Capstone project phase A

# AI-Based Dorsiflexion Angle Measurement Using Foot Keypoint Detection

Project Code : 26-1-D-4


by:

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Git repository link:

https://github.com/Sheli-Zisman/Final_project

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## Abstract

Accurate assessment of ankle dorsiflexion is essential in rehabilitation and orthopedic practice, yet manual goniometric measurement remains prone to variability and limited reproducibility. This project proposes an automated computer vision based approach for estimating dorsiflexion angles directly from still images by detecting clinically relevant anatomical landmarks and applying vector based angle computation.

A customized DeepLabCut model will be trained on a dedicated dataset collected from real participants, and its performance will be evaluated against traditional clinical measurements in collaboration with medical experts. The proposed system aims to provide a reliable and accessible tool for objective dorsiflexion assessment, with potential future applications in remote monitoring and digital clinical workflows.

## 1. Introduction

In recent years, clinical assessment in physical rehabilitation medicine has increasingly relied on quantitative measurements to support diagnosis, monitor recovery, and guide therapeutic decision-making. One of the most fundamental biomechanical parameters in lower-limb evaluation is the ankle dorsiflexion angle, which reflects the range of motion between the foot and the shin. This measurement plays a critical role in the assessment of patients recovering from Achilles tendon injuries, neurological impairments, gait abnormalities, and musculoskeletal disorders. Traditionally, dorsiflexion is measured manually using a goniometer - an instrument that, despite its widespread use, is highly sensitive to examiner experience, positioning inconsistencies, and human error. As a result, the reliability and reproducibility of goniometric measurements remain limited, highlighting the need for more advanced and objective assessment methods[2].

Recent advances in computer vision and deep learning offer new opportunities for enhancing clinical examination through automated, image-based angle estimation[5]. Over the past decade, keypoint detection models have achieved remarkable accuracy in identifying anatomical landmarks and estimating joint angles across various human posture and gait analysis applications. Studies have demonstrated that machine learning–based pose estimation systems can provide reliable biomechanical measurements with reduced variability compared to manual assessment, while enabling scalable and non-invasive data collection[1]. This technological progress is driving a shift toward digital tools that can support clinicians with real-time, standardized, and quantitative feedback.

DeepLabCut has emerged as a powerful framework for markerless keypoint detection in biomedical and biomechanical research. It enables training customized models to identify specific anatomical landmarks from relatively small labeled datasets, while achieving high spatial accuracy using deep neural network backbones such as ResNet50. These properties make it particularly suitable for clinical applications where precise joint angle estimation is critical [5].

Simultaneously, the increased collaboration between clinical practitioners and machine learning researchers has accelerated the development of digital tools intended to replace or supplement traditional measurement devices. Studies in rehabilitation science report that automated angle estimation can improve consistency, reduce observer bias, and enhance long-term tracking of patient progress[3]. Moreover, the growing interest in using mobile devices and cloud-based tools for remote patient monitoring suggests that computer-vision-based measurement systems may soon become integral components of modern healthcare workflows[3].

Despite the growing availability of computer-vision-based pose estimation frameworks, their adoption in routine clinical assessment of ankle dorsiflexion remains limited. Existing solutions often focus on full-body motion analysis, require video-based input, specialized laboratory setups, or are not explicitly designed for precise joint angle measurement in static clinical examinations. Moreover, many current approaches lack clinically validated landmark definitions and are rarely evaluated against standard goniometric measurements under real-world conditions. As a result, there is currently no widely adopted, accessible system that enables accurate, image-based estimation of ankle dorsiflexion using clinically meaningful anatomical landmarks in collaboration with medical experts[8].

The present project aims to contribute to this evolving field by developing a computer vision system for accurate estimation of the ankle dorsiflexion angle from still images. The system will identify clinically relevant anatomical landmarks, namely the shin, ankle, and fifth metatarsal,and compute the joint angle using a vector-based approach. Over the course of an academic year, the project will involve data collection from real participants, model training using multiple algorithmic strategies, and iterative accuracy evaluation. In collaboration with medical experts at Hospital X, the system's performance will be validated against traditional goniometric measurements to ensure clinical relevance. By integrating deep learning, biomechanics, and clinical expertise, the project seeks to deliver a reliable and accessible tool that reduces the limitations of manual assessment and supports future applications such as remote rehabilitation monitoring and deployment in clinical environments [5].

### 1.1.Potential algorithms and technologies for the project

**RTMPose** is a lightweight pose estimation framework designed for fast and real-time keypoint detection. It is optimized for high processing speed and is commonly used in applications that require low latency, such as live motion tracking. While RTMPose performs well for general pose estimation, it is mainly trained on standard human body datasets and focuses on speed rather than high anatomical precision. In the context of this project, RTMPose showed limited accuracy when applied to images of the foot and ankle, where precise detection of small anatomical landmarks is required. For this reason, RTMPose was tested but ultimately replaced by a more accurate, customized solution based on DeepLabCut[8].

**MediaPipe Pose** is a pre-trained pose estimation framework developed by Google for fast and efficient human body keypoint detection. It is optimized for real-time performance and works well in applications that involve full-body pose tracking. However, MediaPipe Pose is designed to detect a fixed set of general body landmarks and typically requires visibility of large body regions. When applied to images focused only on the foot and ankle, the model often fails to detect the required anatomical keypoints accurately. Due to its limited flexibility and reduced accuracy for fine-grained clinical landmarks, MediaPipe Pose was evaluated but not selected for use in this project[8].

**YOLO Keypoints** is an extension of the YOLO object-detection framework that can detect predefined keypoints on the human body in real time. The model is designed for speed and efficiency, making it suitable for applications that require fast processing, such as real-time pose estimation. However, YOLO Keypoints is mainly trained on general, full-body datasets and supports a fixed set of keypoints. As a result, it is less flexible when precise detection of small or clinically specific anatomical landmarks, such as those in the foot and ankle, is required. In this project, YOLO Keypoints was considered as a potential solution but was not selected due to its limited ability to accurately detect fine-grained foot landmarks needed for reliable dorsiflexion measurement[8].

**DeepLabCut –** Custom Keypoint Detection DeepLabCut enables the creation of customized markerless pose-estimation models that can identify specific anatomical keypoints with high precision. Because the system allows researchers to define exactly which landmarks to track, it is particularly suitable for clinical applications that require accurate localization of subtle structures such as the ankle joint and metatarsal heads. In this project, DeepLabCut serves as the primary tool for detecting the foot and ankle landmarks needed for objective dorsiflexion-angle calculation[5].

**ResNet-50** is used as the main deep-learning backbone in the keypoint detection model. Its role is to extract important visual features from the input images, such as shapes and edges around the foot and ankle. The network structure includes skip connections, which help the model keep useful information from earlier layers and improve learning stability. When combined with DeepLabCut, ResNet-50 helps the system detect anatomical landmarks more accurately, even when images differ in lighting conditions, foot orientation, or camera angle[5].

**DeepLabCut and ResNet-50** were selected for this project due to their high accuracy, flexibility, and clear advantages over alternative pose-estimation approaches.

As discussed in the previous sections, DeepLabCut enables precise detection of user-defined anatomical landmarks and is well suited for biomechanical and clinical measurement tasks. Its ability to be trained on a dedicated, task-specific dataset makes it particularly appropriate for dorsiflexion assessment, where small localization errors can significantly affect the final angle calculation. Previous studies have demonstrated that DeepLabCut achieves high accuracy and robustness even with limited annotated data [5].

The choice of a ResNet-50 backbone further supports reliable feature extraction and stable model performance, as residual network architectures have been shown to perform effectively across a wide range of computer-vision and medical-imaging tasks [4]. Together, these properties justify the selection of DeepLabCut with ResNet-50 as the most suitable solution for meeting the clinical accuracy and reliability requirements of the proposed system.

## 2. Background and Literature Review

### 2.1 Background

#### 2.1.1 Clinical Importance of Ankle Dorsiflexion Measurement

The measurement of ankle dorsiflexion is a fundamental component in clinical assessment, and rehabilitation. Dorsiflexion refers to the motion that decreases the angle between the dorsum of the foot and the tibia, and it plays a critical role in human gait, balance, and functional mobility. Limitations in dorsiflexion may indicate underlying musculoskeletal, neurological, or post-injury conditions, and are often associated with impaired walking patterns and altered gait biomechanics[6].

Clinicians commonly assess dorsiflexion during evaluation of patients recovering from Achilles tendon ruptures, ankle sprains, nerve injuries, or surgical interventions. Accurate measurement is essential for monitoring progress over time and for tailoring rehabilitation protocols. Traditionally, dorsiflexion is measured using a manual goniometer, where the examiner visually aligns the instrument with anatomical landmarks to determine the joint angle. Despite being widely used, goniometric measurement suffers from variability between examiners, inconsistencies in landmark identification, and susceptibility to human error. Research repeatedly highlights poor inter-rater reliability and limited repeatability in such manual assessments[2].

These limitations emphasize the need for more objective, reproducible, and automated measurement tools[2]. Over the past decade, advancements in computer vision have enabled markerless pose estimation, allowing machines to detect anatomical keypoints from standard images or videos[1]. This technological trend opens the door to clinical tools that can provide highly consistent and quantitative assessments without requiring specialized equipment or extensive examiner training. A reliable automated dorsiflexion measurement system could therefore improve clinical decision-making, standardize monitoring procedures, and reduce reliance on subjective visual judgment.

#### 2.1.2 Current Method for Measuring Ankle Dorsiflexion

In current clinical practice, ankle dorsiflexion is commonly measured manually using a goniometer. The measurement process begins with positioning the patient in a seated or supine position, often with the knee slightly flexed in order to reduce the influence of the gastrocnemius muscle. Before placing the goniometer, the clinician first identifies the relevant anatomical landmarks through visual inspection and palpation. The primary reference point is the lateral malleolus, which serves as the axis of rotation for the ankle joint.

Once the landmarks are identified, the center (fulcrum) of the goniometer is aligned with the lateral malleolus. The stationary arm of the goniometer is positioned along the longitudinal axis of the tibia, while the moving arm is aligned with the lateral border of the foot, typically following the direction of the fifth metatarsal. The clinician then instructs the patient to actively perform dorsiflexion, or alternatively applies passive movement, while maintaining the alignment of the goniometer arm[7].

After the foot reaches its maximum dorsiflexion position, the clinician visually reads the angle indicated on the goniometer scale. This value represents the measured dorsiflexion range of motion. Because the process relies heavily on manual landmark identification, visual alignment, and subjective angle reading, small deviations in goniometer placement or patient positioning can lead to variability in the measurement. As a result, inter-rater and intra-rater reliability may be limited, highlighting the challenges of manual goniometric assessment in achieving consistent and repeatable measurements[2].

## 2.2 Literature Review

### 2.2.1 Computer-Vision Tools for Clinical Measurement

Recent research demonstrates that computer-vision technologies have become increasingly effective in supporting clinical assessment and biomechanical analysis. Markerless pose estimation models, such as DeepLabCut and similar frameworks, allow accurate detection of anatomical keypoints from images without requiring specialized equipment.These frameworks typically employ deep convolutional neural network backbones, such as ResNet-50, Studies show that these tools significantly improve measurement precision and reduce user-dependent variability compared to traditional manual methods[2].

Automated keypoint detection has been successfully applied in areas such as gait analysis, joint angle estimation, and rehabilitation monitoring, where consistent and objective measurements are essential. The literature highlights that computer-vision-based systems can provide reliable quantitative data, streamline clinical workflows, and support better long-term tracking of patient progress. These findings suggest that automated dorsiflexion measurement has strong potential to enhance clinical accuracy, reduce human error, and serve as an effective alternative to manual goniometric assessment.

### 2.2.2 Markerless Pose Estimation

Markerless pose estimation is a computer-vision technique that identifies anatomical keypoints directly from images without requiring physical markers or sensors. These systems rely on deep neural networks to detect joint locations and extract biomechanical information with high spatial precision.

Modern frameworks such as DeepLabCut, OpenPose, and RTMPose enable researchers and clinicians to analyze human movement efficiently while avoiding the limitations of traditional motion-capture systems, which often require specialized equipment, controlled environments, and extensive calibration[8].

Pose estimation approaches can generally be divided into two categories. Model-based methods use pretrained architectures that detect a standardized set of human joints and are optimized for whole-body analysis[1]. While fast and easy to deploy, they may perform poorly on tasks requiring high accuracy in small or anatomically subtle regions such as the foot and ankle. In contrast, custom keypoint models allow users to define their own anatomical landmarks and train the network specifically for a targeted body region [5]. This enables higher precision and better adaptability to clinical requirements, making such methods particularly suitable for applications that demand reliable joint-angle estimation from still images. By providing automated, markerless measurements that reduce examiner-dependent variability, pose-estimation technologies offer a promising foundation for objective clinical assessment and support the development of digital tools that can complement or replace manual goniometric evaluation[2].

### 2.2.3 Pose Estimation and Deep Learning in Clinical Biomechanics

Recent advances in deep learning have significantly reshaped the field of clinical biomechanics by enabling automated extraction of anatomical information directly from images. Markerless pose estimation systems, such as DeepLabCut, OpenPose, and RTMPose, have made it possible to analyze human movement without physical markers, specialized sensors, or controlled laboratory environments. These technologies shift the focus from manually guided assessment to automated, data-driven analysis, allowing clinicians and researchers to quantify joint positions, movement patterns, and biomechanical parameters with unprecedented ease and consistency[8].

A key advantage of these systems lies in their capacity to detect subtle anatomical features with high spatial accuracy. In contrast to traditional motion capture systems,which require extensive calibration, reflective markers, and expensive multi-camera setups,deep-learning-based approaches can operate on simple 2D images captured from readily available devices such as smartphones or digital cameras. This democratizes movement analysis by reducing both cost and technical barriers, allowing broader clinical accessibility while maintaining research-grade precision[8].

Several domain-specific applications highlight the transformative potential of pose estimation in healthcare. For example, automated gait analysis frameworks have been developed to assess post-stroke mobility deficits, enabling early detection of asymmetries and improving long-term rehabilitation planning[3]. Similarly, deep-learning models have been used to evaluate joint angles during functional movements such as squatting or jumping, providing athletes and therapists with real-time feedback to prevent overuse injuries and optimize performance. These systems offer both operational benefits,such as reduced assessment time,and psychological benefits, as patients gain motivation from receiving immediate, objective feedback that tracks their recovery progress.

In orthopedic and neurological contexts, pose estimation has proven especially valuable for quantifying range of motion (ROM). Research demonstrates that automated ROM measurements often outperform manual goniometry in both consistency and repeatability, reducing the examiner-dependent variability that has long been a limitation of physical assessment tools[2]. This is particularly relevant in cases where small deviations in angle carry significant diagnostic implications - for example, monitoring dorsiflexion deficits following Achilles tendon rupture or evaluating spasticity-related restrictions in neurological patients.

More advanced frameworks integrate pose estimation with biomechanical modeling, enabling real-time estimation of joint kinematics and bridging the gap between keypoint detection and full biomechanical analysis[8]. These hybrid approaches provide intuitive visualizations of joint angles and movement patterns, supporting faster and more confident clinical decision-making in rehabilitation practice[8].

Collectively, the growing body of work in pose estimation demonstrates its potential to revolutionize clinical biomechanics. Whether optimizing athletic performance, supporting remote rehabilitation, or replacing subjective manual measurements, deep-learning–based systems provide a foundation for objective, scalable, and highly accessible movement assessment. As demonstrated by applications in gait analysis, joint-angle evaluation, and real-time kinematic modeling, the future of clinical measurement increasingly lies in these automated technologies that transform complex biomechanical data into intuitive, actionable insights. In this context, an automated dorsiflexion measurement system represents a natural continuation of these developments, with the potential to significantly enhance accuracy, efficiency, and clinical usability in ankle assessment[8].

## 3.Engineering Process

### 3.1 User-Centered Research

The aim of this project is to improve the clinical process of determining range of motion (ROM) in patients by introducing a more objective, accurate, and efficient assessment method. In many hospitals and rehabilitation centers, ROM evaluation is still performed manually, relying heavily on the clinician's experience and on tools such as goniometers. While widely used, these traditional methods often suffer from inconsistency, variability between examiners, and difficulty in standardizing measurements across different clinical environments.

Building on current hospital practices and acknowledging their limitations, this project proposes a solution that leverages modern machine-learning and image-processing techniques to automate the measurement process. By using computer-vision models capable of identifying anatomical keypoints directly from images, the system aims to reduce human error, enhance measurement repeatability, and provide clinicians with reliable, data-driven information. Ultimately, the integration of AI-based analysis into routine assessment workflows has the potential to streamline evaluation, support clinical decision-making, and significantly improve the overall accuracy of ROM monitoring in patient care.

**Project Workflow: Automated Ankle Measurement System**

Figure 1 presents an overview of the project workflow for automated ankle dorsiflexion measurement in three main phases. It begins with the clinical motivation and the limitations of manual goniometric assessment, followed by the evaluation of alternative pose-estimation approaches and the selection of a customized DeepLabCut-based solution. Finally, the diagram illustrates the operational pipeline in which the user uploads an image, anatomical landmarks are detected automatically, and the dorsiflexion angle is computed and displayed.

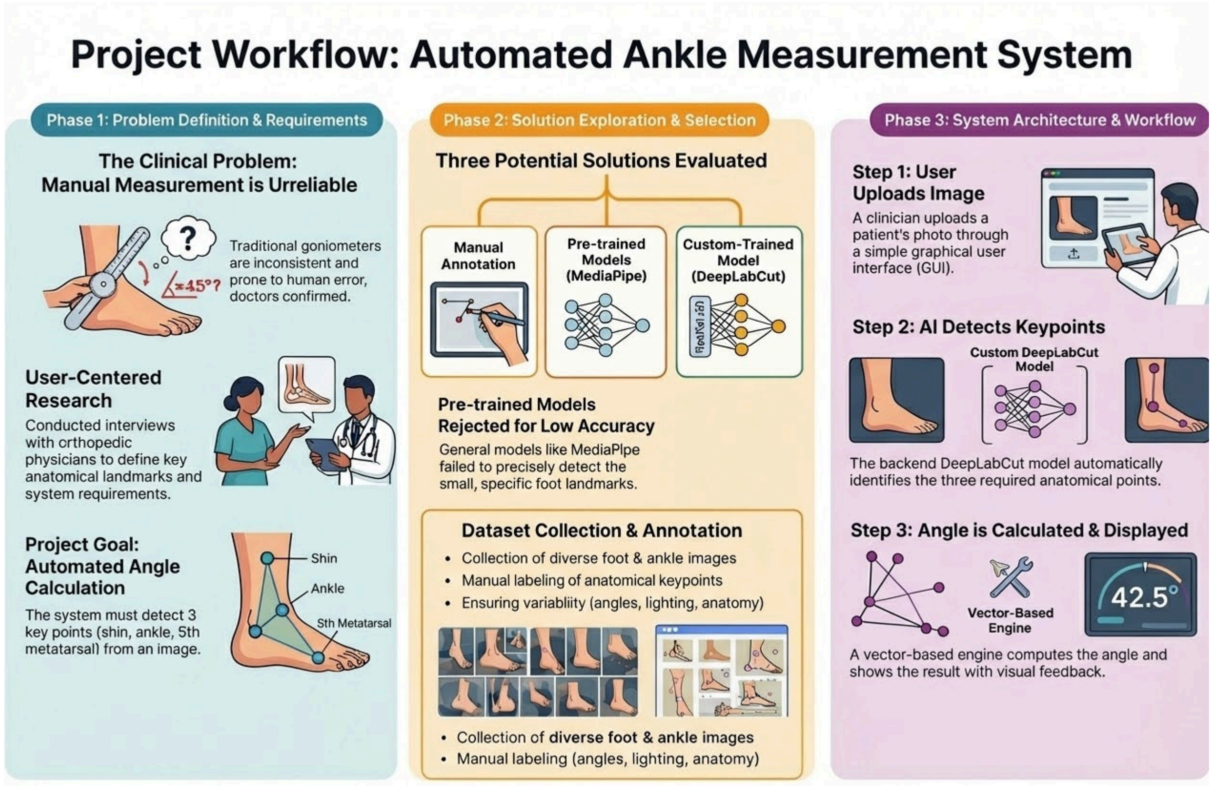


Figure 1:System Workflow for Automated Ankle Dorsiflexion Measurement

Our research process begins with a clear definition of the clinical problem and the identification of user requirements in collaboration with a senior orthopedic physician, head of the foot and ankle orthopedic department at Hospital X. Following this stage, we evaluate potential technological alternatives for automated dorsiflexion measurement, comparing existing pose-estimation tools and assessing their suitability for precise anatomical landmark detection. Based on this analysis, we select the most appropriate technical approach for developing a reliable and clinically meaningful solution. The overall development process for the system centers on creating an automated method for extracting three key anatomical points from an image and computing the dorsiflexion angle using vector-based calculations.

To support this goal, the project involves structured phases of dataset collection, image annotation, model training, accuracy evaluation, and iterative refinement. Throughout the project, multiple algorithms and configurations are tested to identify the model that provides the highest clinical accuracy. To ensure that the proposed solution aligns with real clinical needs, the development process incorporates principles of user-centered design.

Physicians serve as key stakeholders, guiding the selection of anatomical landmarks and validating the accuracy requirements of the system. The project follows an iterative engineering cycle, problem analysis, prototype development, testing, and improvement, to ensure that each stage contributes to a robust and effective measurement tool. This methodology lays the foundation for a reliable system that may eventually support or replace manual goniometric assessment in clinical practice.

**Motivation for AI-Based Ankle Dorsiflexion Assessment**

Figure 2 highlights the motivation for transitioning from traditional manual ankle measurement methods to AI-based precision tools. It summarizes the key limitations of goniometric assessment, including human error, lack of standardization, and inconsistent landmark identification. In contrast, the proposed solution leverages computer vision and deep learning to enable automated, accurate, and clinically reliable dorsiflexion angle estimation from images.

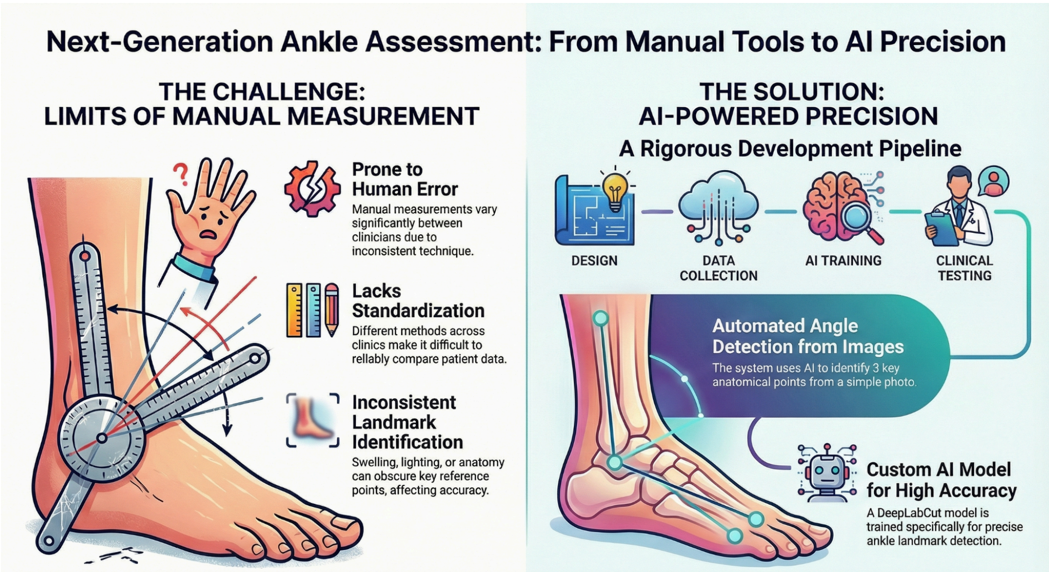


Figure 2: Next-Generation Ankle Assessment

To define the system's functional and clinical requirements, interviews were conducted with key clinical stakeholders, including a senior orthopedic physician , who also serves as the head of the orthopedic department, and an orthopedic resident from hospital X.

Their professional insights highlighted significant challenges in current dorsiflexion assessment practices and played a central role in shaping the design requirements and clinical relevance of the proposed solution.

**Key insights from conversations with doctors:**

1. Manual Measurement Variability (The Goniometer Limitation) Clinicians emphasized that traditional goniometric measurement is highly dependent on the examiner's experience and technique. Small variations in identifying anatomical landmarks ,such as the lateral malleolus or the fifth metatarsal often lead to inconsistent results. As one specialist explained, "even a slight misalignment of the goniometer arm can change the angle significantly, making it difficult to reliably track patient progress over time"(Senior Orthopedic Surgeon).This

variability creates the need for an automated, objective method capable of producing repeatable measurements independent of examiner skill.

2. Difficulty in Identifying Anatomical Landmarks Another major concern involved the precision required to identify key anatomical points on the leg and foot. Clinicians reported that differences in skin tone, lighting conditions, swelling, or foot morphology often obscure important reference points. These inconsistencies not only impact accuracy but also increase the time required for proper assessment. Experts noted that an automated system capable of consistent landmark detection across patients and image conditions would significantly improve the reliability of dorsiflexion evaluation.

3. Clinical Need for Efficient, Image-Based Assessment Physicians expressed interest in tools that could analyze simple images taken during routine examinations. Such tools would support documentation, remote assessment, and early detection of mobility issues. One clinician noted, “if we could get accurate angles from a quick photo, it would save time and allow better monitoring during rehabilitation sessions” (Orthopedic Resident).This reinforced the importance of building a system that performs well even with standard smartphone images and minimal setup.

The quotes were taken from a conversation that took place at Hospital X on November 25, 2025.

**3.2 Requirements**

Most of the functional requirements were gathered through consultations with clinicians from hospital X, while the majority of the non-functional requirements were determined by our development team based on system constraints and performance goals.

Functional Requirements:

1. The system will detect three anatomical keypoints (shin, ankle, fifth metatarsal) from a single image.
2. The system will calculate the dorsiflexion angle based on vector analysis of the detected keypoints.
3. The system will allow uploading or capturing images using a smartphone or computer camera.
4. The system will display the measured angle in a clear and interpretable format.
5. The system will allow storing measurement results for later review or comparison.
6. The system will provide an indication when the keypoints cannot be detected reliably (e.g., due to poor lighting or occlusions).

Non-Functional Requirements :

1. Accuracy – The system shall achieve a dorsiflexion measurement error of ≤ 5° compared to clinical goniometric assessment.
2. Performance – The system shall process and analyze each image within ≤ 10 seconds on a standard mid-range device.
3. Usability – A first-time user shall be able to complete a full measurement cycle in under 2 minute**s** after a single-page introductory tutorial.
4. Reliability – The system shall successfully detect all three keypoints in at least 95% of images taken under standard office lighting
5. Portability – The system shall be deployable on a cloud-based environment and accessible through a web browser on both desktop and mobile devices.

6. Security & Privacy – The system shall comply with data protection regulations (e.g., GDPR), ensuring that all patient images are anonymized and securely handled.
7. Scalability –The backend architecture shall support scalable processing of image-based inputs, allowing the system to handle an increasing number of images without degradation in performance.
8. Maintainability – The system shall be implemented using a modular architecture such that the keypoint detection model and angle-calculation components can be updated independently without changes to other system modules.

### 3.3 Potential solutions

To identify the most suitable approach for automating dorsiflexion measurement, we considered several alternative technical solutions and evaluated them according to clinical needs, feasibility, and performance potential. The following three solutions emerged as the most relevant:

Solution 1: Manual Keypoint Annotation + Classical Geometry
In this approach, clinicians manually mark anatomical keypoints on each image, and the system computes the dorsiflexion angle using geometric formulas. While simple and reliable, this method requires continuous human involvement, is time-consuming, and does not scale well for large datasets or remote monitoring.

Solution 2: Pretrained General Pose-Estimation Models (e.g., MediaPipe, OpenPose)
This solution relies on existing pose-estimation frameworks to detect landmarks automatically. Although fast and easy to implement, such models are typically trained for full-body keypoints and often fail to accurately localize fine-grained foot landmarks required for clinically precise dorsiflexion assessment.

Solution 3: Custom Deep Learning Model Trained with DeepLabCut
This approach involves collecting a dedicated dataset, labeling task-specific anatomical landmarks, and training a customized model. It provides the highest accuracy and clinical relevance, as the model learns the exact keypoints needed for reliable dorsiflexion-angle estimation.

Table 1 summarizes the three evaluated solutions, their main limitations, and the final selection of the preferred approach for this project.

**Table 1. Comparison of Measurement Approaches for Ankle Dorsiflexion**

| Solution | Description | Limitations | Final Decision | Reason for Selection / Rejection |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| **Manual Annotation + Geometric Calculation** | Clinicians manually mark anatomical landmarks on images, followed by geometric angle computation. | High inter- and intra-rater variability, not scalable,increased clinician workload. | Rejected | Rejected due to lack of automation and reliance on continuous human involvement, which prevents consistent and repeatable clinical measurements. |
| **Pre-trained Pose Estimation Models (MediaPipe / OpenPose)** | General-purpose pose-estimation models trained on full-body datasets are used to detect lower-limb landmarks. | Unreliable landmark detection; inaccurate angle estimation in clinical scenarios. | Rejected | Rejected because these models do not provide sufficient precision for fine-grained foot and ankle landmarks required for clinical accuracy. |
| **Custom Deep Learning Model (DeepLabCut + ResNet-50)** | Customized pose-estimation model trained to detect clinically relevant foot and ankle landmarks using DeepLabCut with a ResNet-50 backbone. | Requires dataset collection and annotation, higher initial development effort. | Selected | Selected as it enables precise, automated, and repeatable detection of clinically relevant landmarks while meeting accuracy requirements for dorsiflexion measurement. |

The custom deep learning approach based on DeepLabCut with a ResNet-50 backbone was selected for its ability to deliver precise, automated, and repeatable detection of clinically relevant ankle landmarks. Unlike general-purpose pose estimation models, it enables explicit definition of anatomically meaningful keypoints and training on task-specific data, resulting in improved accuracy for fine-grained joint angle estimation. Despite the required effort for data collection and annotation, this approach best meets the project’s requirements for accuracy, robustness, and clinical applicability.

## 4 System Architecture and Design

### 4.1 System Architecture Overview

The system architecture is designed as a modular pipeline that transforms a simple clinical photograph into an accurate, automated measurement of ankle dorsiflexion. The architecture consists of three primary layers: the user interface layer, the backend processing layer, and the machine-learning inference module. Each component plays a distinct role in receiving input, detecting anatomical landmarks, calculating the dorsiflexion angle, and returning an interpretable result to the clinician.

At the highest level, the process begins when the clinician uploads or captures an image using the system's graphical interface. The image is then forwarded to the backend server through a REST API, which enables structured communication between the client application and the processing services. The backend performs basic preprocessing and passes the image to the machine-learning model. The inference module, implemented using DeepLabCut with a ResNet-50 backbone, identifies the anatomical keypoints required for dorsiflexion analysis (shin, ankle, and fifth metatarsal). These keypoints are returned to the backend, which applies vector-based geometric computation to calculate the dorsiflexion angle.

Once the dorsiflexion angle is computed, the result is returned to the user interface and displayed prominently in a clear numerical format. Alongside the angle value, the system also presents an image with detected keypoints, showing the detected anatomical keypoints and the vectors used to calculate the angle. This visual feedback allows clinicians to verify that the model identified the correct landmarks and provides transparency regarding how the final measurement was derived.

The system architecture also supports optional features such as measurement logging, confidence scoring, and image-quality validation. Its modular design enables independent improvement of individual components such as the deep-learning model or the angle-calculation algorithm without impacting the rest of the system. This flexibility ensures that the platform can scale reliably, operate as a standalone web tool, and eventually extend to cloud-based or real-time rehabilitation environments.

**4.2 Technology Stack Overview**

The system will rely on a combination of modern and widely used technologies:

1. Python 3.x : Main development language for backend and machine-learning modules.
2. DeepLabCut: Framework for markerless keypoint detection using deep learning.
3. ResNet-50: Deep convolutional neural network used as the feature extraction backbone within DeepLabCut to enable accurate detection of anatomical landmarks.
4. TensorFlow / PyTorch – Deep learning libraries used to train and run the model.
5. OpenCV: Image preprocessing, transformations, and utility functions.
6. Flask or FastAPI : Web framework enabling efficient communication between the UI and backend.
7. Cloud Services: Allow remote processing and scalability for large-scale deployment.
8. Local or cloud storage: For saving measurement results when needed.

Together, these technologies create a robust system architecture that supports accurate dorsiflexion measurement, efficient computation, and long-term scalability. The modular structure ensures that each component, UI, backend, machine learning, and storage, can evolve independently as the project expands and moves toward full clinical deployment.

**Architecture diagram :**

Figure 3 presents the high-level architecture of the proposed dorsiflexion measurement system, showing the interaction between the user interface, backend server, and the DeepLabCut-based inference module.

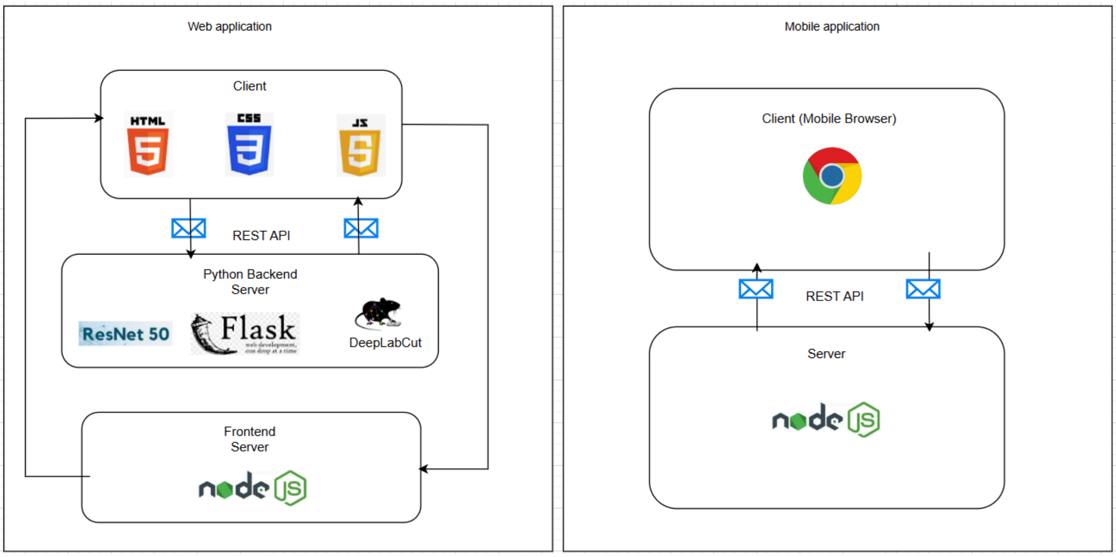


Figure 3:Architecture diagram

### 4.3 System Components and Technology Overview

The system is composed of several modular components that work together to transform an input image into a clinically meaningful dorsiflexion measurement. Each component fulfills a specific role within the processing pipeline, allowing the system to operate efficiently, ensure accuracy, and maintain flexibility for future expansion. The following subsections describe the main components and the technologies that support them.

### 4.3.1 User Interface Layer

The graphical user interface (GUI) of the system is designed to provide clinicians with a clear, intuitive, and streamlined workflow for capturing and analyzing dorsiflexion measurements. The interface emphasizes simplicity and ease of use, ensuring that clinicians with minimal technical experience can operate the system efficiently in both clinical and research settings.

The main screen presents two dedicated upload panels: one for Dorsiflexion (Image 1) and one for neutral position (Image 2). This layout guides users through the process of capturing both ankle positions required for a complete range-of-motion assessment. Each panel includes a large, bordered upload area with an illustrated upload icon, allowing users to drag-and-drop an image or select one from their device. Once an image is uploaded, it appears immediately within the panel, accompanied by a removal button that allows users to replace the image if necessary. This visual feedback ensures that the clinician verifies image quality before analysis begins.

#### 4.3.2 Backend Processing Layer

The backend layer acts as the system's core controller. It receives the uploaded image, performs preliminary preprocessing (such as resizing or normalization), and routes the image to the machine-learning inference module. Once the keypoints are detected, the backend executes the vector-based angle calculation and assembles the final output. This layer is designed to be scalable and modular, enabling seamless integration of new models, algorithms, or preprocessing steps as the system improves over time.

#### 4.3.3 Machine Learning Inference Module

The inference module is responsible for identifying anatomical keypoints from the input image. This module is implemented using DeepLabCut, trained on a customized dataset of foot and ankle images gathered during the project. The model utilizes a ResNet-50 backbone for feature extraction, enabling high-precision identification of clinically relevant landmarks such as the shin, ankle joint, and fifth metatarsal. The output of the inference module is a set of coordinates along with confidence values that indicate model certainty. This modular structure allows retraining or upgrading the model without modifying the rest of the system.

#### 4.3.4 Angle-Computation Engine

After receiving the predicted keypoints, this component performs the dorsiflexion angle calculation using vector-based geometric methods. By constructing vectors between anatomical points and computing the angle between them through trigonometric operations, the system generates a precise and repeatable measurement. This approach is transparent and easy to interpret, which is important for clinical use, and can be extended in the future if needed.

#### 4.3.5 Data Storage and Logging

Depending on clinical requirements, the system can incorporate a lightweight storage module that saves measurement results, timestamps, and confidence scores. This enables longitudinal tracking of patient progress and supports potential integration with electronic medical record (EMR) systems. Stored data can also be used for future model retraining, improving detection accuracy as more cases are collected.

### 4.4 Design Diagrams

#### 4.4.1 Use Case Diagram

**Ankle Dorsiflexion Use Cases:**

Figure 4 presents the main interactions between the user and the automated ankle dorsiflexion measurement system. The primary process involves uploading two foot images: initial and dorsiflexion, after which the system automatically detects anatomical landmarks, performs angle calculation, and generates ROM visualization. These steps are modeled as included use cases since they are essential for the measurement workflow. An additional optional use case allows comparison with manual goniometric measurements to support clinical validation. Overall, the diagram clarifies the system boundary and the division between user actions and automated processing.

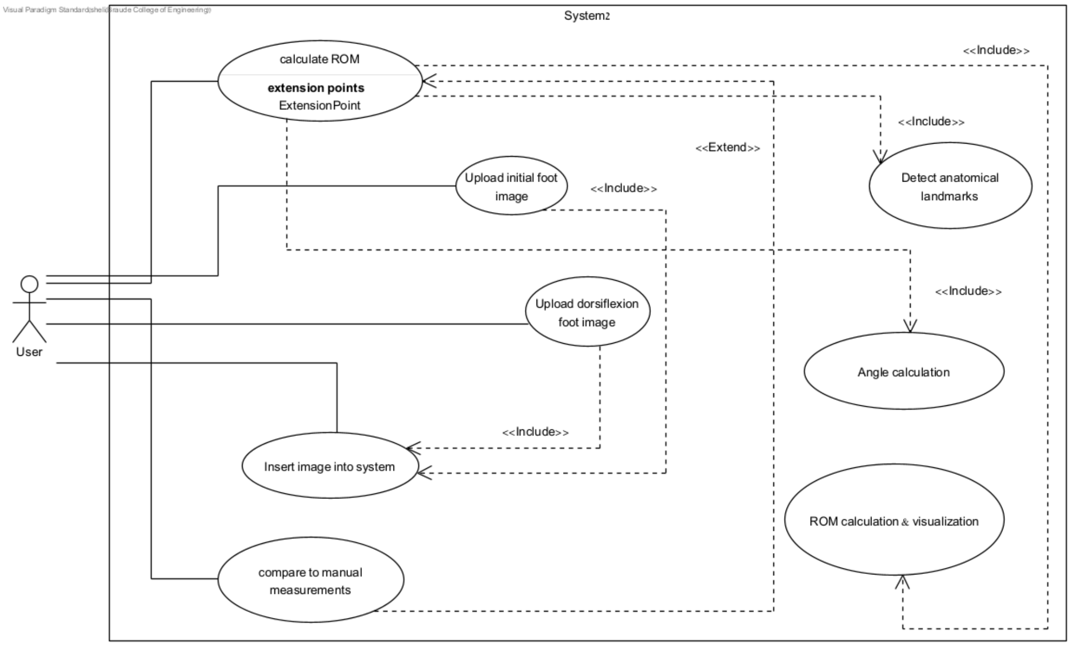

Figure 4:Ankle Dorsiflexion Use Cases

**4.4.2 Activity Diagram**

**Ankle Dorsiflexion Measurement Activity:**

Figure 5 illustrates the workflow of the automated dorsiflexion measurement process, divided between user actions and system processing. The user allows camera access and uploads the required foot images, while decision points ensure the inputs are suitable for analysis. The system then performs landmark detection, computes foot vectors, and assesses the dorsiflexion ROM. Finally, the result is returned to the user for visualization, completing the session.

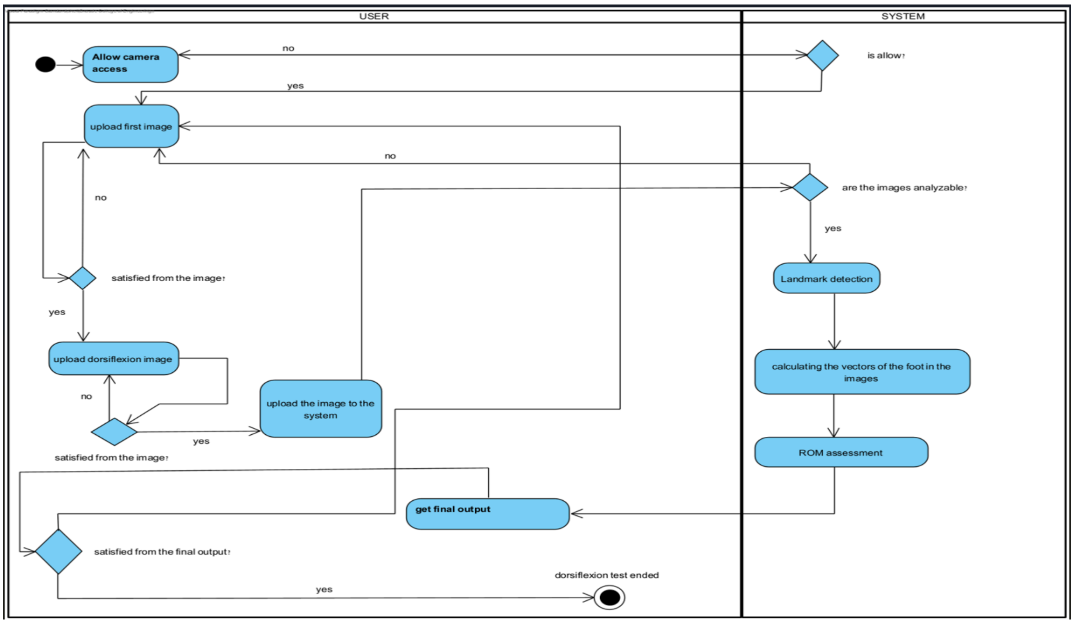

Figure 5: Ankle Dorsiflexion Measurement Activity

## 4.5 Experiment design

### 4.5.1 Experimental Procedure

The experiment is designed to evaluate the performance of the proposed automated ankle dorsiflexion measurement system in terms of accuracy, reliability, and processing time, compared to standard clinical goniometric assessment.

Each experiment will be conducted based on a measurement session, defined as the analysis of two static images of the same participant:

1. An image captured in a neutral ankle position
2. An image captured in maximum dorsiflexion

The experimental procedure will be divided into sequential stages that simulate a realistic clinical workflow.

Experimental Stages

1. Image Acquisition –
   Two images of the foot and ankle will be captured for each participant on a white background, under standard office lighting conditions.

2. Data Upload –
   The images will be uploaded to the system and treated as a single measurement session.

3. Automated Keypoint Detection –
   The system will apply a DeepLabCut-based model to detect three anatomical

landmarks (shin, ankle, and fifth metatarsal) in each image.

4. Angle Computation –
   The system will calculate the dorsiflexion angle using vector-based geometric analysis based on the detected keypoints from both images.

5. Reference Measurement –
   A manual dorsiflexion measurement will be performed using a clinical goniometer and will serve as the reference value (ground truth).

6. Result Logging –
   Automated results, manual measurements, and total processing time will be recorded for subsequent analysis

**Experimental Procedure Summary:**

**Table 2: Time Estimates for Each Stage of the Measurement Process**

| **Stage** | **Description** | **Estimated Time** |
|---|---|---|
| Image acquisition | Capture of two images per participant | ~1 minute |
| Data upload | Upload images to the system | ~15 seconds |
| Keypoint detection | Automated landmark detection | ~5 seconds |
| Angle calculation | Vector-based computation | <1 second |
| Manual measurement | Goniometric assessment | ~1 minute |
| Data recording | Logging of results | ~10 seconds |

### 4.5.2 Participant Characteristics

The experiment will be conducted with healthy adult participants, primarily undergraduate students.
Participants will have no known musculoskeletal disorders or ankle injuries at the time of the experiment.

The participant group will include individuals aged 20 to 30 years, representing a young adult population.
All participants will provide informed consent prior to participation.

**4.5.3 Expected Results**

The automated system is expected to produce dorsiflexion angle measurements with a mean absolute error of $\leq 5°$ compared to manual goniometric assessment.
The system is also expected to successfully detect all required anatomical keypoints in at least 95% of measurement sessions.

In addition, the total processing time for a complete measurement session is expected to remain under 10 seconds, supporting suitability for clinical use.

**4.5.4 Data Processing**

All collected images will be processed using the developed application.
The application will automatically perform keypoint detection, angle calculation, and result visualization.
Final measurement values will be stored for comparison with manual assessments and further analysis.

**4.5.5 Evaluation Metrics**

System performance will be evaluated using quantitative metrics derived from the project's non-functional requirements (NFRs), with primary emphasis on measurement accuracy.

1. **Measurement Accuracy**

Accuracy will be evaluated by comparing the dorsiflexion angle produced by the system to a manual clinical goniometric measurement.
The error will be calculated as the absolute difference between the two values, and overall accuracy will be reported using the Mean Absolute Error (MAE).
The system is expected to meet the NFR requirement of MAE $\leq 5°$.

2. **Keypoint Detection Reliability**

Reliability will be measured as the percentage of measurement sessions in which all three required anatomical keypoints are successfully detected in both images.
This metric corresponds to the NFR requirement of $\geq 95\%$ successful detection.

3. **Processing Time**

Processing time will be defined as the total duration from image upload to final angle output for a complete measurement session.
Performance will be considered acceptable if this duration remains within ≤ 10 seconds.

4. **Efficiency**

Efficiency will be evaluated based on the time required for a first-time user to complete a full measurement session after reviewing a brief tutorial. The system must enable successful completion of the entire workflow in no more than 120 seconds.

5. **System Robustness**

Robustness will be evaluated by testing the system on images from participants with diverse foot anatomies. The system must successfully detect all required keypoints in at least 90% of sessions across different participants, ensuring stable performance under natural anatomical variability.

### 4.6 Expected Challenges

Developing an automated dorsiflexion-measurement system presents several challenges that must be addressed to ensure reliable clinical use. First, the quality of images captured by different devices may vary in lighting, angle, and background, which can influence the model's ability to correctly detect anatomical keypoints. In addition, accurately identifying small foot landmarks, such as the ankle joint or fifth metatarsal, can be difficult when patient anatomy, skin tone, or swelling obscure these features.
Another expected challenge involves the limited availability of diverse, labeled training data. Since DeepLabCut requires representative examples to generalize well, the model may initially struggle with unusual foot shapes or clinical conditions not present in the training set. Performance differences may also arise when using the system in new environments or with different patient populations.

From a computational perspective, running deep-learning models such as ResNet-50 may introduce latency on lower-power devices, requiring optimization for smooth operation. Finally, achieving clinical acceptance depends on validating the system against manual goniometric measurements and ensuring that the interface communicates results clearly, especially in cases where detection confidence is low. Addressing these challenges is essential for developing a system that is accurate, robust, and suitable for real clinical workflows.

### AI Tools

Google Gemini: **https://gemini.google.com/**
Was used as an auxiliary AI tool to assist in generating and refining key visual diagrams for the project, including the project workflow overview (Figure 1), the next-generation ankle assessment illustration (Figure 2), and the system architecture schematic (Figure 3) presented in this book.

ChatGPT (OpenAI): **https://chat.openai.com/**
Was used as an AI-based research and writing assistant to support literature understanding, academic phrasing, and clarification of technical concepts throughout the project.

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