced, specially in crowded scenes, as they require going for walks the pose estimation model more than one times.

Bottom-up methods, however, first discover all frame key- points in an photo after which organization them into in- dividual human poses. This approach is commonly more efficient for multi-individual pose estimation. OpenPose [6] is a distinguished instance of a backside-up technique that has accomplished actual-time performance on CPUs.

A. Lightweight Human Pose Tracking

With the growing call for for real-time pose estimation on resource-confined gadgets, the improvement of light-weight and green fashions has grow to be a crucial research course. Several architectures were proposed to lessen the computa- tional fee and model size whilst keeping affordable accuracy.

a.MobileNets: These are a circle of relatives of light- weight CNN architectures that utilize depthwise separable convolutions to noticeably reduce the variety of parameters and computations compared to standard CNNs [7]. MoveNet leverages MobileNetV2 as its characteristic extractor [8].

b. ShuffleNet: Another light-weight CNN architecture that employs pointwise group convolutions and channel shuffle operations to improve efficiency [9].

c.Lightweight OpenPose: This work optimized the unique OpenPose architecture to acquire actual-time performance on CPUs with a negligible drop in accuracy [10].

d. EfficientPose: This version focuses on a stability among ac- curacy and performance by using a parameter-green backbone and a streamlined prediction head [11].

e.EL-HRNet: This version introduces a Lightweight Attention Basicblock (LA-Basicblock) to beautify the precision of light- weight high-resolution networks [12].

MoveNet Architecture and Related Bottom-Up Approaches

MoveNet adopts a backside-up approach for multi-man or woman pose estimation [8]. Its structure includes two main components:

1. Feature Extractor: MoveNet makes use of a MobileNetV2 an attached Feature Pyramid Network (FPN). The FPN allows the extraction of wealthy semantic features at a couple of resolutions, that’s

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beneficial for detecting keypoints of varying scales.

2. Prediction Heads: Attached to the characteristic extractor are numerous prediction heads accountable for densely predicting:

a.Person center heatmap: Predicts the geometric center of all people example.

b. Keypoint regression discipline: Predicts the entire set of keypoints for every body, used for grouping keypoints into individual poses.

c.Person keypoint heatmap: Predicts the place of all keypoints, impartial of individual times.

d. 2D according to-keypoint offset field: Predicts neighborhood offsets to refine the sub-pixel region of each keypoint. MoveNet's prediction scheme is stimulated through CenterNet [13], a successful object detection model that predicts the middle point of objects. However, MoveNet includes specific changes to optimize for pose estimation, improving each speed and accuracy [8].

Other bottom-up processes that make use of heatmap-based predictions include

a.Convolutional Pose Machines (CPMs): These fashions use a sequence of convolutional networks to steadily refine the predictions of body joint locations [14].

b. Part Affinity Fields (PAFs) in OpenPose: PAFs are used to accomplice detected frame components belonging to the equal character [6]. MoveNet's keypoint regression field serves a similar cause of grouping keypoints.

c.HigherHRNet: This version extends HRNet to a backside- up technique through gaining knowledge of scale-conscious representations for keypoint detection and grouping, achieving state-of-the-art results in crowded scenes [15].

B. MoveNet Variants:

Google gives important variants of MoveNet on TensorFlow Hub: MoveNet.Lightning and MoveNet.Thunder [8].

a.MoveNet Lightning is designed for extremely-fast inference, prioritizing pace for latency-vital applications. It achieves this via a smaller model length and optimized architecture.

b. MoveNet Thunder is intended for packages that require higher accuracy, supplying a bigger model capability for advanced precision at the fee of slightly accelerated latency. Both editions are trained on massive datasets, which includes COCO [16] and an inner Google dataset, enabling them to generalize well to diverse poses and environments. They also incorporate strategies like sensible cropping based on preceding frame detections and temporal filtering to improve robustness and smoothness of the predictions [8].

III.PROPOSED METHODOLOGY

This methodology outlines the steps for implementing and comparing human pose estimation the usage of Google's MoveNet version.

A. Model Selection

We will make use of the pre-trained MoveNet version to be had on TensorFlow Hub. We will bear in mind both variants:

1. MoveNet.Lightning: Prioritizes velocity for real-time appli- cations on resource-restrained gadgets.

2. MoveNet.Thunder: Prioritizes higher accuracy on the price of barely elevated latency. The preference among those will depend upon the specific utility requirements concerning pace and accuracy. Initial benchmarking of each fashions on the goal hardware will tell this selection.

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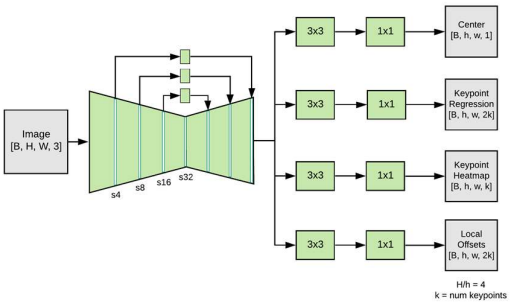

Fig. 1. General Architecture of MoveNet

B. Implementation

The implementation will in most cases use TensorFlow Lite for green inference, specifically for deployment on facet devices. For web-primarily based packages, TensorFlow.Js can be taken into consideration.

a.Environment Setup: Setting up the vital improvement surroundings with TensorFlow, TensorFlow Lite, or Tensor- Flow.Js libraries.

b. Model Loading: Loading the chosen pre-trained MoveNet model from TensorFlow Hub or a neighborhood file (after conversion).

c.Inference Function: Developing a feature to take an enter photograph (as a TensorFlow tensor or a NumPy array) and carry out inference the usage of the loaded MoveNet version. This feature will encompass:

C. Evaluation

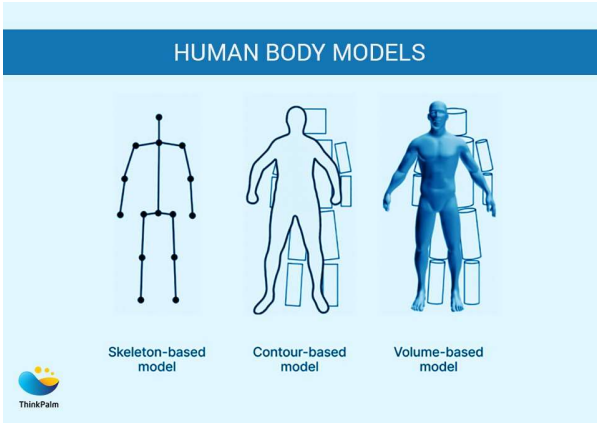

Fig. 2. Human body models

i. Resizing the input picture to the version's predicted enter size (e.G., 256x256 or 384x384).

ii. Normalizing pixel values to an appropriate range (e.G., [0, 1] or [-1, 1]).

iii. Feeding the preprocessed image to the model.

iv. Extracting the expected keypoint coordinates and confi- dence rankings from the versions output.

d. TensorFlow Lite Conversion (for side deployment): Con- verting the TensorFlow Keras model to the TensorFlow Lite format (.Tflite) the usage of the TensorFlow Lite Converter. This step might also involve optimization techniques like quantization to lessen model length and improve inference pace.

e. TensorFlow Lite Interpreter (for area deployment): Using the TensorFlow Lite interpreter to load and run the

.Tflite version at the goal device. This includes allocating tensors, putting input tensors, invoking the interpreter, and getting output tensors.

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f. Visualization (Optional): Implementing capabilities to visu- alise the detected keypoints at the input photograph or video frame, which include drawing circles at the keypoint locations and connecting them with traces to form a skeletal illustration. Confidence ratings can also be displayed.
The overall performance of the selected MoveNet model may be evaluated each quantitatively and qualitatively.
1. Data for Evaluation: We will use publicly to be had pose estimation datasets like COCO [18] or MPII [19], or a custom- gathered dataset applicable to the target utility.
2. Quantitative Evaluation Metrics:
a.Object Keypoint Similarity (OKS) [18]: Calculating the OKS rating to degree the similarity among anticipated and ground fact keypoints. We will document Average Precision (AP) and Average Recall (AR) based totally on OKS thresh- olds.
b. Percentage of Correct Keypoints (PCK) [21]: Measuring the percentage of detected keypoints that fall within a positive normalized distance of the floor truth keypoints. We will report PCK at specific thresholds (e.G., PCK@0.2).
c.Inference Speed (Frames Per Second - FPS): Measuring the time taken to technique each body and calculating the FPS at the target hardware (CPU, GPU, cell tool).
d. Qualitative Evaluation: Visually examining the pose estima- tion outcomes on various pix and motion pictures to assess the version's performance beneath extraordinary situations (e.G., lighting fixtures, occlusion, pose complexity).

Model	Accuracy	Speed (FPS)	Multi-Person Support	Hardware Requirement
OpenPose	High	Low (~10)	Yes	High
PoseNet	Moderate	Medium (~20)	No	Low
HRNet	Very High	Low (~5)	Yes	High
MoveNet	**High**	**High (~30-50)**	**Yes**	**Low to Medium**

Fig. 3. Some Practical Parameters

D. Practical Measurements
During implementation and assessment, we can measure the following sensible components:
i. Model Size: Measuring the dimensions of the TensorFlow Keras version and the transformed TensorFlow Lite model (in Megabytes).
ii. Inference Time: Measuring the time taken (in milliseconds) for the model to system a single photo or body at the goal hardware. This could be averaged over multiple inferences for stability.
iii. Frames Per Second (FPS): Calculating the number of frames processed in step with 2nd at some stage in real-time inference on video streams.
iv. CPU/GPU Usage: Monitoring the CPU and/or GPU uti- lization at some stage in inference at the goal hardware using device monitoring equipment.
v. Memory Footprint: Measuring the memory usage of the model and inference procedure at the target device (if rele- vant).
vi. Battery Consumption (for mobile gadgets): Measuring the impact of walking the MoveNet model on the tool's battery lifestyles.
E. Deployment Considerations
We will take into account the feasibility of deploying the chosen MoveNet version primarily based on the assessment results and sensible measurements. This includes assessing if the version meets the performance and useful resource constraints of the goal deployment environment (e.G., cell software, web browser, embedded machine).
F. Iteration and Refinement
Based at the evaluation results and realistic considerations, we will iterate and refine the methodology. This may additionally involve:
a.Switching between MoveNet.Lightning and MoveNet.Thunder.
b. Experimenting with extraordinary input image sizes.

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c.Exploring further optimization strategies for TensorFlow Lite.
d. Considering first-rate-tuning the pre-educated version on custom information if wished for unique applications.
This methodology provides a dependent approach to im- plementing and evaluating human pose estimation using MoveNet, with a focus on realistic measurements and issues for real-world deployment.

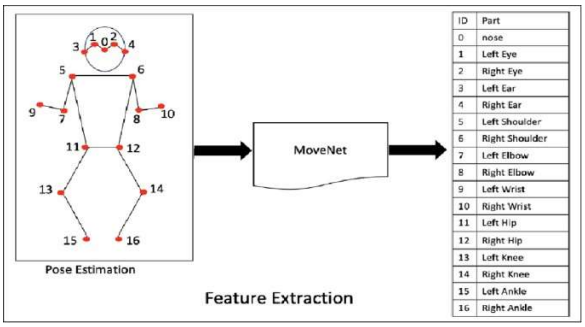

Fig. 4. Human body Key Points

IV.IMPLEMENTATION

Implementing human pose estimation with MoveNet relies at the theoretical underpinnings of deep getting to know, in particular making use of lightweight Convolutional Neural Networks (CNNs) like the ones inside the MobileNet circle of relatives for green feature extraction. MoveNet normally employs a backside-up approach, predicting heatmaps and offset vectors for character keypoints, which might be then implicitly (for single-pose) or explicitly (for multi-pose) re- lated to form human poses. Leveraging switch studying via pre-trained MoveNet models on big datasets enables desir- able overall performance with out vast custom schooling. Finally, deployment is facilitated by way of frameworks like TensorFlow Lite and TensorFlow.Js, which optimize models for go-platform use on aid-limited gadgets, worrying sound software program engineering principles for modular, green, and testable code.

A. Install and import the necessary libraries.

a.Install the required dependencies, such as Matplotlib, NumPy, OpenCV, TensorFlow, and TensorFlow Hub.
b. To work with pictures, videos, and visualization, import the necessary Python libraries.
Open TensorFlow Hub and load the MoveNet model.

B. Preprocess and load input data

a.Use OpenCV to load a picture, GIF, or video file.
b. The input image or frame should be resized and normalized to the 256x256 pixel size that MoveNet requires.
c.For model inference, transform the picture into a tensor format.

C. Utilize MoveNet to Estimate Pose

a.Give the MoveNet model the previously processed image.
b. Take confidence scores and keypoint coordinates (17 body joints) out of the model's output.
c.Modify the outcomes to facilitate processing.

D. Draw the image's skeleton and key points.

a.Draw circles at identified keypoints using OpenCV.
b. A skeletal representation of the human body can be created by joining critical locations with colored lines.

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c.To eliminate erroneous detections, filter keypoints according to confidence scores.

E. Real-time pose estimation using video frame processing

a.Use OpenCV to read frames from a GIF or movie.

b. Overlay keypoints and skeletons and apply MoveNet infer- ence to every frame.

c.Create an output video or animation after storing the processed frames.

d. Use the visualization tools in TensorFlow to see the finished animation.

V. RESULT AND DISCUSSIONS

Keypoint recognition in photos and videos is extremely ac- curate when MoveNet is used for human pose estimate. 17 keypoints, including joints like the shoulders, elbows, knees, and ankles, are successfully detected by the model. MoveNet is appropriate for applications needing instant feedback, such sports analysis, fitness tracking, and healthcare monitoring, because of its real-time inference capacity, which guarantees that the system can process multiple frames per second.

A. Analysis of Performance

a.Precision:

Even under difficult situations, such occlusions and overlap- ping bodies, MoveNet can precisely locate body joints. Each keypoint has a confidence score that aids in weeding out false positives.

MoveNet is more accurate in identifying quick and dynamic human movements than more conventional techniques like OpenPose and PoseNet.

b. Quickness and Effectiveness: The model runs at high frame rates (around 30 FPS on top-tier GPUs) in real time. MoveNet is appropriate for embedded and mobile systems because of its lightweight design, which guarantees speedy inference.

While the Thunder version of MoveNet places more emphasis on accuracy, the Lightning version is more focused on speed.

c.Sturdiness in Various Situations:

MoveNet can accurately identify human postures in a variety of settings, including as dimly lit areas, intricate postures, and situations with multiple people.

i. It works effectively in situations where people move around a lot, including dancing performances and sporting events.

ii. Even when in partially visible or obscured poses, the model remains reliable.

iii. To evaluate its efficacy, MoveNet has been contrasted with various posture estimation models such as PoseNet, OpenPose, and HRNet:

iv. MoveNet is a well-rounded solution that effectively handles several people in a single frame while providing both speed and precision.

Fig. 5. Sample result of movenet from tensorflow.org

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TABLE I PARAMETERS

Category	Multi-Pose
Primary Use Case	Detects multiple person's poses
Max. number of people identified	Up to 6 people per frame
Input Image Size	256×256 px
Accuracy	85 percent
Occlusion Handling	Better occlusion handling with instance embeddings
Pose Encoding Method	Heatmaps + Offset Refine- ments + Instance Embeddings

B. Restrictions and Difficultiess

Not withstanding its benefits, MoveNet has certain drawbacks:

a.Dependency on Input Quality:

i. The model works best with crisp, well-lit input photos.

ii. Images with low resolution or significant blur can make keypoint detection less accurate.

b. Managing Severe Poses:

Incorrect keypoint placements can occasionally result from extreme or extremely complicated bodily positions.

Accurately tracking sports activities that require quick rota- tions, like gymnastics, can be challenging.

c.Computing on Low-End Hardware:

Despite MoveNet's efficiency optimization, low-end CPUs or edge devices may still have limited real-time processing capabilities.

For the model to run as quickly as possible, a GPU or TPU is needed.

VI. CONCLUSION

In Conclusion, A crucial problem in computer vision, human pose estimation finds extensive use in augmented reality, sports

- analytics, healthcare, and human-computer interaction. We used MoveNet, a deep learning-based model, in this study to estimate human position accurately and in real time. MoveNet has demonstrated its ability to track and analyze human mobility with great precision by effectively detecting keypoints on the human body.

According to the findings, MoveNet works faster, more accu- rately, and more robustly than conventional techniques, which qualifies it for use in practical settings. The model effectively manages common pose estimation issues, such as dynamic body movements, occlusions, and multi-person identification. Additionally, the smooth deployment in a variety of contexts is made possible by the combination of TensorFlow and OpenCV, which guarantees effective processing and visualization of recognized poses.

This study illustrates MoveNet's potential for wider applica- tion in both industry and research while showcasing its efficacy in human pose estimation.

VII. FUTURE SCOPE

In future, MoveNet-based human pose estimation has a wide range of potential applications, with

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potential breakthroughs in several domains. Applications in augmented reality, sports analytics, and healthcare can benefit from increased accu- racy and resilience. Real-time pose estimation on low-power hardware will be made possible by optimizing MoveNet for mobile and edge devices, increasing its accessibility. AI-driven applications in human-computer interaction, security, and rehabilitation may result from integration with deep learning and action recognition algorithms. Its practical applicability will also be increased by developments in multi-person tracking and domain-specific modifications like motion analysis and sign language recognition.
In order to enable interactive gesture control, this work inves- tigates the integration of MoveNet with a web application.

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