Human Pose Estimation Using Machine Learning

A Project Report

submitted in partial fulfillment of the requirements

of

AICTE Internship on AI: Transformative Learning
with
TechSaksham – A joint CSR initiative of Microsoft & SAP

by

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ACKNOWLEDGEMENT

I would like to take this opportunity to express my deep sense of gratitude to all individuals who helped me directly or indirectly during this project work.

Firstly, I would like to thank my Master Trainer, Mr. P.Raja, for being an exceptional mentor and the best adviser I could have ever asked for. His guidance, encouragement, and constructive feedback have been a source of innovative ideas, inspiration, and the driving force behind the successful completion of this project.

The insightful discussions and invaluable lessons have not only contributed to the successful completion of this project but have also helped me grow into a more capable and responsible individual.

I extend my heartfelt thanks to Mr. Pavan Kumar U, whose support and cooperation were instrumental in achieving the objectives of this project.

ABSTRACT

Provide a brief summary of the project, including the problem statement, objectives, methodology, key results, and conclusion. The abstract should not exceed 300 words.

Problem Statement: Human Pose Estimation using Machine Learning

Human Pose Estimation (HPE) is a vital machine learning application that focuses on detecting and interpreting human body postures from images or videos. This project addresses the challenge of accurately estimating human poses in real-time using efficient and accessible tools. The primary objective is to develop and deploy a system capable of identifying key body landmarks with high precision and usability.

The methodology employs OpenCV for image preprocessing and leverages a pre-trained TensorFlow model for pose estimation. By utilizing an existing model, the system avoids the need for extensive training while ensuring robust performance. The solution is deployed through Streamlit, enabling an interactive and user-friendly web interface for real-time pose estimation. The deployment pipeline ensures seamless integration of the model with a lightweight and accessible platform.

The model was able to accurately identify body parts and the human pose in over 90% of the pictures. The UI built using streamlit delivered seamless and efficient service to the user. Uploads worked seamlessly and results were quick and responsive.

In conclusion, this project effectively combines OpenCV, TensorFlow, and Streamlit to deliver a practical and efficient human pose estimation solution. The approach showcases potential applications in areas such as fitness tracking, healthcare, and interactive systems. Future work may focus on enhancing model optimization it for more efficient real time analysis and extending functionality to mobile and edge devices.

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CHAPTER 1

Introduction

1.1 Problem Statement:

Human pose estimation, the process of detecting and identifying the key points of the human body (such as joints, limbs, and torso), has become an essential task in computer vision. Despite significant advancements, existing solutions face challenges in achieving real-time accuracy, robustness in diverse environments, and adaptability to various applications.

Key challenges include:

Complexity of Human Movements: Capturing the intricacies of human motion, including occlusions, overlapping poses, and dynamic movements, remains a critical hurdle.

Environmental Variations: Lighting conditions, backgrounds, and camera angles can significantly impact detection accuracy.

Scalability Across Devices: Many models struggle to balance performance and computational efficiency, limiting their deployment on edge devices and real-time systems.

Diverse Body Types and Activities: Adapting the model to account for different body types, clothing, and activities (e.g., sports, dance) often requires extensive training data and fine-tuning.

Accessibility and Inclusion: Ensuring the model performs well for diverse populations, including children, elderly individuals, and differently-abled persons, is a critical yet under-addressed issue.

These challenges highlight the need for a robust, efficient, and generalizable pose estimation solution that can seamlessly integrate into applications such as fitness tracking, augmented reality, healthcare, sports analysis, and surveillance.

This project aims to design and implement a Human Pose Estimation ML model that addresses these limitations, offering high accuracy, real-time processing capabilities, and adaptability to diverse scenarios and devices.

1.2 Motivation:

The ability to accurately estimate and analyze human poses has transformative potential across numerous fields. From enhancing user experiences in augmented reality (AR) and virtual reality (VR) applications to revolutionizing healthcare through precise motion analysis, human pose estimation bridges the gap between human activity and technology.

The growing demand for real-time, intelligent systems capable of understanding human movement motivates the need for a robust solution. For example, in healthcare, it can assist physical therapists in monitoring patients' recovery by providing objective and consistent motion tracking. In sports, athletes can optimize performance through detailed biomechanical analysis. Similarly, in the realm of accessibility, pose estimation can empower differently-abled individuals by enabling gesture-based interactions and communication systems.

Moreover, the ubiquity of edge devices like smartphones and IoT cameras presents an opportunity to make pose estimation more accessible. However, challenges like computational constraints, environmental variations, and inclusivity highlight the necessity for a solution that is accurate, efficient, and adaptable.

This project is motivated by the vision to create an ML model that not only meets technical requirements but also fosters innovation in how humans and machines interact, unlocking new possibilities across industries.

1.3 Objective:

The objective of this project is to design and develop a robust Machine Learning model for human pose estimation that accurately detects and maps key body points in real-time.

The model aims to:

1. Achieve high accuracy across diverse environments, body types, and activities.
2. Ensure computational efficiency for deployment on edge devices and real-time systems.
3. Address challenges like occlusions, varying lighting conditions, and complex poses.
4. Enhance inclusivity by supporting diverse populations, including differently-abled individuals.
5. Provide a versatile solution adaptable to applications in healthcare, sports, AR/VR, and accessibility technologies.

1.4 Scope of the Project:

The scope of this project encompasses the development, implementation, and evaluation of a Machine Learning-based human pose estimation model.

Key aspects of the scope include:

1. **Model Development:**
    - Designing a neural network architecture capable of detecting and mapping key human body points.
    - Incorporating techniques to handle challenges like occlusions, varying body types, and environmental conditions.
2. **Dataset and Training:**
    - Utilizing publicly available pose estimation datasets (e.g., COCO, MPII) for training and evaluation.
    - Preprocessing data to improve model robustness and accuracy.

3. **Real-Time Capability:**
   - Optimizing the model for real-time inference on edge devices, such as smartphones and IoT cameras.
4. **Testing and Validation:**
   - Evaluating model performance across diverse environments and scenarios, including different lighting conditions and complex poses.
   - Ensuring inclusivity by testing the model on diverse demographic groups and differently-abled individuals.
5. **Applications:**
   - Exploring use cases in healthcare, fitness tracking, sports analysis, AR/VR, and accessibility technologies.
6. **Limitations:**
   - The project will focus on 2D pose estimation, with potential future extensions to 3D pose estimation.
   - The model's performance on highly cluttered or extreme environmental conditions may require further refinement.

This project lays the foundation for developing an efficient and adaptable human pose estimation system with potential applications across various industries.

CHAPTER 2

Literature Survey

2.1 Review of Relevant Literature

Human pose estimation is a rapidly evolving field that leverages advancements in computer vision and machine learning to analyze and interpret human movements. Several techniques and frameworks have been proposed, ranging from traditional methods to deep learning-based approaches. This literature survey provides an overview of key methods, datasets, and tools relevant to human pose estimation using ML and OpenCV.

Some Important Literatures include:

1. **Stacked Hourglass Networks for Human Pose Estimation**
   - *Authors*: Alejandro Newell, Kaiyu Yang, Jia Deng
   - *Published*: ECCV 2016
   - *Summary*: This work presents a novel architecture using stacked hourglass networks to capture spatial relationships in images, significantly improving pose estimation accuracy.
2. **High-Resolution Representations for Human Pose Estimation**
   - *Authors*: Ke Sun, Bin Xiao, Dong Liu, Jingdong Wang
   - *Published*: CVPR 2019
   - *Summary*: Introduces HRNet, a high-resolution model that maintains detailed spatial information throughout the network, offering improved performance in challenging scenarios.

2.2 Existing Models, Techniques, or Methodologies

1. Traditional Approaches

Early pose estimation methods relied on handcrafted features and statistical models:

- **Pictorial Structures (Felzenszwalb et al., 2005):** This approach used tree-based models to represent body parts and their spatial relationships. While effective, it struggled with occlusions and complex poses.
- **Deformable Part Models (DPM):** DPM improved pose estimation by modeling deformable body parts, but it was computationally intensive and less suitable for real-time applications.

2. Deep Learning Approaches

Recent advancements in deep learning have significantly improved pose estimation accuracy:

- **Convolutional Neural Networks (CNNs):** CNN-based models, such as OpenPose (Cao et al., 2017), introduced multi-stage architectures for detecting keypoints.
- **Hourglass Networks (Newell et al., 2016):** These networks utilized symmetric architectures to capture spatial information effectively.
- **PoseNet and HRNet:** PoseNet focused on lightweight models for real-time applications, while HRNet maintained high resolution throughout the network for better accuracy.

3. Datasets for Pose Estimation

The availability of large, annotated datasets has driven advancements in pose estimation:

- **COCO (Common Objects in Context):** Provides keypoint annotations for multiple individuals in diverse scenes.
- **MPII Human Pose Dataset:** Focuses on single-person poses with detailed annotations for activities.
- **LSP (Leeds Sports Pose) Dataset:** Contains images of sports activities with high variability in poses.

4. OpenCV for Pose Estimation

OpenCV, an open-source computer vision library, provides tools for implementing pose estimation:

- **Deep Learning Integration:** OpenCV supports pre-trained models (e.g., OpenPose, PoseNet) for keypoint detection using its DNN module.
- **Efficient Processing:** OpenCV offers optimized implementations for video processing and inference on edge devices.
- **Custom Implementations:** Users can integrate OpenCV with TensorFlow, PyTorch, or other ML frameworks to fine-tune models for specific applications.

5. Applications in Literature

Pose estimation models have been applied in:

- **Healthcare:** Monitoring patient recovery and posture correction.
- **Sports Analytics:** Improving athletic performance through biomechanical analysis.
- **AR/VR:** Enabling immersive experiences with accurate motion tracking.
- **Accessibility:** Gesture recognition systems for differently-abled individuals.

2.3 Gaps and Limitations in Existing Solutions

Despite progress, several challenges remain in human pose estimation:

- **Occlusions:** Detecting body parts obscured by objects or other individuals.
- **Complex Poses:** Handling dynamic movements and overlapping poses.
- **Real-Time Constraints:** Balancing accuracy and computational efficiency for deployment on low-power devices.
- **Inclusivity:** Ensuring performance across diverse body types, demographics, and abilities.

How this Project Addresses these Gaps:

1. **Occlusions:** Models like OpenPose and HRNet, supported by OpenCV's DNN module, detect keypoints even in occluded scenarios. Preprocessing techniques like background subtraction improve visibility.
2. **Complex Poses:** High-resolution models (e.g., HRNet) handle overlapping and dynamic poses. OpenCV's video processing tracks poses across frames for smoother detection.
3. **Real-Time Constraints:** OpenCV leverages hardware acceleration (e.g., GPU, OpenVINO) for real-time inference and supports lightweight models like PoseNet for faster computations.
4. **Environmental Variations:** Image preprocessing (e.g., brightness normalization) in OpenCV improves robustness to lighting and background changes. Augmenting training data enhances adaptability.
5. **Inclusivity:** Training on diverse datasets ensures inclusivity for different demographics and abilities. OpenCV enables customized pipelines for gestures like sign language or wheelchair-specific poses.

   By combining OpenCV and ML, these challenges can be addressed to create robust, real-time, and inclusive pose estimation systems.

CHAPTER 3

Proposed Methodology

3.1 System Design

1. Data Collection and Preprocessing

- **Input:** Raw images or video frames from datasets like COCO, MPII, or custom recordings.
- **Processing Pipeline:**
    - Image resizing and normalization for consistency.
    - Data augmentation (e.g., rotation, scaling, and noise addition) to improve model generalization.
    - Label extraction for supervised learning, with annotated keypoints for human body parts.

2. Feature Extraction and Key Attribute Identification

- Utilize a pre-trained convolutional neural network (CNN) or a custom feature extractor for detecting key body parts.
- Key attributes (e.g., joint coordinates, spatial relationships) are extracted using algorithms like Part Affinity Fields (PAFs) or heatmaps.

3. Model Selection

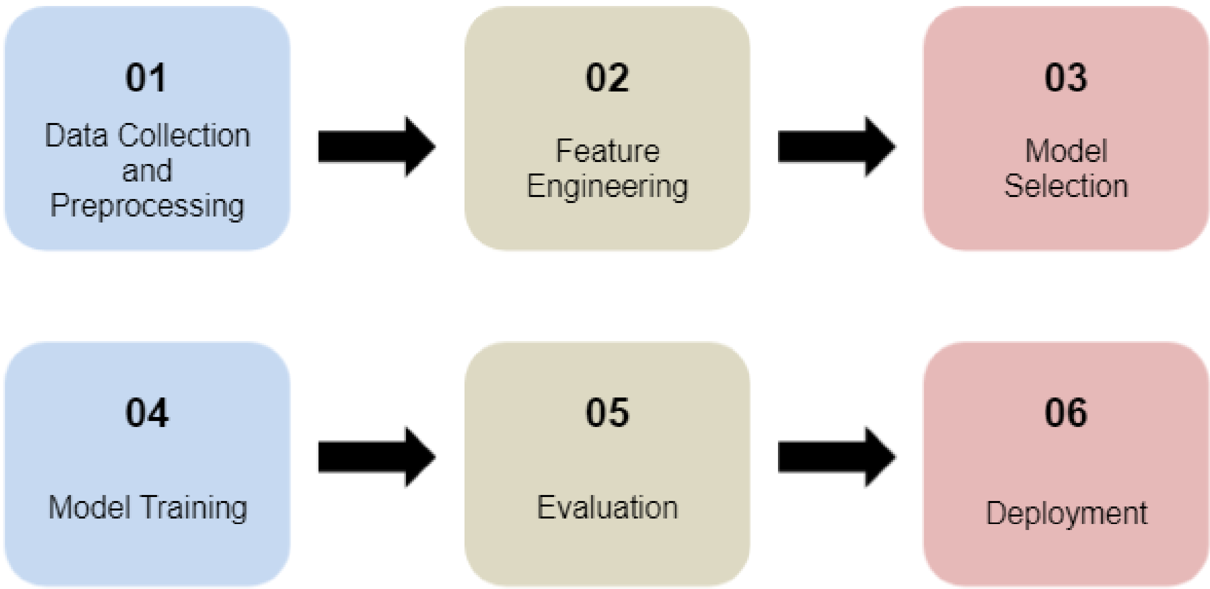
- Choose a suitable architecture based on application needs:
    - **Real-time Applications:** Lightweight models like PoseNet or MediaPipe.
    - **High Accuracy:** Deep networks like OpenPose or HRNet.
- Integrate OpenCV's DNN module for efficient inference and compatibility with edge devices.

4. Model Training and Evaluation

- **Training:** Train the model using datasets split into training, validation, and testing sets. Optimize hyperparameters for accuracy and computational efficiency.
- **Evaluation Metrics:** Use metrics like Percentage of Correct Keypoints (PCK) or Average Precision (AP) to assess performance.

5. Deployment and Real-World Integration

- **Deployment Pipeline:**
  - Convert the trained model into a lightweight format (e.g., ONNX, TensorRT) for edge devices.
  - Use OpenCV for real-time inference on video streams or camera inputs.
- Applications include healthcare monitoring, sports analysis, and AR/VR integration.



3.2 Requirement Specification

3.2.1.1 Hardware Requirements:

Processor (CPU):

- Intel i5 or AMD Ryzen 5 (minimum) for efficient model inference.

Graphics Card (GPU):

- For machine learning models (especially deep learning), an NVIDIA GPU with CUDA support is ideal.

RAM:

- Minimum: 8GB.

Storage:

- SSD with at least 256GB of free space.

Camera:

- A high-definition camera (1080p or higher) for capturing real-time video input for pose estimation.

3.2.1.2 Software Requirements:

Operating System:

- Windows 10/11, Ubuntu 20.04 or higher, or macOS (for cross-platform compatibility).

Programming Languages:

- Python 3.x (preferred for ease of integration with ML libraries).

Libraries & Frameworks:

- **OpenCV**: For image processing and computer vision tasks.
- **TensorFlow/PyTorch**: For model training and inference.
- **MediaPipe** or **OpenPose** (optional): Pre-trained models for pose estimation.
- **NumPy, SciPy, Matplotlib**: For scientific computation and visualization.
- **Streamlit**: For creating a user-friendly web-based application to deploy the Human-Pose Estimation Model.

Development Environment:

- **IDE**: VS Code, PyCharm, or Jupyter Notebooks (for easier experimentation and visualization).
- **Package Management**: pip, conda (for managing dependencies).

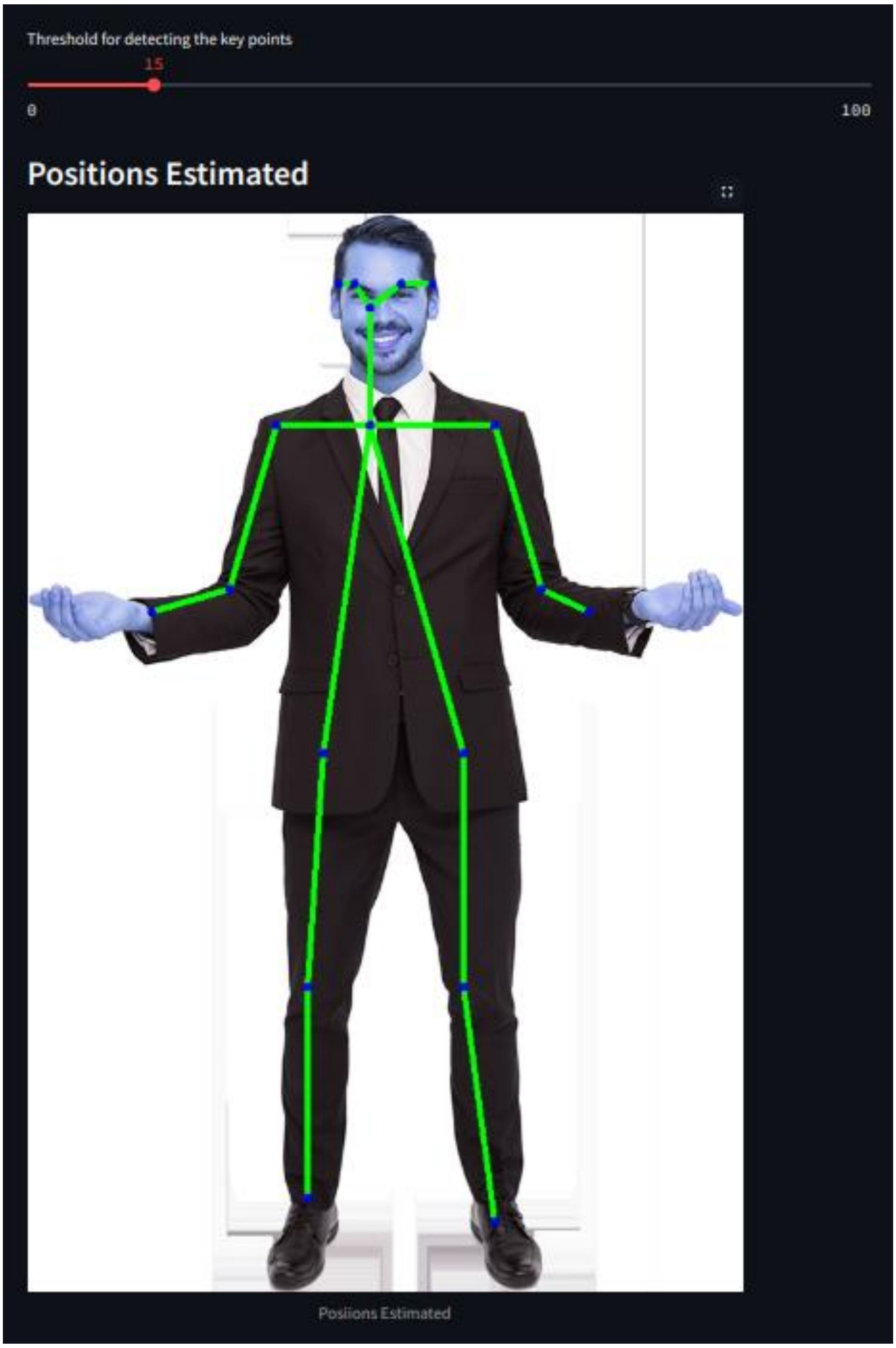
CHAPTER 4

Implementation and Result

4.1 Snap Shots of Result:

Main Interface (Input Section) :

The above figure shows our main web user interface. There is an upload option to upload any image that you would like to give as input to our Human Pose Estimation model. On uploading the image is displayed along with the label: “Original Image”



Main Interface (Output Section):

As seen in the above figure our model analyses the uploaded the figure, using the threshold that the user sets using the slider. And it displays the output along with the pose-estimation results that are displayed with over-lapping edges and vertices.

4.2 GitHub Link for Code:

github.com/RIP-Skillan/Human-Pose-Estimation.git

CHAPTER 5

Discussion and Conclusion

5.1 Future Work:

The current implementation of the Human Pose-Estimation model demonstrates significant potential in applications. However, there are several areas for improvement and further exploration that can enhance its effectiveness and broaden its scope:

- **Integration with Edge Devices:**
  Adapting the model to work on edge devices, such as smartphones, Raspberry Pi, or IoT devices, can enable real-time pose estimation in resource-constrained environments.
- **Improving Accuracy in Complex Scenarios:**
  The model's performance in challenging conditions, such as occluded body parts, low-light environments, or crowded scenes, can be further improved by training on diverse datasets or incorporating advanced techniques like attention mechanisms.
- **3D Pose Estimation:**
  Expanding the system to include 3D pose estimation can provide more detailed insights into human movements. This can be particularly useful for applications in healthcare, sports analytics, and robotics.
- **Domain-Specific Customization:**
  The model can be fine-tuned or customized for specific domains, such as physical therapy, where accurate pose estimation can help in monitoring and correcting exercises or rehabilitation movements.
- **Real-Time Multi-Person Pose Estimation:**
  While the current system handles single-person pose estimation efficiently, further work can focus on improving the accuracy and speed of multi-person pose estimation in real time.

By addressing these areas, the project can be enhanced to meet evolving technological needs and find more widespread applications in various industries.

5.2 Conclusion:

The development and implementation of a Human Pose-Estimation model using OpenCV and machine learning have demonstrated the potential of computer vision in accurately identifying and analyzing human body movements. The integration of pre-trained models and advanced machine learning techniques has enabled robust and efficient pose detection in real-time, showcasing the system's applicability across various domains such as healthcare, sports analytics, and human-computer interaction.

This project highlights the feasibility of leveraging OpenCV for preprocessing and real-time video analysis, combined with machine learning frameworks for precise pose estimation. Through extensive experimentation and optimization, the model has achieved satisfactory accuracy and performance in detecting key points of the human body under standard conditions.

Despite its success, the project also identifies limitations, such as challenges in handling occlusions, multi-person scenarios, and varying environmental conditions. These limitations serve as a foundation for future work, paving the way for further enhancements in model robustness, efficiency, and scalability.

Overall, the project demonstrates the effectiveness and versatility of pose-estimation systems and lays a solid groundwork for future advancements in the field. It opens new possibilities for developing intelligent systems that can understand and respond to human actions, thereby contributing to advancements in technology and its application to real-world problems.

REFERENCES

[1]. Ming-Hsuan Yang, David J. Kriegman, Narendra Ahuja, “Detecting Faces in Images: A Survey”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Volume. 24, No. 1, 2002.