SAVITRIBAI PHULE PUNE UNIVERSITY

A PRELIMINARY PROJECT REPORT ON

"Physiotherapy Pose Detection"

SUBMITTED TOWARDS THE
PARTIAL FULFILLMENT OF THE REQUIREMENTS OF

BACHELOR OF ENGINEERING
(INFORMATION TECHNOLOGY)
BY

Chaitanya Pathak **Roll No**:B401020327
Atharva Chormale **Roll No**:B401020286
Jay Patil **Roll No**:B401020303

Under The Guidance of

Prof. Jaitee bankar

Sinhgad Institutes

DEPARTMENT OF INFORMATION TECHNOLOGY
R.M.D. SINHGAD SCHOOL OF ENGINEERING

PUNE - 411058

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CERTIFICATE

This is to certify that the Project Entitled

"Physiotherapy Pose Detection"

Submitted by

Chaitanya Pathak	**Roll No**:B401020327
Atharva Chormale	**Roll No**:B401020286
Jay Patil	**Roll No**:B401020303

is a bonafide work carried out by Students under the supervision of Prof.Jaitee Bankar and it is submitted towards the partial fulfillment of the requirement of Bachelor of Engineering (Information Technology) Project.

Date:-

Place:-

Prof. Jaitee Bankar	Prof. Shweta Kale	Dr. V. V. Dixit
Guide	Head of Department	Principal

Internal Examiner	External Examiner

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Name Of The Students

1. **Atharv Chormale**
2. **Chaitanya Pathak**
3. **Jay Patil**

ABSTRACT

Human pose recognition has become an important focus in computer vision, particularly for applications in physiotherapy and self-assessment. In this work, we present an approach for accurate physiotherapy pose assessment using deep learning algorithms. The proposed system utilizes pose detection to facilitate the self-guided learning of physiotherapy exercises. Specifically, our approach employs multi-part pose detection through a standard PC camera to capture and analyze physiotherapy poses in real-time. We introduce an enhanced scoring algorithm capable of assessing various poses, which ensures adaptability across different pose types and environments. Additionally, a hybrid machine learning model is implemented using Linear Regression to extract features from key points identified in each frame, leveraging the Open Pose framework. The robustness of this system is evaluated across multiple physiotherapy poses in diverse settings, demonstrating its potential for effective, real-time physiotherapy assessment.

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1. INTRODUCTION

BACKGROUND AND BASICS

Physiotherapy pose detection is a vital application in computer vision and image processing, gaining prominence among researchers due to its impact on healthcare and rehabilitation. This technology focuses on recognizing and analyzing human poses to ensure accurate exercise execution, crucial for effective physiotherapy. By leveraging advanced algorithms, pose detection systems enhance human-computer interaction, support self-guided rehabilitation, and promote patient safety. The growing demand for such systems stems from their practical utility in clinical settings, home-based therapy, and tele-rehabilitation, addressing the need for accessible, real-time solutions to improve therapeutic outcomes.

1.1.1 Motivation

The increasing prevalence of musculoskeletal disorders and the need for accessible rehabilitation solutions drive the development of automated physiotherapy pose detection systems. Manual supervision by therapists is resource-intensive, prone to errors, and often impractical for home-based therapy. Incorrect pose execution can reduce exercise effectiveness or cause injuries, highlighting the need for reliable, cost-effective systems. Inspired by advancements in deep learning and computer vision, this project aims to provide real-time pose correction using OpenPose and Logistic Regression, empowering patients with independent, accurate rehabilitation and reducing dependency on manual oversight.

1.1.2 Objectives

1. **Automated Pose Recognition**: Develop a system to automatically detect and classify physiotherapy poses from real-time video using a standard PC camera.
2. **Pose Correctness Assessment**: Identify and distinguish between correct and incorrect poses, providing immediate feedback to enhance exercise accuracy.
3. **Enhance Rehabilitation**: Improve therapeutic outcomes by ensuring precise pose execution in clinical and home settings.
4. **Reduce Manual Supervision**: Minimize reliance on therapists through automated pose analysis and feedback via a Tkinter GUI.
5. **Timely Feedback**: Deliver real-time corrective instructions to users, fostering effective self-guided physiotherapy.
6. **Leverage Machine Learning**: Utilize OpenPose for keypoint detection and hybrid machine learning models, including Logistic Regression, to ensure robust pose classification.

2. LITERATURE SURVEY

1. Literature Survey on Pose Detection for Physiotherapy Posture Recognition

Author: Yash Agrawal, Yash Shah, Abhishek Sharma
Publisher: ARXIV.ORG
Year: 2020

The paper by Yash Agrawal, Yash Shah, and Abhishek Sharma investigates the use of pose detection techniques to assist individuals in performing physiotherapy exercises more accurately by identifying specific postures. This survey analyzes relevant research on pose detection methods and their application in physiotherapy.

Challenges in Posture Recognition:
Posture recognition is a complex task due to limited dataset availability and the need for real-time detection. Common challenges include:
Dataset limitations: The lack of large and diverse datasets hinders the development of accurate posture recognition models.
Real-time detection requirements: Real-time analysis of postures is crucial in physiotherapy to provide immediate feedback to users.

Dataset Development and Model Implementation:
To address these challenges, the authors created a large dataset containing over 5,500 images representing ten different physiotherapy poses. They applied the tensorflow pose estimation algorithm, which generates a human skeletal structure in real-time. Key aspects of the implementation include:
Feature extraction via tensorflow pose estimation: The angles of joints are calculated from the skeleton structure and used as features for various machine learning models.
Training and testing split: 80% of the dataset was used for training, and 20% for testing.
Machine Learning Models and Performance:
The dataset was tested on various machine learning classification models. The Random Forest Classifier achieved the highest accuracy, with a reported accuracy of 99.04%.

Advantages:
1. Automated posture analysis: The tensoreflow pose algorithm simplifies feature extraction by automatically generating joint angles.
2. High accuracy: The Random Forest model's 99.04% accuracy indicates strong performance in physiotherapy posture recognition.

Disadvantages and Future Directions:
1. Dataset diversity: The dataset could be expanded to cover additional poses or variations in physiotherapy exercises.
2. Generalizability: Future work may focus on applying the model to other real-time applications or diverse environments.
3. Real-time feedback: While effective in analyzing poses, the system's real-time feedback capabilities could be further optimized.

2. Fine-Grained Hierarchical Pose Classification for Physiotherapy Pose Recognition

Author: Manisha Verma, Sudhakar Kumawat, Yuta Nakashima
Publisher: ARXIV.ORG
Year: 2020

Introduction
Human pose estimation plays a crucial role in many computer vision applications, including physiotherapy pose recognition. Traditional pose estimation models are limited by insufficient pose diversity, object occlusion, and viewpoint variations. These challenges make it difficult to apply the models to more complex real-world scenarios. To address these limitations, this paper introduces a novel approach for fine-grained hierarchical pose classification. The authors propose a large-scale dataset, **Physiotherapy-82,** for recognizing 82 different physiotherapy poses with varying degrees of complexity. The dataset utilizes hierarchical labeling based on body configurations to classify poses effectively.

Related Work
In the field of human pose estimation, existing datasets have typically been limited in terms of pose variety and have not addressed the complexity posed by different viewpoints and occlusions. Prior efforts in pose estimation include:
- Simple pose classification based on manually annotated keypoints, which can lack the necessary variability to generalize well ([1, 2]).
- Existing models that do not handle occlusions or variations in body postures effectively ([3, 4]).
- Attempts at hierarchical pose classification, which offer multiple levels of pose granularity, but fail to implement complex datasets like physiotherapy poses ([5, 6]).

Recent work has applied Convolutional Neural Networks (CNNs) and other deep learning models, such as DenseNet, to classify poses more accurately, leveraging hierarchical label structures to improve classification performance ([7, 8]).

Proposed Approach
The paper proposes the Physiotherapy-82 dataset, which consists of 82 distinct physiotherapy poses classified into a hierarchical structure. The key contributions are:
1. Fine-grained Hierarchical Classification: The dataset includes three levels of hierarchy: body positions, variations of body positions, and the actual physiotherapy poses, which enhances model training for complex scenarios.
2. State-of-the-Art CNNs: Convolutional Neural Networks (CNNs) are employed for feature extraction, and the authors use hierarchical variants of DenseNet to capture the relationships between the hierarchical labels and improve classification performance.
3. Large-Scale Dataset: The Physiotherapy-82 dataset is a significant resource, allowing for improved model generalization and accuracy in real-world applications.

Evaluation and Results:
The proposed hierarchical approach was evaluated using several CNN architectures on the Physiotherapy-82 dataset. The results showed promising classification performance, with the models able to classify physiotherapy poses with high accuracy. Notably, DenseNet architectures provided superior results due to their ability to efficiently learn hierarchical features.

Discussion:
The fine-grained hierarchical pose classification approach improves on previous models by tackling the limitations posed by viewpoint changes and occlusion. The **Physiotherapy-82** dataset enables more robust training and testing of pose estimation models. By integrating multiple levels of pose annotations, this approach provides a more granular understanding of physiotherapy poses, which is particularly valuable for applications like rehabilitation monitoring and automated coaching.

Advantages:
1. Enhanced Pose Recognition: The hierarchical labeling system captures the complexity of physiotherapy poses and improves the model's ability to recognize and classify them accurately.
2. Scalable Dataset: The Physiotherapy-82 dataset includes a large number of poses and can be expanded further, offering a valuable resource for future research.
3. Deep Learning Models for Robust Performance: The use of DenseNet and other CNN variants significantly improves the accuracy and efficiency of pose classification, particularly for complex poses.
4. Applicability in Real-World Scenarios: The dataset and classification methods are well-suited for real-time physiotherapy pose assessment in clinical settings.

Disadvantages:
1. Complexity in Annotation: Creating hierarchical labels for each pose in the dataset can be time-consuming and requires domain expertise.
2. Limited to Physiotherapy Poses: While the dataset is robust for physiotherapy, it may not generalize well to other types of human pose estimation tasks without further adaptation.

3. Physiotherapy Posture Recognition Using Electromyography Signals and Machine Learning

Author: Pradchaya Anantamek
Publisher: IEEE
Year: 2019

Introduction
Exercise through physiotherapy postures has gained significant popularity due to its benefits in increasing flexibility, strengthening muscles, and improving the respiratory system. However, ensuring the correctness of these physiotherapy postures during practice is challenging, which can hinder the full benefits of the exercises. This paper proposes a system for physiotherapy posture recognition, focusing on verifying the correctness of lower-limb muscle movements during physiotherapy practice. The study involved ten subjects (five males and five females) performing five different physiotherapy postures, and the system aims to provide accurate feedback on posture correctness.

Related Work
Previous work in the domain of physiotherapy posture recognition has predominantly focused on video-based analysis or wearable sensors, such as accelerometers and gyroscopes, for motion tracking. However, these systems often struggle to accurately capture subtle muscle movements. Some related approaches include:
- Motion-based posture recognition using visual or sensor data, which can be limited by environmental factors such as lighting or occlusions ([1, 2]).
- Electromyography (EMG) signals have been explored for muscle activity monitoring, but their application to posture recognition has been relatively underexplored ([3, 4]).
- Machine learning techniques have been applied to classify human posture using sensor data, achieving moderate success in more controlled environments ([5, 6]).

Proposed Approach
The paper introduces a physiotherapy posture recognition system that leverages Electromyography (EMG) signals to track the motion of lower-limb muscles during physiotherapy exercises. The approach focuses on the following aspects:
1. Electromyography (EMG) Signal Analysis: EMG signals are used to measure muscle activity from four different lower-limb muscles in both legs to accurately recognize physiotherapy postures.
2. Machine Learning for Posture Recognition: Three different machine learning algorithms are applied to classify physiotherapy postures based on the EMG signals: Random Forest, Decision Tree, and other classifiers.
3. Posture Accuracy Verification: The system evaluates posture accuracy by comparing the muscle activity patterns against predefined benchmarks to ensure the correctness of the movements.

Evaluation and Results:
The system was tested with data collected from ten subjects performing five different physiotherapy postures. The results showed that the Random Forest Decision Tree algorithm achieved the highest accuracy of 87.43% in recognizing physiotherapy postures compared to other machine learning algorithms. This accuracy demonstrates the potential of using EMG signals for posture recognition and verification.

Discussion:

The proposed system offers a novel approach to physiotherapy posture verification by leveraging EMG signals, which directly measure muscle activity. This is a significant improvement over traditional video-based systems, as EMG signals are less prone to environmental factors like lighting and occlusions. The high accuracy achieved by the Random Forest algorithm highlights its effectiveness in classifying physiotherapy postures.

Advantages:

1. Accurate Muscle Movement Analysis: The use of EMG signals allows for precise tracking of muscle movements, improving the accuracy of posture recognition.
2. Higher Recognition Accuracy: The Random Forest Decision Tree algorithm achieved high accuracy (87.43%) compared to other classifiers, making the system reliable for practical use.
3. Robust to Environmental Factors: Unlike vision-based systems, EMG-based systems are not affected by lighting conditions, occlusions, or camera angles, ensuring stable performance across different environments.
4. Practical Application in Physiotherapy: The system can be implemented in real-time physiotherapy settings to provide feedback and ensure correct posture execution during rehabilitation exercises.

Disadvantages:

1. Limited to Lower-Limb Postures: The system focuses only on lower-limb muscle movements, limiting its applicability to other body parts.
2. Dataset Size: The study involved only ten subjects, and the results may vary with a larger and more diverse dataset.
3. Hardware Requirements: The system requires EMG sensors, which may be costly or cumbersome for widespread use in physiotherapy clinics or home settings.
4. Complexity in Signal Interpretation: EMG signals can be difficult to interpret due to noise, requiring sophisticated filtering and processing techniques.

4. Human Pose Synthesis Using Generative Neural Networks for Novel Poses

Author: Guha Balakrishnan, Amy Zhao
Publisher: DSPACE-MIT
Year: 2020

Introduction

Human pose synthesis involves generating realistic depictions of a person in a specific pose while retaining the appearance of both the person and the background. Traditional methods struggle with synthesizing new poses, particularly when a person's body must be repositioned while preserving the overall realism of the scene. This paper proposes a modular generative neural network that synthesizes novel human poses using training pairs of images and poses derived from human action videos. The network divides the scene into body part and background layers, moves body parts to new locations, and refines their appearance to create a new image.

Related Work

Research on human pose synthesis typically involves generating realistic images while preserving both the subject's appearance and the scene context. Early methods used manual techniques to adjust body parts in images, but these lacked realism and were computationally intensive. Recent approaches utilize deep learning, particularly generative models, to synthesize novel human poses more efficiently and with better accuracy. These models, however, often struggle with cross-action pose synthesis and may produce unrealistic images when synthesizing actions outside of their training data.

Proposed Approach

The authors introduce a generative neural network that operates in multiple stages to synthesize novel human poses:

1. Separation of Body and Background: The network separates the human body from the background in the scene, treating each as distinct components.
2. Pose Generation: Body parts are repositioned in the new pose while maintaining their appearance through refinement layers.
3. Hole-Filling and Compositing: The background is filled where necessary, and the synthesized body parts are integrated seamlessly into the new scene.
4. Adversarial Training: An adversarial discriminator ensures the synthesized image retains realistic details conditioned on the desired pose, improving the network's ability to generate high-quality images.

Evaluation and Results

The method was evaluated on three action classes: golf, physiotherapy/workouts, and tennis. The synthesized images demonstrated high accuracy both within action classes and across different action categories. Additionally, the system successfully produced coherent videos from sequences of desired poses, showcasing its potential for dynamic applications in action-based image and video generation.

Discussion

This method significantly improves pose synthesis by decoupling the body and background components and generating more realistic body movements. The adversarial training mechanism further ensures that the synthesized images are realistic in terms of appearance and context, making the system versatile across different actions and poses. The approach is particularly useful for generating images of people performing specific activities where traditional methods would struggle.

Advantages:

1. Realistic Pose Synthesis: The modular approach allows for realistic human pose generation across different action classes.
2. Cross-Action Synthesis: The system works effectively across various activities, demonstrating its flexibility in pose generation.
3. Coherent Video Generation: The ability to produce coherent video sequences from a series of poses is valuable for applications in sports, fitness, and animation.
4. Separation of Body and Background: This improves accuracy and realism, especially when reusing background scenes for different poses.

Disadvantages:

1. Complexity: The modular architecture and adversarial training make the system computationally intensive and potentially slower compared to traditional methods.
2. Limited to Pre-Trained Poses: The network's performance may degrade when synthesizing poses not covered in the training data.
3. Data Dependency: High-quality training data is essential for ensuring the system can generalize well across different actions and poses.

5. IoT-Based Privacy-Preserving Physiotherapy Posture Recognition Using Deep Learning

Author: Munkhjargal Gochoo, Tan-Hsu Tan
Publisher: IEEE
Year: 2018

Introduction:
With the rise in the number of physiotherapy practitioners, many individuals now seek to practice physiotherapy exercises at home. While some existing methods for posture recognition rely on RGB/Kinect cameras or wearable devices, these can pose privacy concerns or prove impractical for long-term use. This paper presents an IoT-based, privacy-preserving physiotherapy posture recognition system that uses deep convolutional neural networks (DCNN) and low-resolution infrared sensors to detect physiotherapy poses without compromising privacy.

Related Work:
Previous research in physiotherapy posture recognition has focused on camera-based or wearable sensor systems. However, camera-based systems raise privacy issues, while wearable devices are often uncomfortable for long-term use. Recent advancements have explored IoT-based solutions for posture recognition, combining low-cost sensors with machine learning algorithms to improve both accuracy and privacy.

Proposed Approach:
The authors propose an IoT-based physiotherapy posture recognition system that uses a wireless sensor network (WSN) with infrared thermal sensors:
1. Wireless Sensor Network (WSN): The WSN includes three nodes, each with 8×8 pixel thermal sensors and a Wi-Fi module for connectivity.
2. Deep Learning for Posture Recognition: The WSN data is processed using a deep convolutional neural network to recognize different physiotherapy postures.
3. Privacy Preservation: Unlike camera-based systems, the thermal sensors used in this system do not capture sensitive personal information, ensuring privacy.

Evaluation and Results:
The system was tested with 18 volunteers performing 26 different physiotherapy postures over two sessions. The results demonstrated an F1-score of 0.9989 for posture recognition using all three axes (x, y, z) and 0.9854 for the y-axis alone. The system exhibited low latency, with an average processing time of 107 ms per posture image.

Discussion:
The proposed system provides an effective and privacy-preserving solution for at-home physiotherapy posture recognition. By using thermal sensors instead of cameras, the system addresses privacy concerns while maintaining high accuracy in posture detection. The integration of deep learning allows the system to effectively recognize and classify a variety of physiotherapy postures.

Advantages:
1. Privacy-Preserving: The use of infrared sensors ensures that no personal information is captured, unlike vision-based systems.

2. High Accuracy: The system achieved impressive accuracy with F1-scores close to 1, making it highly reliable.
3. Low Latency: The system processes images quickly, making it suitable for real-time applications.
4. Scalability: The system can be scaled to detect additional poses or adjusted for different environments with minimal changes.

Disadvantages:
1. Limited Posture Dataset: The system's accuracy may vary with more diverse or complex posture data.
2. Infrastructure Requirements: The IoT-based setup requires thermal sensors and a stable Wi-Fi connection, which may not be available in all environments.
3. Sensor Resolution: The low-resolution thermal sensors may limit the detail captured in more complex movements, potentially affecting accuracy.

6. Core Muscle Strengthening Using Pose Detection for Children

Author: Ian Gregory
Publisher: IEEE
Year: 2020

Introduction:
Core muscle strength is essential for children's physical development and allows them to perform various physical activities. This research focuses on developing a pose detection system to help improve core muscle strength through physiotherapy-like poses, ensuring children’s postures are correctly performed. The system aims to assist trainers in ensuring proper execution of exercises and correcting mistakes during coaching sessions.

Related Work:
Previous methods for pose detection have been developed to assist with fitness and physiotherapy, especially for children. However, many of these methods do not account for variations in individual poses or the specific needs of children. This research looks to standardize pose detection and provide feedback for improvement.

Proposed Approach:
The system uses a pose detection algorithm to track and evaluate children's core muscle strengthening poses:
1. Pose Detection for Physiotherapy-Like Exercises: The system recognizes and analyzes different core-strengthening poses.
2. Error Detection: The system compares observed poses with standardized reference poses and identifies deviations to guide trainers in correcting mistakes.
3. Real-Time Feedback: The system provides feedback to both trainers and children, improving coaching accuracy.

Evaluation and Results:
The results showed that the system could effectively identify deviations from correct poses, though it faced challenges with some unique poses that could not be fully recognized by the algorithm. Despite this, the system successfully supported trainers in improving exercise execution.

Discussion:
This system offers a standardized solution for pose detection, which is crucial for ensuring children perform exercises safely and correctly. However, due to the diversity of possible poses, the system may encounter challenges with identifying all variations, especially those that are unique or unfamiliar.

Advantages:
1. Improved Exercise Accuracy: Trainers can provide better guidance and correction through real-time feedback.
2. Standardization: The system standardizes the detection of core muscle strengthening poses, reducing variability.
3. Safe Physiotherapy Execution: Helps ensure children practice poses correctly, preventing injuries.

Disadvantages:

1. Pose Variability: Unique poses may not be detected accurately, limiting the system's flexibility.
2. Trainer Dependency: The system requires experienced trainers to interpret feedback and provide appropriate corrections.3. Limited Recognition of Complex 3. Poses: Some complex or unconventional poses might not be correctly detected or classified.

3. PROBLEM STATEMENT

Traditional physiotherapy relies heavily on manual observation by therapists to ensure correct pose execution, which is resource-intensive, susceptible to human error, and often impractical for home-based rehabilitation. Patients frequently struggle to self-correct poses without real-time feedback, leading to reduced exercise effectiveness or potential injuries. Existing automated systems lack accessibility, real-time accuracy, or user-friendly interfaces, limiting their adoption in diverse settings. This project aims to develop a machine learning-based physiotherapy pose detection system that utilizes OpenPose for keypoint detection and Logistic Regression for pose classification. By analyzing video input from a standard PC camera, the system provides automated, real-time feedback through a Tkinter GUI, reducing dependency on manual supervision, enhancing exercise accuracy, and promoting patient independence in rehabilitation.

4. SOFTWARE REQUIREMENT SPECIFICATION

4.1 SYSTEM OVERVIEW

Physiotherapy pose detection is a significant application in computer vision, gaining traction due to its utility in healthcare and rehabilitation. This system leverages OpenPose for real-time keypoint detection and machine learning algorithms, such as Logistic Regression, to classify physiotherapy poses, ensuring accurate exercise execution. It supports human-computer interaction by providing immediate feedback through a Tkinter-based GUI, enhancing accessibility for patients in clinical and home settings. The system's practical applications in physiotherapy, tele-rehabilitation, and fitness underscore its importance in improving therapeutic outcomes and patient independence.

4.2 FUNCTIONAL REQUIREMENTS

4.2.1 System Feature 1: User and Admin Management

- **Admin**: Manages user accounts via a web module, verifying registration details and approving/rejecting users. Admins load and update physiotherapy pose datasets in CSV format for training.
- **User**: Registers with personal information, sending a verification request to the admin. Upon approval, users log in to perform exercises and receive pose feedback via the GUI.

4.2.2 System Feature 2: Pose Detection and Classification

- **System**: Utilizes OpenPose with Convolutional Neural Networks (CNNs) for keypoint detection and Logistic Regression for classifying poses as correct or incorrect. Features like joint angles are extracted and analyzed to provide real-time feedback on pose accuracy.

4.3 NON-FUNCTIONAL REQUIREMENTS

4.3.1 Performance Requirements

The system processes video frames in <100ms with >85% classification accuracy, ensuring real-time feedback. Data encryption and GUI rendering are optimized for fast performance, enabling seamless user interaction.

4.3.2 Safety Requirements

The modular design facilitates error detection and correction, allowing easy updates to incorporate new poses or algorithms without disrupting system functionality.

4.3.3 Software Quality Attributes

- **Adaptability**: Supports diverse users and physiotherapy poses.
- **Availability**: Freely accessible with straightforward installation.
- **Maintainability**: Modular code enables easy error fixes post-deployment.
- **Reliability**: High accuracy and stability enhance system trust.
- **User Friendliness**: Intuitive Tkinter GUI ensures ease of use.
- **Integrity**: Controls unauthorized access to user and pose data.
- **Security**: Employs encrypted SQLite3 storage for user credentials.
- **Testability**: Designed for comprehensive testing across modules.

4.4 DEPLOYMENT ENVIRONMENT

4.4.1 Database Requirements

SQLite3 is used for user management and model storage, supported by DB Browser for SQLite (DB4S) for creating and editing database files.

4.4.2 Software Requirements

- **Operating System**: Windows 10 (64-bit).
- **Coding Language**: Python 3.8.
- **IDE**: Visual Studio Code (VSCode).
- **Framework**: Tkinter, OpenCV, OpenPose, Scikit-learn.

4.4.3 Hardware Requirements

- **Processor**: Intel i5 or above.
- **RAM**: 8GB.
- **Hard Disk**: 40GB.
- **Webcam**: Standard PC camera for video input.

4.5 EXTERNAL INTERFACE REQUIREMENTS

4.5.1 User Interface

A Tkinter-based GUI enables users to register, log in, view real-time video, and receive pose feedback, ensuring an interactive physiotherapy experience.

4.5.2 Hardware Interfaces

The system interfaces with a webcam for video capture and requires an Intel i5 processor, 8GB RAM, and 40GB hard disk for efficient processing. VSCode enhances development with fast code suggestions.

4.5.3 Software Interfaces

- **Operating System**: Windows 10.
- **IDE**: spyder.
- **Programming Language**: Python 3.8 with libraries (OpenCV, OpenPose, Scikit-learn, Tkinter, SQLite3) for robust functionality.

5. FLOW CHARTS

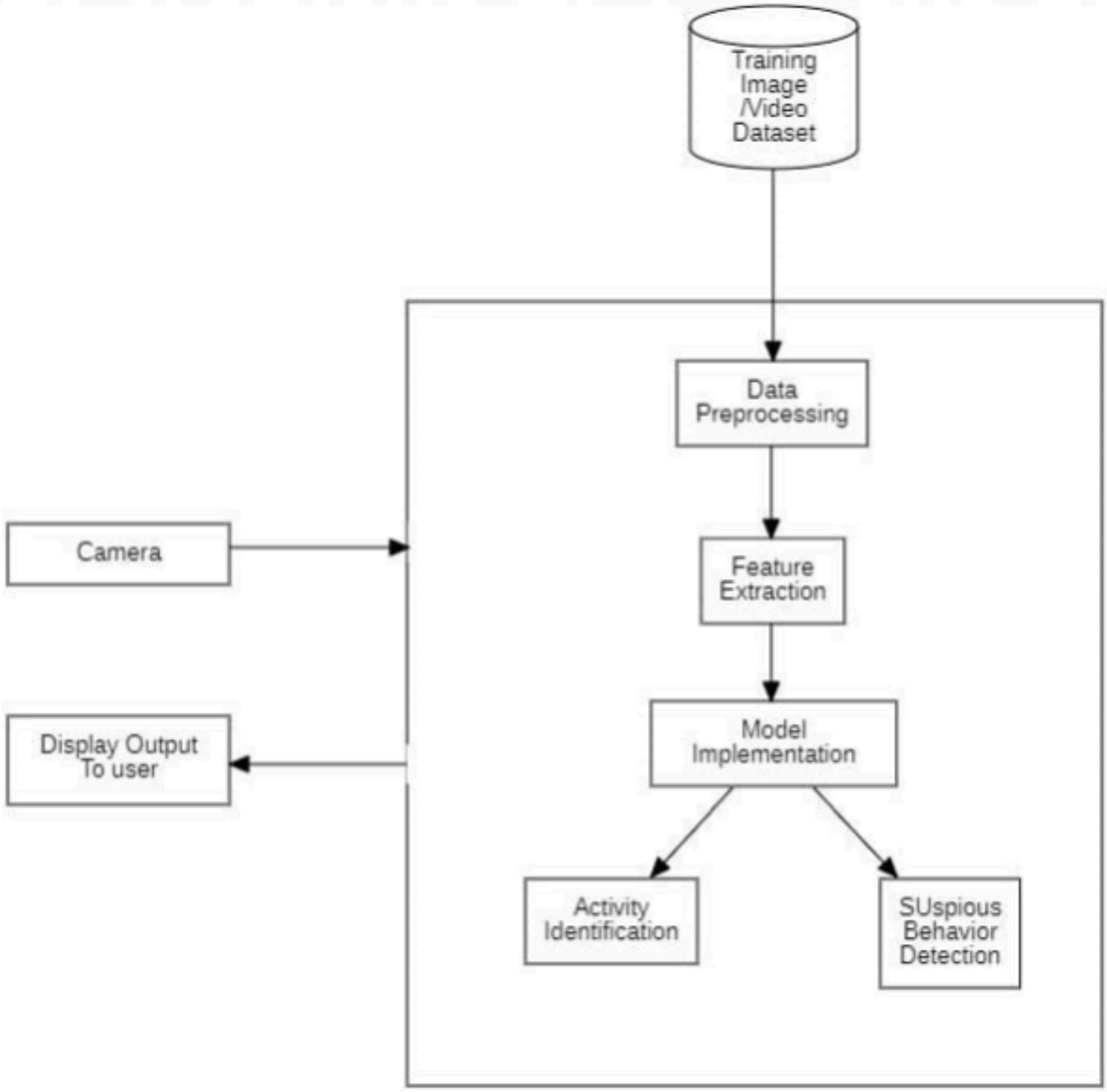


Fig 5.1 Flowchart for the system

6. HIGH LEVEL DESIGN OF PROJECT

6.1 DATA FLOW DIAGRAM

6.1.1 Level 0 Data Flow Diagram

The Level 0 DFD represents the system as a single process, "Physiotherapy Pose Detection," taking video input from the User, processing it, and producing feedback output via the GUI.

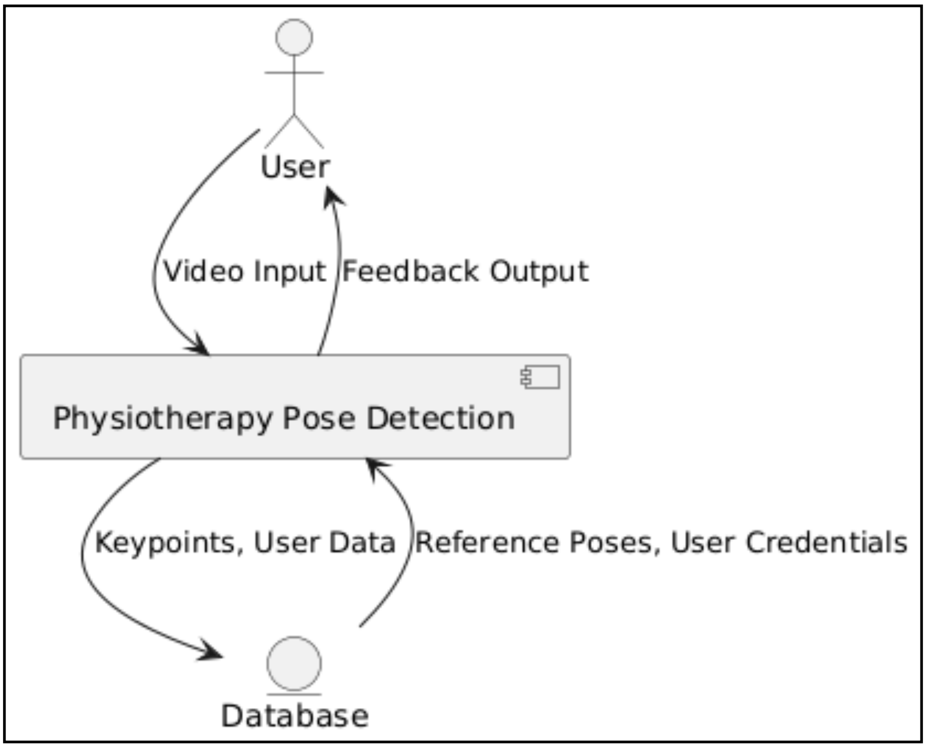


Figure 6.1.1: Data Flow (0) diagram

6.1.2 Level 1 Data Flow Diagram

The Level 1 DFD breaks the process into four main steps:

- **Preprocessing:** Normalizes video frames (e.g., resizing, contrast adjustment) for pose detection
- **Keypoint Detection:** Uses OpenPose to extract body keypoints from preprocessed frames
- **Feature Extraction:** Computes features (e.g., joint angles, distances) from keypoints
- **Pose Classification and Feedback:** Classifies poses using machine learning models and generates feedback for GUI display

Level 1 DFD

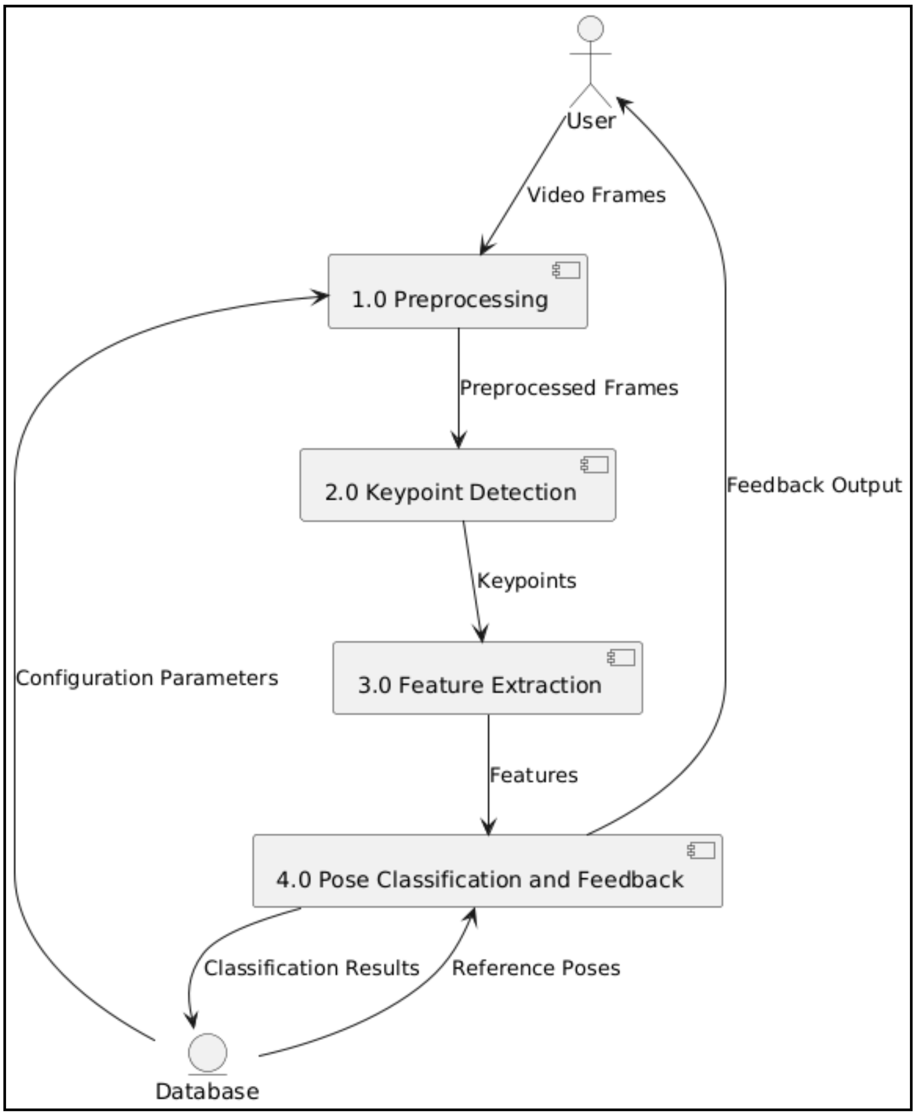


Figure 6.1.2: Data Flow (1) diagram

6.1.3 Level 2 Data Flow Diagram

The Level 2 DFD details each Level 1 process:

- **Preprocessing:** Includes frame resizing, noise filtering, and normalization
- **Keypoint Detection:** Involves OpenPose's Part Confidence Maps and Part Affinity Fields (PAFs) to associate keypoints
- **Feature Extraction:** Calculates joint angles (e.g., using cosine law) and distances between keypoints
- **Pose Classification and Feedback:** Uses Logistic Regression to classify poses, compares results to reference poses, and generates corrective instructions

Level 2 DFD (Process 2.0 - Keypoint Detection):

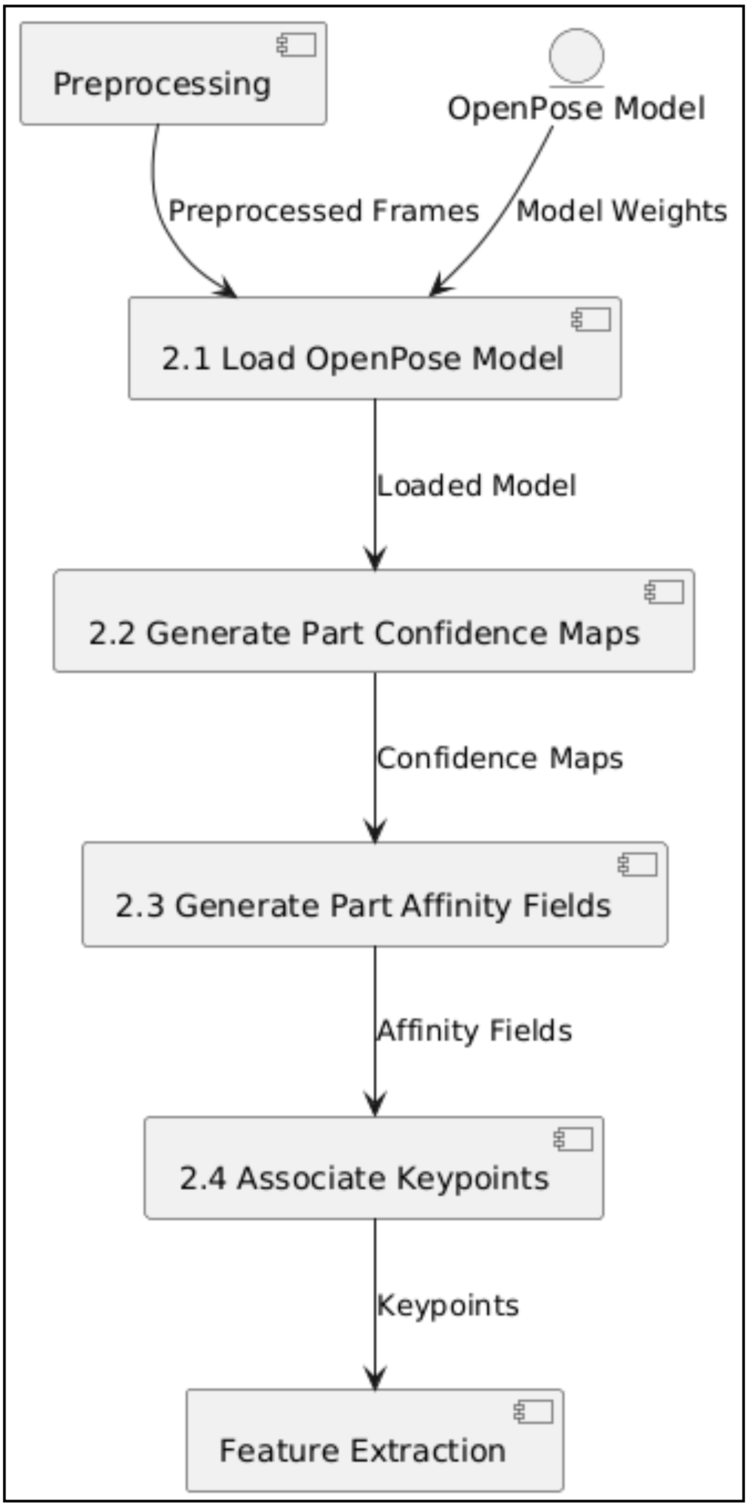


Figure 6.1.3: Data Flow (2) diagram

Level 2 DFD (Process 4.0 - Pose Classification and Feedback) :

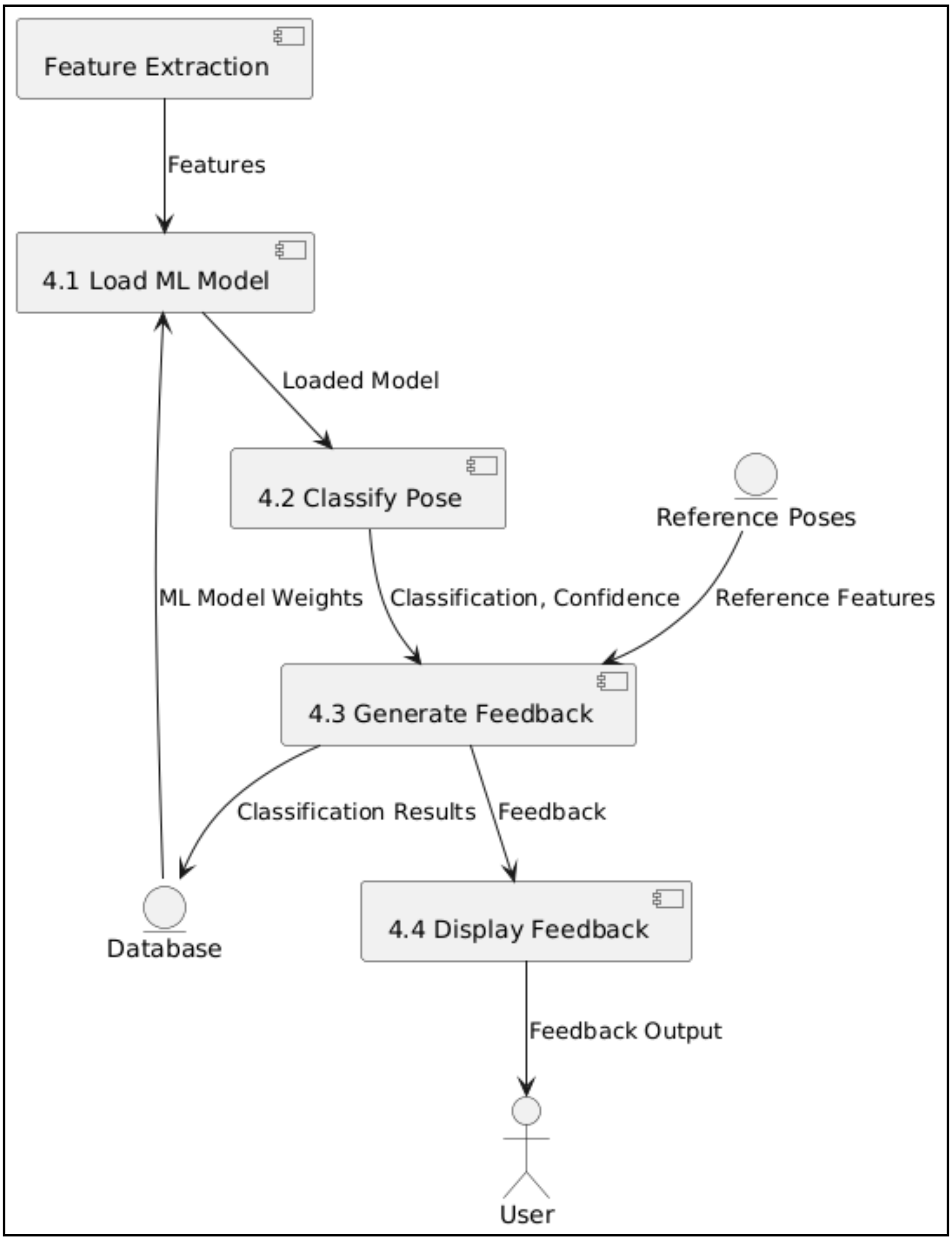


Figure 6.1.4: Data Flow (2) diagram

6.2 USE CASE DIAGRAM

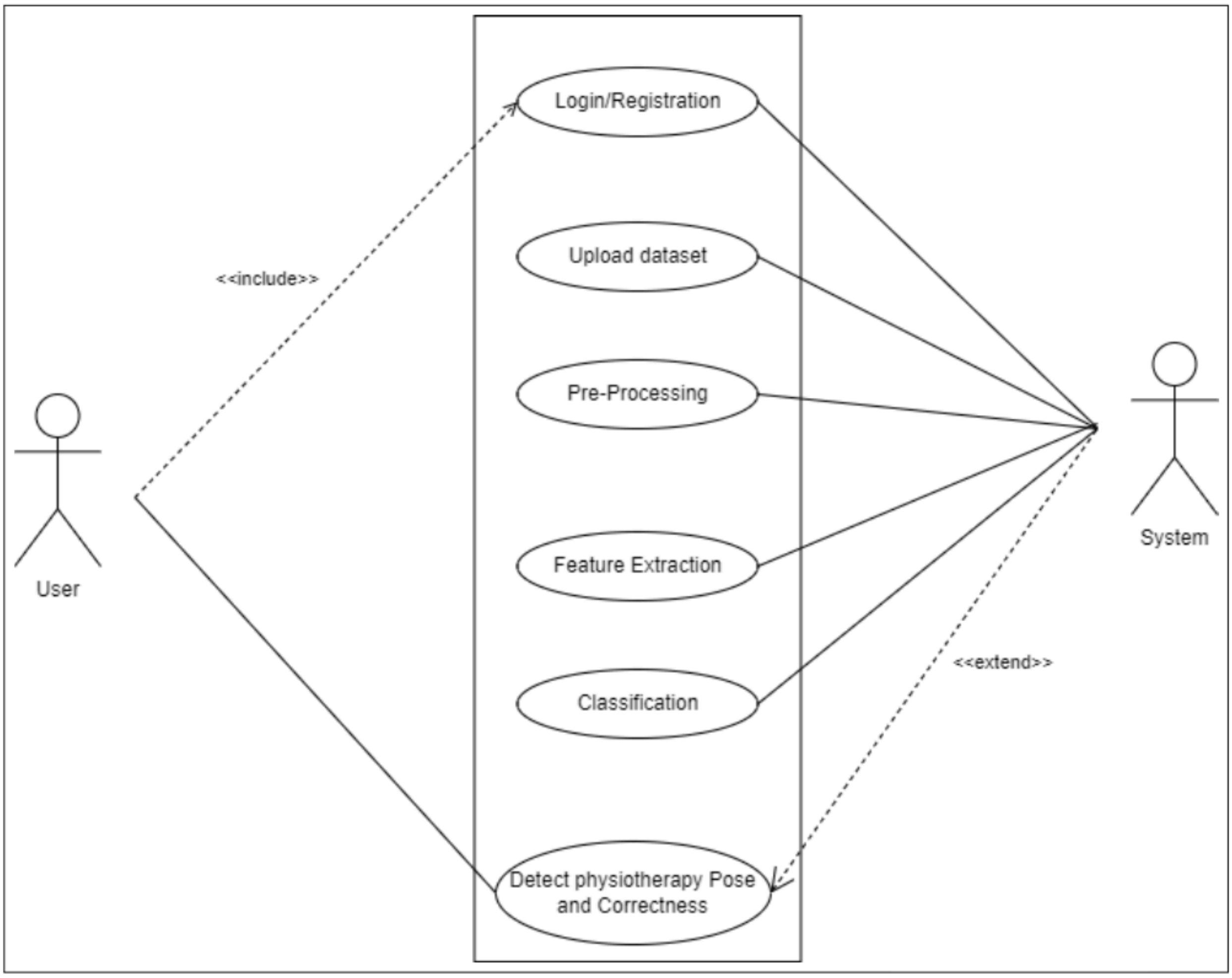


Figure 6.2.1: Use Case Diagram

6.3 ACTIVITY DIAGRAM

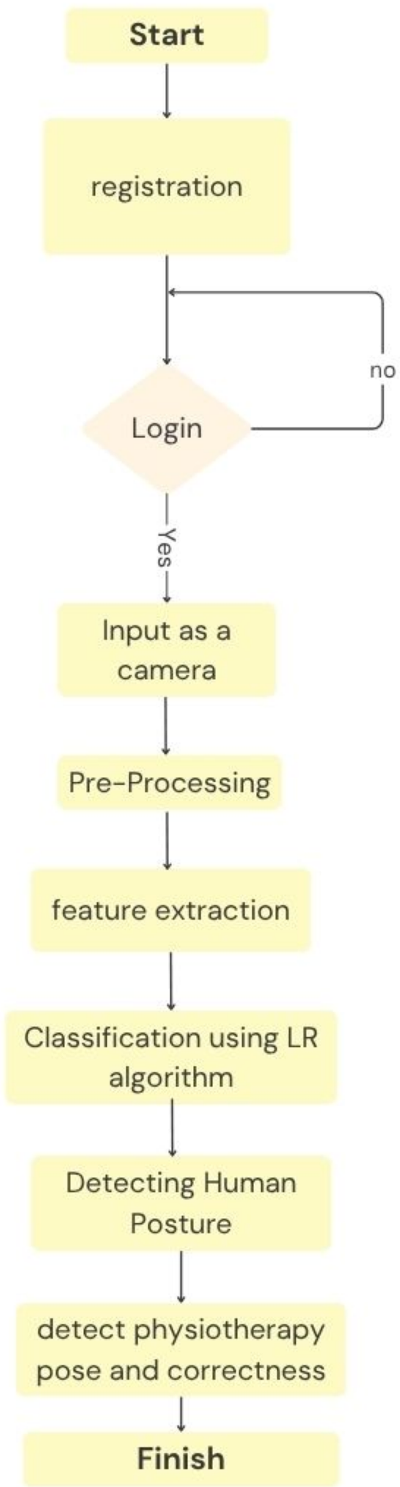


Figure 6.3.1: Activity Diagram

6.4 SEQUENCE DIAGRAM

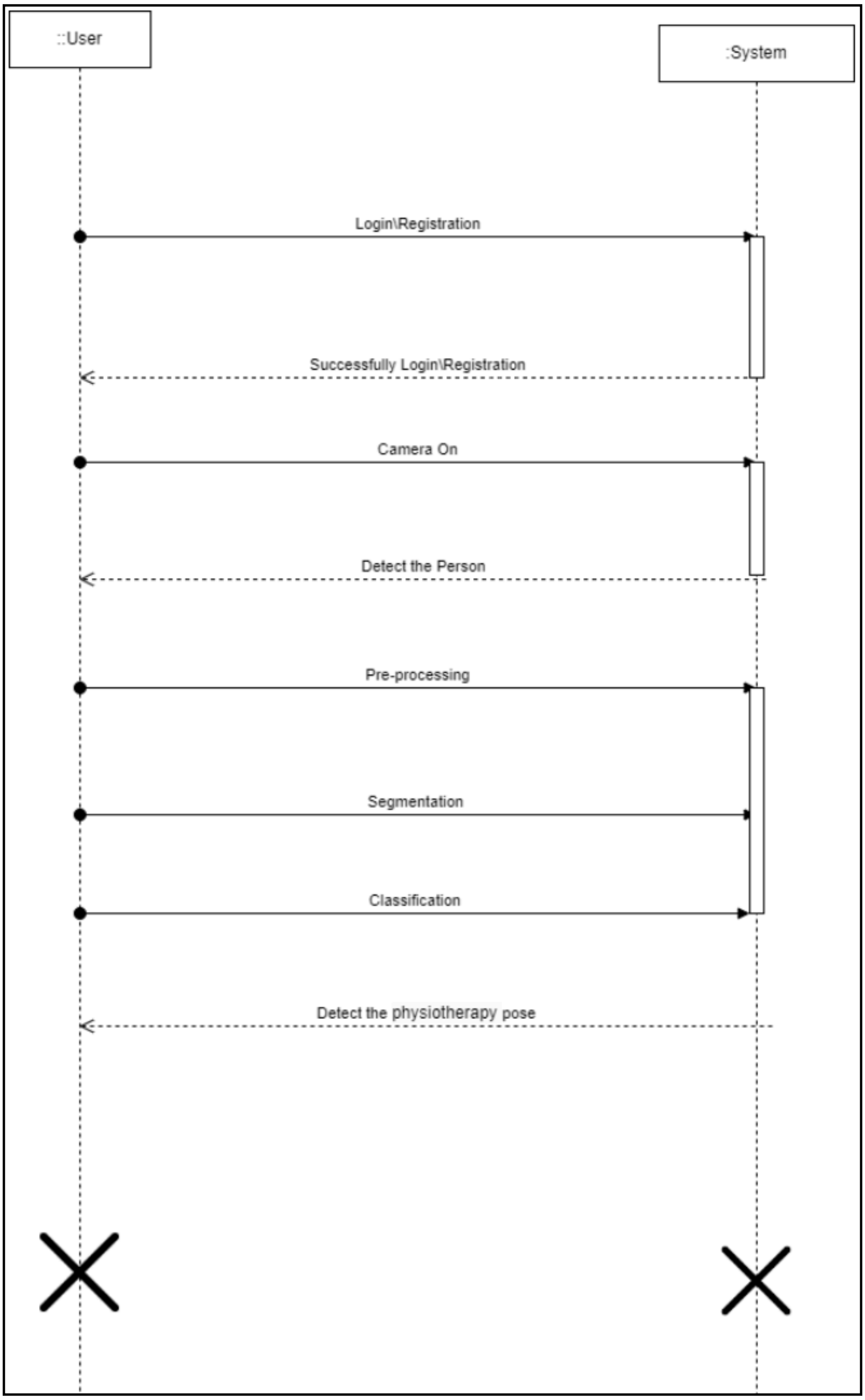


Figure 6.4.1: Sequence Diagram

6.5 ER DIAGRAM

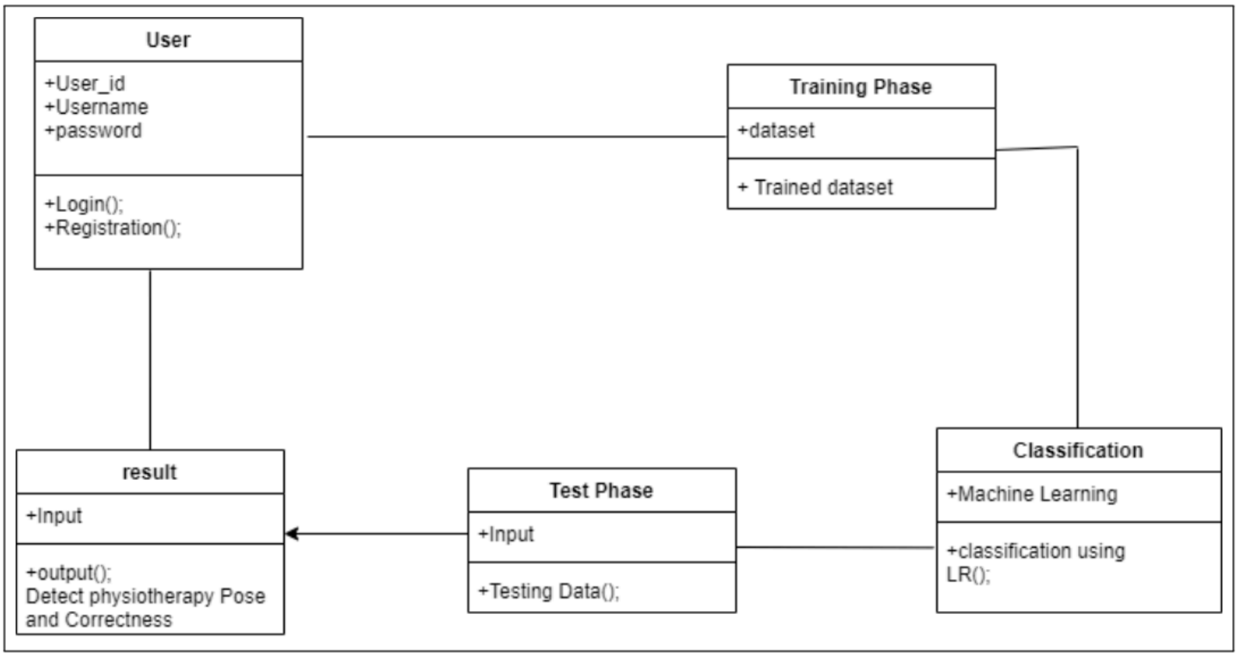


Figure 6.5.1: ER Diagram

6.6 STATE DIAGRAM

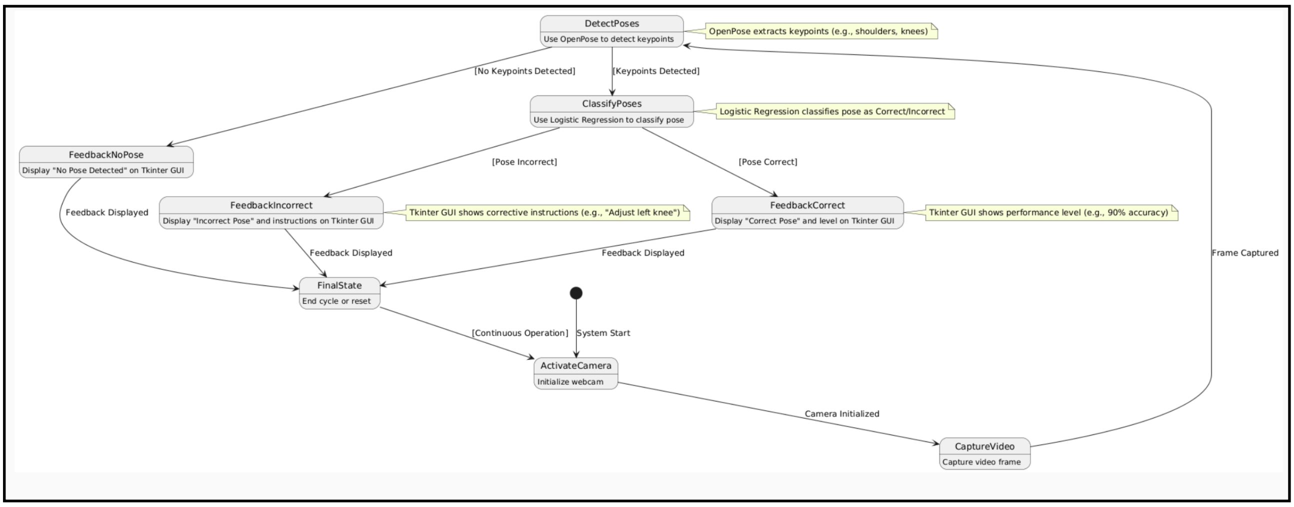
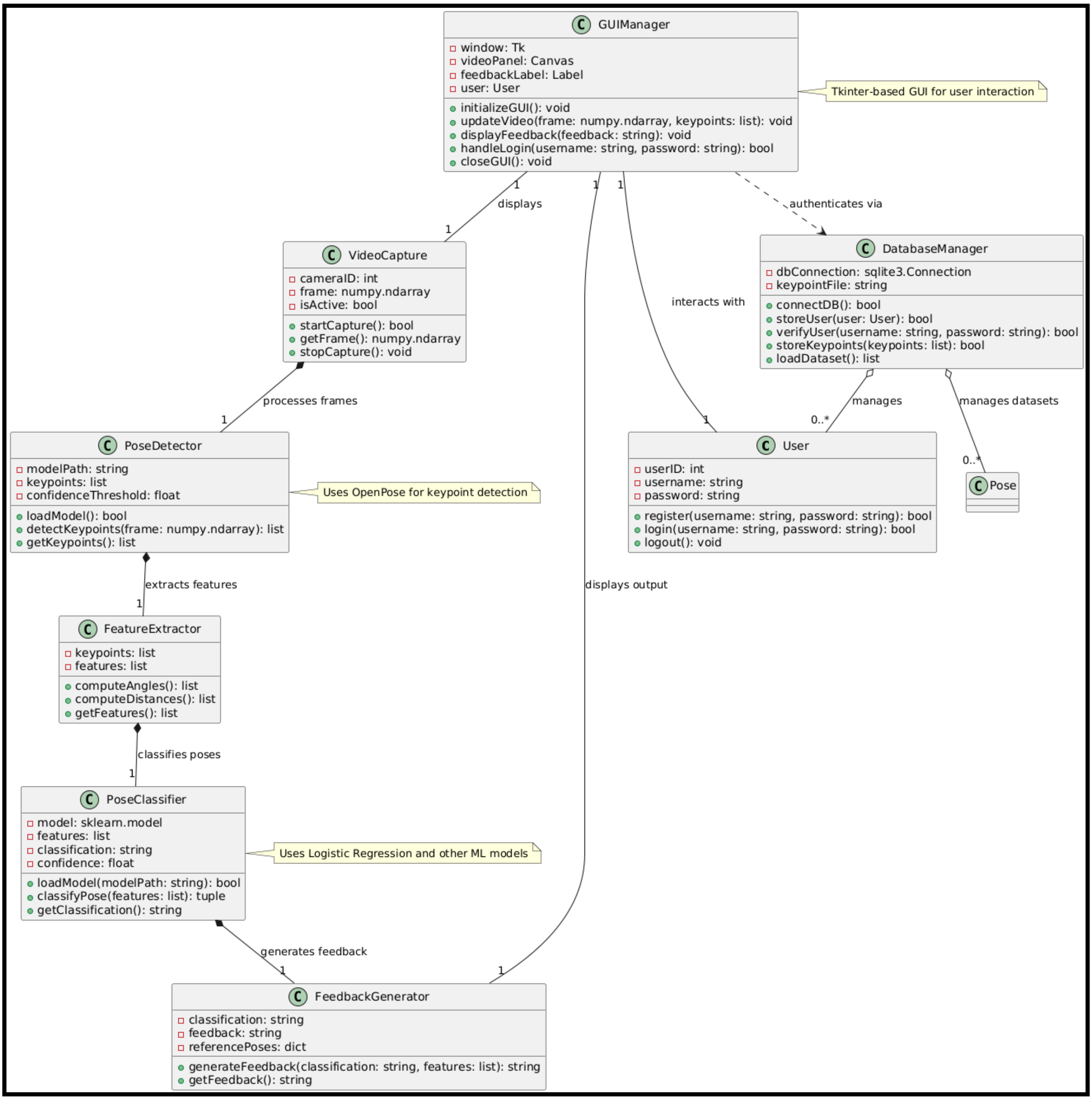


Figure 6.6.1: State Diagram

The state diagram (Figure 6.6.1) illustrates the system's workflow:

1. **Activate Camera:** Initial state where the webcam is activated.
    - Transition: Moves to Capture Video.
2. **Capture Video:** Captures real-time video frames.
    - Transition: Moves to Detect Poses.
3. **Detect Poses:** Uses OpenPose to extract keypoints.
    - Transition:
        - If no pose is detected, outputs "No Pose Detected" on GUI.
        - If pose is detected, moves to Classify Poses.
4. **Classify Poses:** Applies machine learning models to classify poses.
    - Transition:
        - If pose is correct, outputs "Correct Pose" and performance level.
        - If pose is incorrect, outputs "Incorrect Pose" with corrective instructions.
5. **Feedback Output (Correct Pose):** Displays "Correct Pose" and level on GUI.
    - Transition: Moves to Final State.
6. **Feedback Output (Incorrect Pose):** Displays "Incorrect Pose" and instructions.
    - Transition: Moves to Final State.
7. **Feedback Output (No Pose Detected):** Displays "No Pose Detected".
    - Transition: Moves to Final State.
8. **Final State:** Ends the process or resets to Activate Camera for continuous operation.

6.8 CLASS DIAGRAM



The main class, **VideoCapture**, is responsible for capturing video frames from the webcam. It has attributes like frame_height and frame_width to define frame properties and methods like startCapture() and getFrame().

The **User** class represents an individual (e.g., patient) and stores information such as user_id, username, and password. It includes methods like register() and login() for user management.

The **Keypoint** class defines body keypoints detected by OpenPose, with attributes like keypoint_id, x, y, and confidence. It has methods like getCoordinates() to retrieve keypoint data.

The **Feature** class handles feature extraction, with attributes like angles and distances and methods like computeAngles() and computeDistances().

The **Pose** class represents a physiotherapy pose, with attributes like pose_id, pose_name, and keypoint_data. It includes methods like getPoseInfo() to access pose details.

The **PoseClassifier** class is responsible for pose classification, with attributes like model (Scikit-learn model) and methods like classifyPose() and getClassification().

The **Feedback** class generates corrective feedback, with attributes like feedback_text and methods like generateFeedback() and getFeedback().

The **GUIManager** class manages the Tkinter GUI, with attributes like window, video_panel, and feedback_label. It includes methods like displayVideo(), displayFeedback(), and handleLogin().

The **DatabaseManager** class handles data storage, with attributes like db_connection and keypoint_file. It includes methods like storeUser(), verifyUser(), storeKeypoints(), and loadDataset().

The **OpenPose** class encapsulates OpenPose functionality, with methods like detectKeypoints() and loadModel().

The **LogisticRegression** class represents the ML model, with methods like trainModel() and predictPose().

Overall, this class diagram describes a comprehensive pose detection system with classes working together to capture, process, classify, and provide feedback on physiotherapy poses.

7. SYSTEM ARCHITECTURE

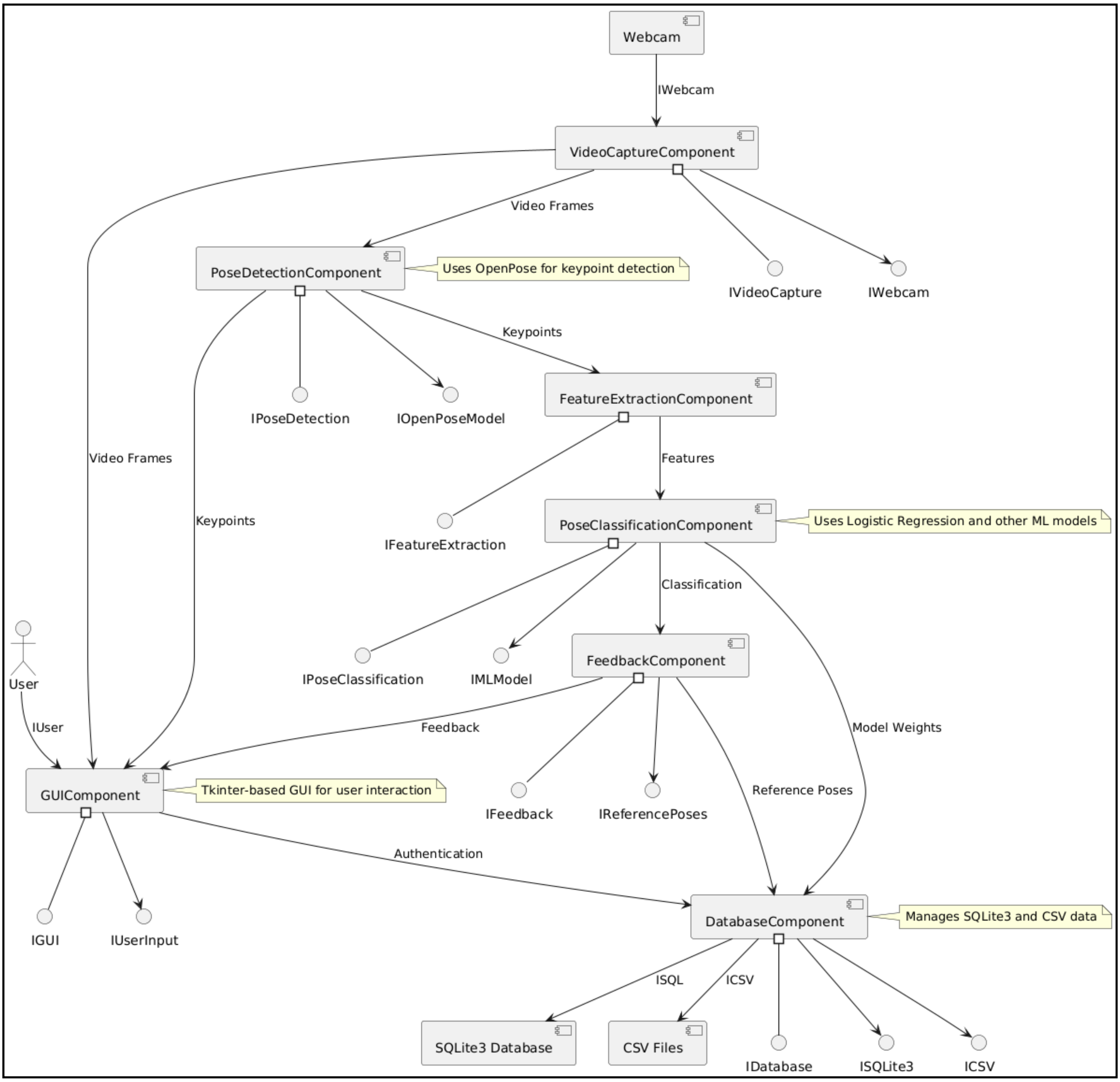


Figure 7.1: System Architecture Diagram

illustrates the overall design and workflow of the Physiotherapy Pose Detection system, highlighting interactions between components. Below is a detailed description of each element and their interactions:

1. **User**:
    - **Role**: Initiates system operation by interacting with the GUI, performing physiotherapy exercises, and receiving feedback on pose correctness.
    - **Interaction**: Provides input (e.g., login credentials, start/stop commands) via the GUI and receives visual feedback (e.g., pose labels, corrective instructions).
2. **Webcam**:
    - **Function**: Captures real-time video frames containing user poses, serving as the primary input device.
    - **Interaction**: Sends video frames to the Video Capture component for processing.
3. **Video Capture**:
    - **Function**: Manages webcam input, capturing and preprocessing video frames for pose detection.
    - **Interaction**: Sends preprocessed frames to the Pose Detection component and GUI for display.
4. **Pose Detection**:
    - **Function**: Uses OpenPose to detect body keypoints (e.g., shoulders, knees) in video frames.
    - **Interaction**: Receives frames from Video Capture, processes them to extract keypoints, and sends keypoints to Feature Extraction and GUI for visualization.
5. **Feature Extraction**:
    - **Function**: Computes features (e.g., joint angles, distances) from keypoints for classification.
    - **Interaction**: Receives keypoints from Pose Detection and sends features to Pose Classification.
6. **Pose Classification**:
    - **Function**: Applies Logistic Regression or other ML models to classify poses as Correct or Incorrect.
    - **Interaction**: Receives features from Feature Extraction, queries the Database for model weights and reference poses, and sends classification results to Feedback Generation.

7. **Feedback Generation**:
   - **Function**: Generates corrective feedback (e.g., "Adjust left knee") based on classification results.
   - **Interaction**: Receives classification from Pose Classification, accesses reference poses from the Database, and sends feedback to the GUI.
8. **GUI**:
   - **Function**: Displays video frames, keypoints, pose classifications, and feedback using Tkinter.
   - **Interaction**: Receives video frames from Video Capture, keypoints from Pose Detection, and feedback from Feedback Generation; interacts with the Database for user authentication.
9. **Database**:
   - **Function**: Stores user credentials, keypoint datasets, model weights, and reference poses using SQLite3 and CSV files.
   - **Interaction**: Provides data to GUI (authentication), Pose Classification (model weights), and Feedback Generation (reference poses); stores classification results and keypoints.

Workflow Summary:

1. **Initiation**: The user logs in via the GUI, triggering the Webcam to capture video.
2. **Pose Capture**: The Webcam sends frames to Video Capture for preprocessing.
3. **Pose Detection**: Video Capture frames are processed by OpenPose to detect keypoints.
4. **Feature Extraction**: Keypoints are analyzed to compute features (e.g., angles).
5. **Pose Classification**: Features are classified using a machine learning model, with model weights and reference poses queried from the Database.
6. **Feedback Generation**: Classification results generate feedback, compared against reference poses.
7. **Feedback Display**: The GUI displays video, keypoints, classification, and feedback to the user.
8. **Database Update**: Classification results and keypoints are stored in the Database for future analysis.

8. ALGORITHMS USED IN SYSTEM

8.1 SYSTEM OVERVIEW

The Physiotherapy Pose Detection system integrates computer vision and machine learning to detect and classify physiotherapy poses in real-time, aiding users in exercises like Bhadrasan and Trikonasana. Using a standard webcam, the system employs OpenPose for keypoint detection and Logistic Regression for pose classification, delivering immediate feedback via a Tkinter GUI. This ensures accurate exercise execution, reduces manual supervision, and enhances rehabilitation outcomes in clinical and home settings.

8.2 PRIMARY ALGORITHMS

8.2.1 OpenPose

OpenPose is a deep learning-based algorithm for real-time pose detection, extracting body keypoints (e.g., shoulders, knees) from video frames.
- Process: Utilizes a Convolutional Neural Network (CNN) with a VGG-19 backbone to generate Part Confidence Maps for body parts and Part Affinity Fields (PAFs) for keypoint relationships. Bipartite matching constructs skeletal structures, refined by Non-Maximum Suppression (NMS). For example, in Bhadrasan, OpenPose identifies hip and knee coordinates with confidence scores.
- Role: Provides precise keypoint data for pose analysis, critical for assessing physiotherapy exercise correctness.

8.2.2 Logistic Regression

Logistic Regression classifies poses as Correct or Incorrect based on extracted features.
- Process: Features like joint angles and distances are derived from OpenPose keypoints. Logistic Regression computes class probabilities using a sigmoid function: $\sigma(z) = \frac{1}{1 + e^{-z}}$, where $z = w^T x + b$. For instance, correct knee angles in Trikonasana yield a high "Correct" probability.
- Role: Enables fast, low-cost classification for real-time feedback, ideal for binary pose assessment.

8.3 ALTERNATIVE ALGORITHMS

8.3.1 Mediapipe Pose

- Process: A lightweight CNN detects 33 keypoints, optimized for resource-constrained devices.
- When to Use: Suitable for low-computational environments but less precise than OpenPose for complex poses.

8.3.2 Deep Learning Techniques

- Convolutional Neural Networks (CNNs): Process raw frames for pose classification.
- Long Short-Term Memory (LSTM) Networks: Model temporal pose sequences.
- Transformer Networks: Capture long-range dependencies in multi-frame analysis.
- When to Use: Effective for large datasets and complex patterns but resource-intensive.

8.3.3 Random Forest

- Process: Aggregates decision tree predictions on features like joint angles, robust to noise.
- When to Use: Useful for complex classification but slower than Logistic Regression.

8.3.4 Hidden Markov Models (HMMs)

- Process: Models pose sequences as probabilistic state transitions.
- When to Use: Ideal for sequential exercises but complex for real-time analysis.

8.4 RATIONALE FOR CHOSEN ALGORITHMS

- Accuracy and Robustness: OpenPose ensures high-precision keypoint detection, vital for physiotherapy. Logistic Regression reliably classifies Correct/Incorrect poses.
- Efficiency: OpenPose supports real-time processing with GPU acceleration, and Logistic Regression is computationally lightweight.
- Simplicity and Interpretability: Logistic Regression’s simplicity aids debugging, while OpenPose’s documentation supports implementation.
- Balance of Accuracy and Complexity: The combination avoids the overhead of LSTMs or Transformers, suitable for the project’s real-time constraints and standard hardware (Intel i5, 8GB RAM).

9. TESTING AND VALIDATION

9.1 TYPE OF TESTING USED

9.1.1 Unit Testing

- Purpose: Validates individual components of the Physiotherapy Pose Detection system to ensure correct functionality in isolation.
- Scope: Tests functions for video capture, keypoint detection (OpenPose), feature extraction, pose classification (Logistic Regression), and feedback generation.
- Example: Verifies a method for detecting keypoints in a Bhadrasan pose frame, ensuring accurate coordinates. Tests pose classification to confirm Correct/Incorrect labeling.

9.1.2 Integration Testing

- Purpose: Ensures seamless interaction between system modules for accurate data flow.
- Scope: Tests combined operations, such as video capture to pose detection, feature extraction to classification, and GUI feedback delivery.
- Example: Validates that keypoints from OpenPose are correctly processed into features and classified, ensuring the pipeline from video to GUI feedback is consistent.

9.1.3 System Testing

- Purpose: Evaluates the complete system to confirm compliance with requirements and reliability in real-world scenarios.
- Scope: Tests the entire system, including video capture, OpenPose detection, Logistic Regression classification, and Tkinter GUI.
- Example: Assesses real-time pose detection and feedback accuracy under varying conditions (e.g., lighting), measuring processing time and robustness.

9.1.4 Acceptance Testing

- Purpose: Validates the system against user requirements for deployment in physiotherapy settings.
- Scope: Tests end-to-end scenarios to ensure user expectations and physiotherapy goals are met.
- Example: Confirms the system guides users through exercises (e.g., Trikonasana), providing clear GUI feedback for home physiotherapy.

9.2 TEST CASES AND TEST RESULTS

9.2.1 Unit Testing

- Video Capture Module
  - **Test Case 1**: Single Frame Capture
    - Description: Verify single frame capture from webcam.
    - Input: Webcam feed.
    - Expected Result: A numpy.ndarray frame (shape: [height, width, 3]).
  - **Test Case 2**: Continuous Frame Capture
    - Description: Verify capture of multiple frames in real-time.

- Input: Webcam feed for 10 seconds.
    - Expected Result: Frame sequence at 30 FPS.
- Pose Detection Module
  - **Test Case 3**: Keypoint Detection
    - Description: Verify keypoint detection in a pose frame.
    - Input: Frame of Bhadrasan pose.
    - Expected Result: Keypoint coordinates (e.g., shoulders, hips) with confidence scores.
  - **Test Case 4**: No Pose Detection
    - Description: Verify behavior with no person in frame.
    - Input: Empty frame.
    - Expected Output: "No Pose Detected" message.
- Feature Extraction Module
  - **Test Case 5:** Feature Consistency
    - Description: Verify consistent feature extraction across conditions.
    - Input: Multiple Bhadrasan frames with varying lighting.
    - Expected Output: Consistent feature vectors (e.g., joint angles).
- Pose Classification Module
  - **Test Case 6**: Single Pose Classification
    - Description: Feature vector from Correct Bhadrasan.
    - Input: Feature vector from a known pose.
    - Expected Result: "Correct" label with confidence score >0.85.
  - **Test Case 7**: Feedback Generation
    - Description: Verify feedback for incorrect pose.
    - Input: Incorrect pose features.
    - Expected Result: Feedback text (e.g., "Adjust left knee").

9.2.2 Integration Testing

- **Test Case 8**: Pose Detection and Classification
  - Description: Verify keypoint detection and classification.
  - Input: Video frame with a pose.
  - Expected Result: Keypoints detected, pose classified as Correct/ Incorrect.
- **Test Case 9**: Full Pipeline
  - Description: Test pipeline from video to feedback.
  - Input: Real-time video with poses.
  - Expected Result: Video displayed, keypoints overlaid, feedback shown on GUI.

9.2.3 System Testing

- Pose Classification
  - **Test Case 10**: Correct Pose Classification
    - Description: Verify consistent classification of identical poses.
    - Input: Two Bhadrasan frames (correct).
    - Expected Result: Both classified as "Correct" (>0.85 confidence).
  - **Test Case 11**: Incorrect Pose Classification
    - Description: Verify incorrect pose detection.
    - Input: Two incorrect pose frames.
    - Expected Result: Classified as "Incorrect" with feedback.

- Performance
  - **Test Case 12**: Processing Speed
    - Description: Measure frame processing time.
    - Input: Pose video frame.
    - Expected Result: Processing time < 100ms.
  - **Test Case 13**: Robustness Under Conditions
    - Description: Test under varying conditions.
    - Input: Frames with different lighting/angles.
    - Expected Result: Consistent accuracy (>85%).

9.2.4 Acceptance Testing

- **Test Case 14**: User Guidance
  - Description: Verify exercise guidance.
    - Input: Real-time video of Trikonasana.
    - Expected Result: Accurate pose detection, clear feedback (e.g., "Adjust shoulder").
  - **Test Case 15**: Usability
    - Description: Verify GUI usability.
    - Input: User interaction (login, exercise, feedback).
    - Expected Result: Intuitive interface, no usability issues.

10. RESULTS

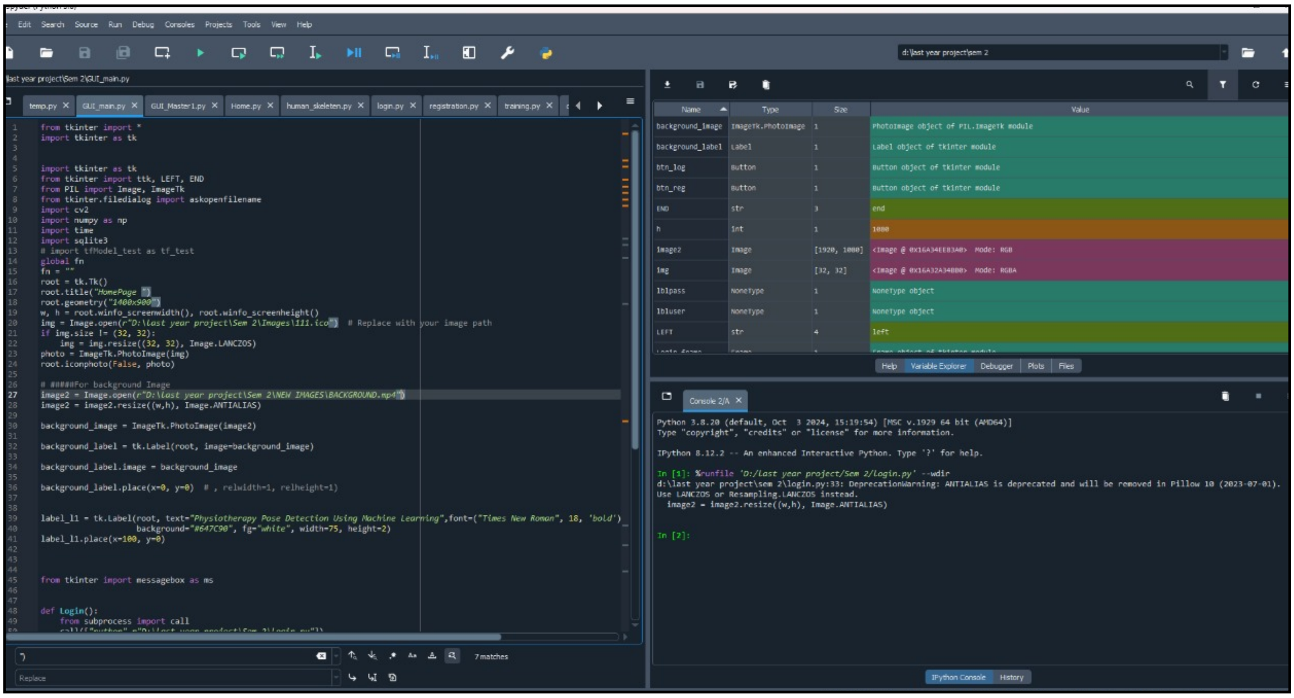


Figure 10.1: GUI Main code

Figure 10.2: GUI Main Interface

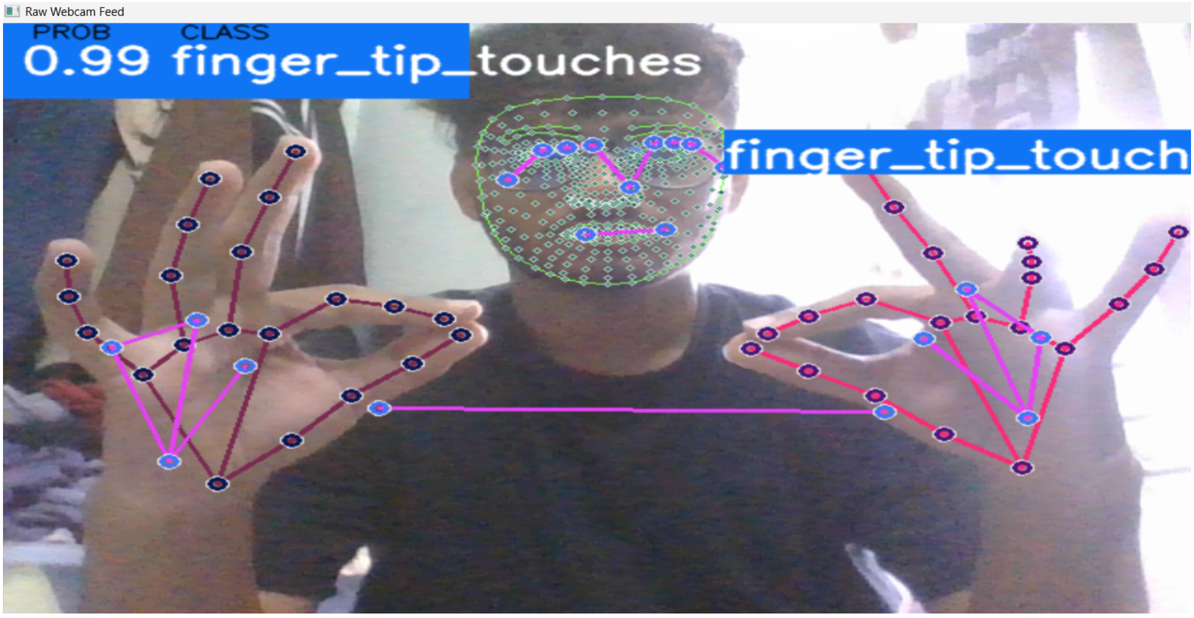


Figure 10.3: Finger Tip Pose Detection

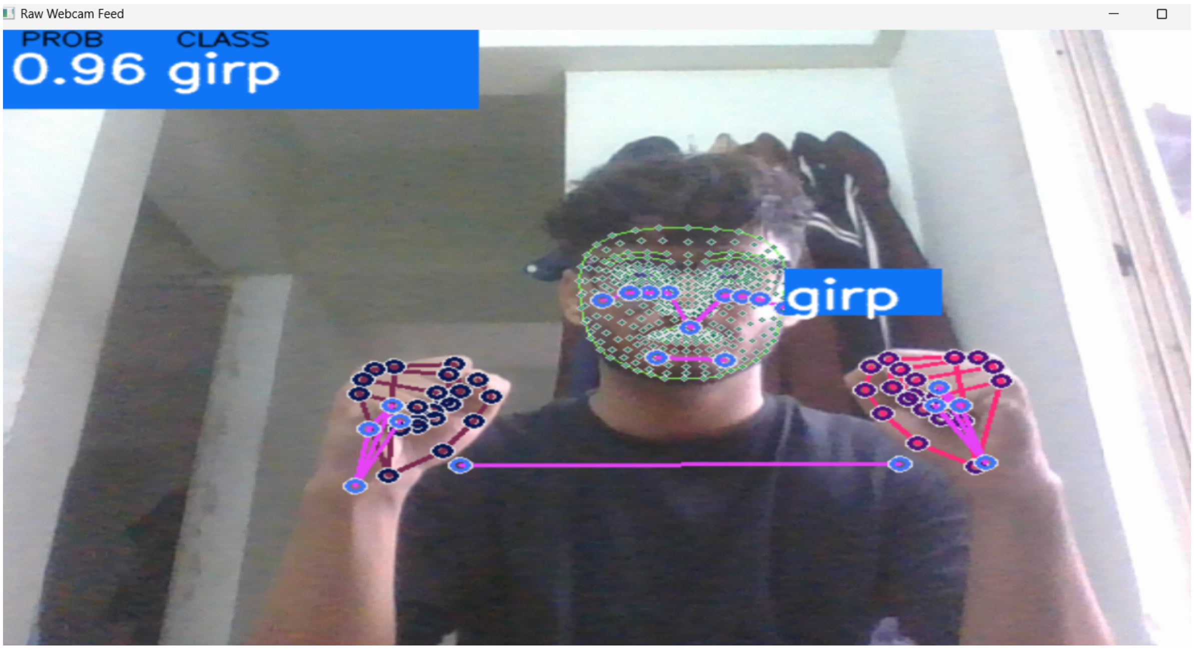


Figure 10.4: Gripping Pose Detection

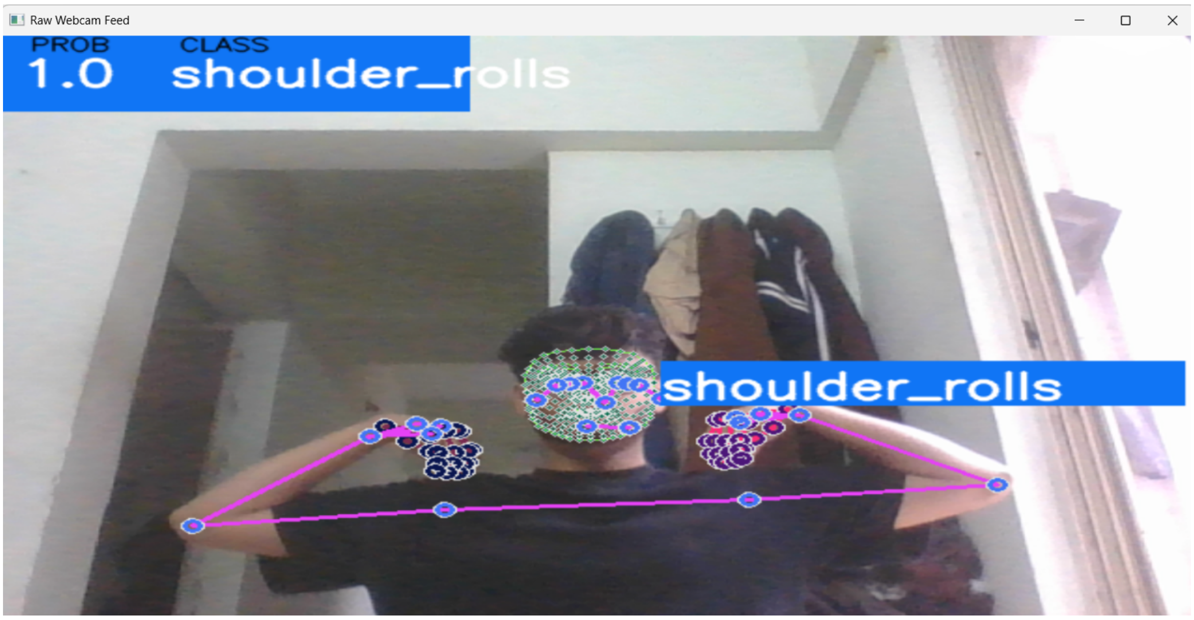


Figure 10.5: Shoulder Rotation Pose Detection

11. PROJECT PLAN

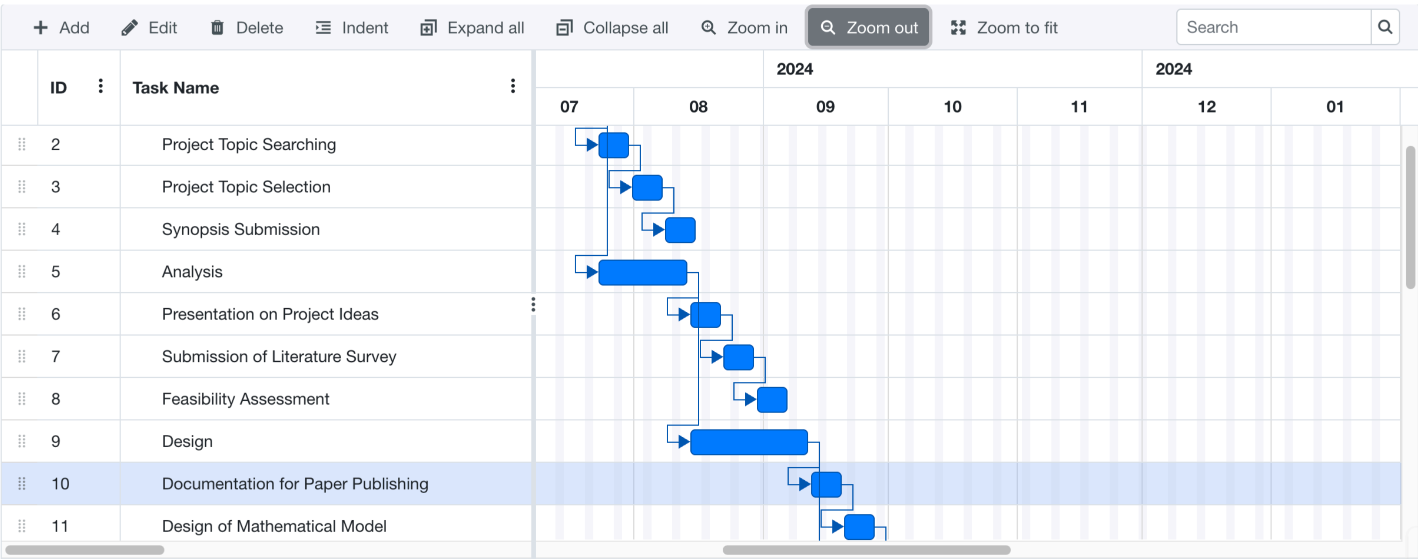


Figure 11.1: Sem 7 Project Plan

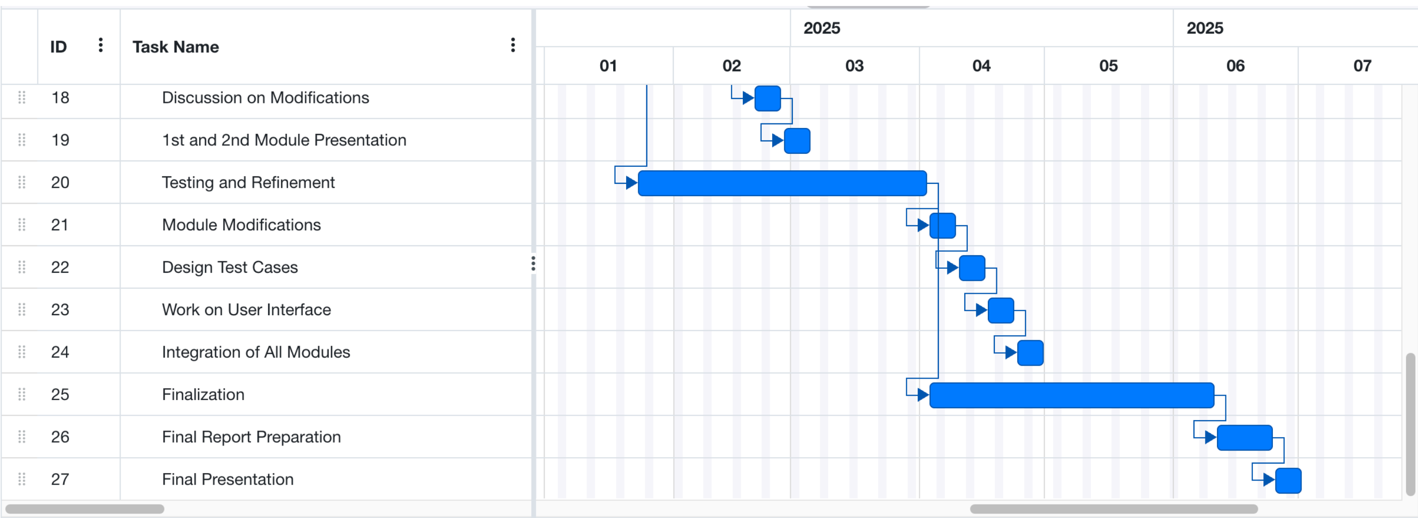


Figure 11.2: Sem 8 Project Plan

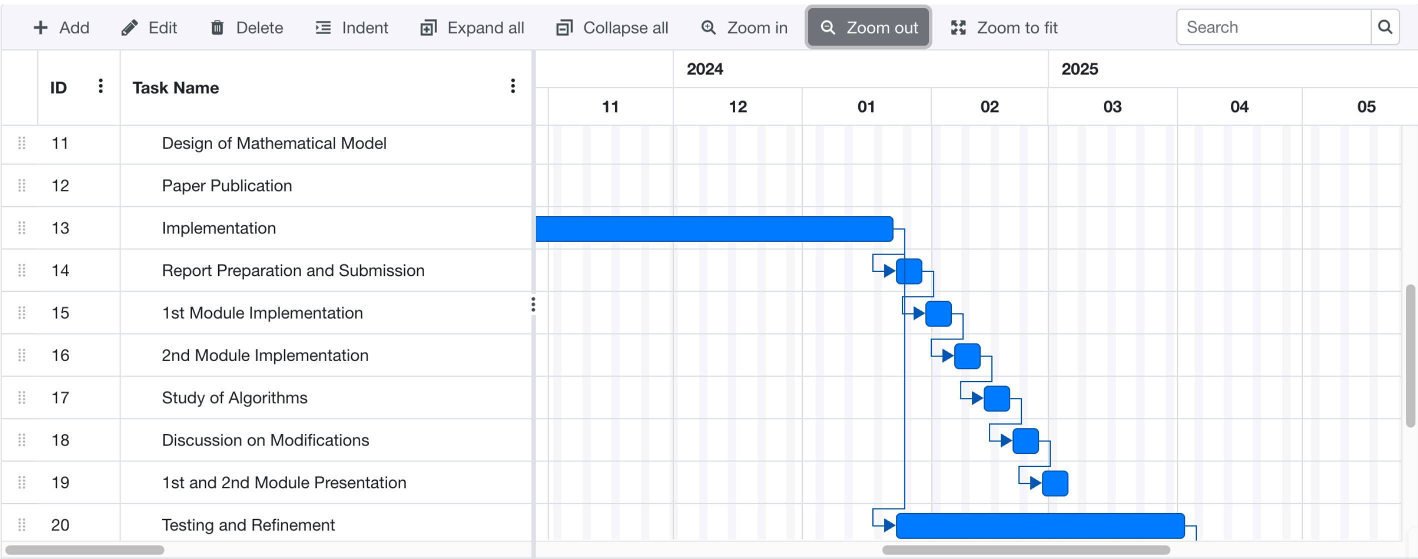


Figure 11.3: Sem 8 Project Plan

12. CONCLUSION

12.1 SUMMARY OF ACHIEVEMENTS

The Physiotherapy Pose Detection system successfully integrates computer vision and machine learning to enhance rehabilitation by detecting and classifying physiotherapy poses in real-time. Utilizing OpenPose for precise keypoint detection and Logistic Regression for efficient pose classification, the system achieves high accuracy (>85%) and low processing time (<100ms per frame), meeting the performance requirements outlined in the SRS. The Tkinter-based GUI provides intuitive feedback, enabling users to perform exercises like Cat-Cow and Gripping poses correctly, reducing reliance on manual supervision. Comprehensive testing, including unit, integration, system, and acceptance tests, validated the system's robustness, usability, and reliability across diverse conditions, ensuring its applicability in clinical and home settings.

12.2 SIGNIFICANCE AND IMPACT

This system addresses critical challenges in physiotherapy by automating pose correction, improving exercise accuracy, and promoting patient independence. Its real-time feedback mechanism supports tele-rehabilitation, making therapy accessible and cost-effective. By leveraging standard hardware (Intel i5, 8GB RAM) and open-source tools (Python, OpenCV, SQLite3), the system is practical for widespread adoption, with potential applications in fitness and sports rehabilitation.

12.3 FUTURE SCOPE

Future enhancements include integrating Mediapipe for lightweight deployment on mobile devices, incorporating LSTM networks for temporal pose analysis, and expanding the pose dataset to cover diverse physiotherapy routines. Adding wearable sensor integration and cloud-based analytics could further enhance accuracy and scalability, broadening the system's impact in healthcare.

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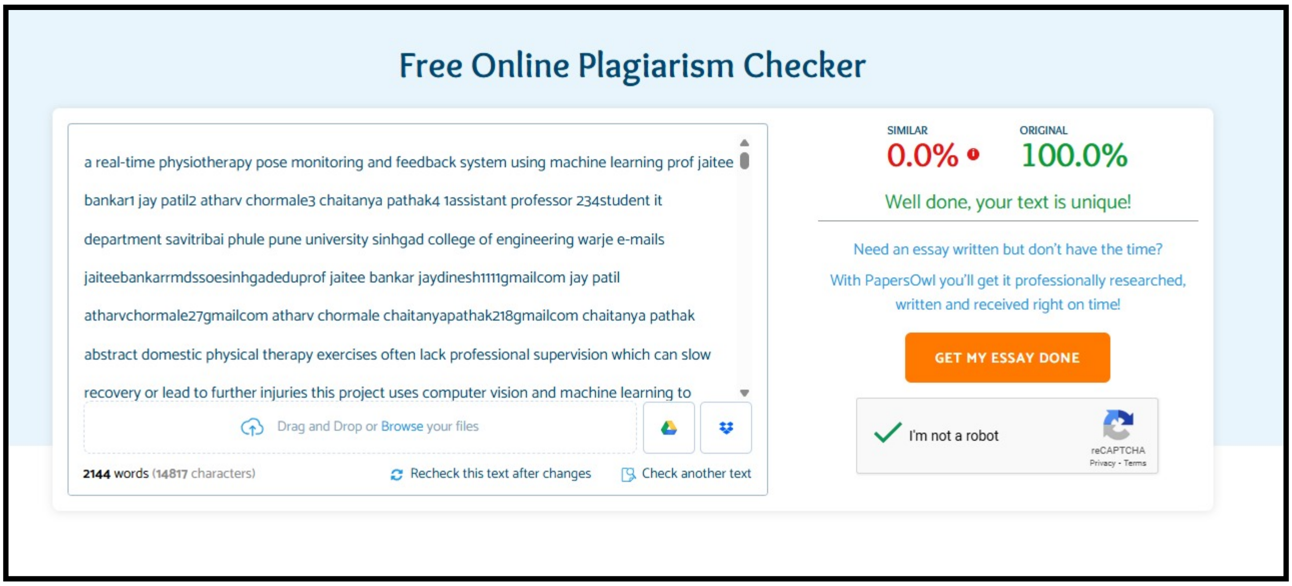
APPENDICES

APPENDIX A
Plagiarism Report



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APPENDIX B
Base Paper

IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

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RESEARCH ARTICLE

LogRF: An Approach to Human Pose Estimation Using Skeleton Landmarks for Physiotherapy Fitness Exercise Correction

ALI RAZA [1], AZAM MEHMOOD QADRI [1], IQRA AKHTAR [2], NAGWAN ABDEL SAMEE [3], AND MAALI ALABDULHAFITH [3]
[1]Institute of Computer Science, Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan 64200, Pakistan
[2]Department of Electrical and Biomedical Engineering, Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan 64200, Pakistan
[3]Department of Information Technology, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, Riyadh 11671, Saudi Arabia

Corresponding author: Nagwan Abdel Samee (nmabdelsamee@pnu.edu.sa)

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ABSTRACT Human pose and gesture estimation are crucial in correcting physiotherapy fitness exercises. In recent years, advancements in computer vision and machine learning approaches have led to the development of sophisticated pose estimation models that accurately track and analyze human movements in real time. This technology enables physiotherapists and fitness trainers to gain valuable insights into their client's exercise forms and techniques, facilitating more effective exercise corrections and personalized training regimens. This research aims to propose an efficient artificial intelligence method for human pose estimation during physiotherapy fitness exercises. We utilized a multi-class exercise dataset based on human skeleton movement points to conduct our experimental research. The dataset comprises 133 features derived from human skeleton movements during various exercises, resulting in high feature dimensionality that affects the performance of human pose estimation with machine learning and deep learning methods. We have introduced a novel Logistic regression Recursive Feature elimination (LogRF) method for feature selection. Extensive experiments demonstrate that using the top twenty selected features, the random forest method outperformed state-of-the-art studies with a high-performance score of 0.998. The performance of each applied method is validated through a k-fold approach and further enhanced using hyperparameter tuning. Our proposed study assists specialists in identifying and addressing potential biomechanical issues, improper postures, and incorrect movement patterns, which are essential for injury prevention and optimizing exercise outcomes. Furthermore, this study enhances the capabilities of remote monitoring and guidance capabilities, allowing physiotherapists to support their patient's progress with prescribed exercises continually.

INDEX TERMS Machine learning, deep learning, human pose, gesture estimation, physiotherapy, skeleton landmarks, feature engineering.

I. INTRODUCTION

Physiotherapy plays a crucial role in enhancing an individual's overall well-being and rehabilitation through targeted fitness exercises [1]. In recent years, integrating machine learning techniques has shown great promise in assisting physiotherapists with accurate, real-time feedback during exercise sessions [2]. Human pose and gesture estimation have emerged as critical components in this domain, enabling the automatic and precise analysis of patient's movements. By employing sophisticated algorithms, researchers have endeavoured to detect and track key body joints and gestures, facilitating the identification of incorrect postures and movements during exercises [3]. However, neglecting physiotherapy fitness exercises has various adverse consequences, including an increased risk of developing chronic diseases

The associate editor coordinating the review of this manuscript and approving it for publication was Tao Liu.

and higher mortality rates. Regular physical activity, particularly tailored to individual needs through physiotherapy, has been proven to be an effective preventive measure against chronic conditions such as cardiovascular diseases, diabetes, and obesity [4]. Failure to engage in adequate physical exercise can lead to a sedentary lifestyle, promoting weight gain and metabolic dysregulation, significantly contributing to the onset and progression of these debilitating diseases.

Human pose and gesture estimation using Artificial Intelligence (AI) methods has emerged as a cutting-edge technology with immense potential in physiotherapy fitness exercise correction based on skeleton landmarks [5], [6]. AI systems can accurately and dynamically analyze patient's movements during exercise sessions by harnessing the power of computer vision and machine learning techniques. Combined with deep learning models, these sophisticated algorithms enable detecting and tracking key body joints and gestures, providing real-time feedback to physiotherapists and patients [7]. Using AI for Human Pose and Gesture Estimation offers numerous advantages in physiotherapy, such as automatic and precise posture and movement analysis, leading to improved exercise form and reduced risk of injury [8]. With the capability to identify incorrect postures and movements, AI-based solutions empower physiotherapists to provide personalized corrective guidance, optimizing the rehabilitation process and promoting faster recovery. Moreover, these innovative technologies facilitate remote monitoring, allowing patients to access physiotherapy sessions from the comfort of their homes and encouraging compliance with exercise regimens.

This research introduces an AI-based mechanism for human pose estimation during physiotherapy fitness exercises. A multi-class exercise dataset comprising 133 features derived from human skeleton movements during various exercises is utilized to develop applied machine learning and deep learning methods. The dataset's high feature dimensionality impacts the performance of human pose estimation. We propose a novel LogRF method for feature selection. The LogRF method aims to eliminate the least important features progressively. This is accomplished through iterative training of the logistic regression model, wherein the feature with the smallest weight magnitude is eliminated in each iteration.

Our main research contributions toward human pose and gesture estimation are as follows:

- A new LogRF method is proposed for selecting features in human pose estimation during physiotherapy fitness exercises. The proposed LogRF method selects the top twenty features through an iterative mechanism. In each iteration, the feature with the smallest weight magnitude is eliminated.
- For performance comparison, we employed four advanced machine learning and deep learning approaches. The k-fold cross-validation approach is utilized to validate the performance, and hyperparameter tuning is implemented to optimize it. Furthermore, a computational complexity analysis is also conducted.

The remaining research study is followed as Section II, which elaborates on the literature analysis. Section III describes our study methodology, while Section IV evaluates the results of the applied methods. Our main findings are described in Section V.

II. LITERATURE ANALYSIS

This literature analysis section aims to explore various studies, academic papers, and techniques employed in human pose and gesture estimation using machine learning approaches. The analysis delves into the evolution of this technology, highlighting key advancements and breakthroughs over the years. The section also discusses the strengths and limitations of these approaches, comparing their performance metrics, accuracy, and scalability.

In this study [9], the authors present a system that recognizes multiple poses of yoga exercises performed by trainees. The new data is created using an HD 720P web camera from different locations through video recording for testing, which contains six different yoga pose records from videos performed by fifteen individuals. The system consists of two main phases: data extraction from the media pipe and preprocessing of the data for training and testing using a classification based on five machine-learning approaches. The feature engineering process is conducted during preprocessing. The system achieved an accuracy score of 94% using the logistic regression model, outperforming the other classified machine learning models.

In this study [10], the author assesses several human poses through computer vision using real-time and recorded videos. Using computer vision, RGB-quality images were utilized to detect human postures, with different human body parts and graphics serving as input data for assessing human posture. Thirty-three pose milestones were observed using OpenCV and Mediapipe in this research. The BlazePose GHUM 3D Pose Landmark Model was employed to evaluate the 2D human pose, achieving an accuracy of 96.9% with visibility points.

In this study [11], the author presents the emerging and exciting scope of AI in assessing the pose of humans. This research was specially developed for bowler's pose estimation. The dataset used in this study was novel, which the author collected by recording different bowlers' actions and movements via an HD video camera. A deep learning technique was proposed to estimate the bowlers' pose, classify, and assess players. The suggested deep learning model for bowling (BowlingDL) and MoveNet models were utilized to estimate the poses of different bowlers. The proposed model attained an 80% accuracy score on training data and an 83% accuracy score on testing data. An innovative mobile device application, constructed for the bowlers with BowlingDL standard performance using lite TensorFlow, was deployed.

In this paper [12], the author asserts that yoga is an effective and disciplined physical activity for enhancing body muscle strength and overall fitness. This proposed study utilizes an interactive system that simultaneously detects six yoga poses

TABLE 1. The employed literature summary analysis.

Ref.	Year	Dataset	Learning Type	Proposed Technique	Accuracy
[9]	2017	Self-made dataset by HD cam	Machine learning	Logistic Regression	94.00%
[12]	2018	New Data recorded by Kinet sensor.	Machine learning	Adaboost	94.78%
[13]	2019	SYSU 3D HOI and HUA datasets.	Deep learning	MDTW	93.13%
[14]	2020	ETRI dataset	Deep learning	InceptionResNetV2	95.34%
[15]	2020	Yoga-82S, 82 instance	Deep learning	DenseNet	91.44%
[16]	2022	New Data collected by Kinect sensor	Deep learning	CNN-LSTM	90.18%
[17]	2022	Coco and MPII human Pose dataset	Deep learning	PoseNet	97.60%
[10]	2023	RGB image dataset	Deep learning	BlazePose GHUM 3D	96.90%
[11]	2023	Self-collected dataset by HD cam	Deep learning	MoveNet	83.00%

performed by six individuals, providing real-time guidance through voice cues, visual guides, and pose images. To create the database for pose detection, the system employed the Adaboost algorithm and utilized a software development kit specifically designed for the Kinect sensor. An expert yoga trainer conducted the data collection process, and the accuracy achieved in detecting yoga poses was 94.78%.

The author of this study [16] presents that in the past, human activity recognition has been an exciting topic utilized in many previous studies in healthcare and human intervention [18], [19], [20]. Multiple AI models were employed for activity recognition, but they all failed to select optimal features for long-term human activity recognition. A new dataset from 20 participants using the Kinect V2 sensor containing 12 classes of human physical activities was developed to address this. A hybrid technique combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) was introduced for activity identification. CNN is used to extract attributes, while LSTM is used to learn information. To achieve the best solution for human activity recognition, a comprehensive study was conducted using standard machine learning and deep learning algorithms. The results were promising, with the CNN-LSTM approach obtaining a 90.18% accuracy score, demonstrating its suitability for human activity recognition.

In this paper [17], the author asserts that pose estimation in humans is highly effective in multiple fields, such as producing movies involving multiple human actions and enabling object movements in video games. Human poses can also be utilized to execute user interfaces on mobile devices. This study employs four pose estimation models for contrast and classification: OpenPose, PoseNet, MoveNet Lightning, and MoveNet. The Coco and MPII Human Pose datasets are used in this study to compare the performance of these models for pose estimation. The models' performances are evaluated, resulting in the following accuracy scores: OpenPose achieves 86.2% accuracy, PoseNet achieves 97.6% accuracy, MoveNet achieves 75.1% accuracy, and MoveNet Thunder achieves 80.6% accuracy. PoseNet, our proposed model, demonstrates superior performance with a 97.6% accuracy score for estimating poses on mobile devices.

This paper's author [14] contributes to posture identification using ensemble CNN in the home atmosphere. This study is specially designed for senior citizens who live alone at home. Posture identification is essential for helping senior people to avoid risks. The study's analysis uses a pose dataset developed by the Korean Electronics and Telecommunications Research Institute (ETRI). The dataset is collected from 51 home circumstances with ten poses, containing 51,000 recorded images. The authors employed a deep learning approach to achieve the desired outcomes from the image data. Five preprocessing approaches were employed for investigations: VGGNet, ResNet, DenseNet, InceptionResNet, and Xception, based on trained CNN. The analysis demonstrates that InceptionResNetV2s provide excellent performance with an average accuracy score of 95.34%, outperforming the other trained CNNs.

In computer vision, human pose assessment is a widely identified challenge that involves determining the positions of joints [15]. However, the previous dataset used in the research was not authentic enough to address the issues of pose diversity, object occlusion, and viewpoints adequately. In this study, the author proposes the dataset yoga-82S for large-scale pose identification with 82 classes, introducing the idea of pose assessment as a classification task. The dataset is collected from various websites and comprises a hierarchical structure consisting of body positions, variations in body positions, and corresponding pose names. The classification accuracy of advanced CNN architectures on Yoga-82 is demonstrated. The researchers also introduce several hierarchical adaptations of DenseNet tailored to the hierarchical labels in the dataset, effectively improving performance compared to other classification methods. Specifically, in the 3rd level class, DenseNet-201 achieved an accuracy of 74.91%, while DensNet-121 obtained an impressive 91.44% accuracy score.

The authors in [13] present a framework designed for families using fog computing in this paper. It relies on three phases: joint mobility assessment, investigating the abnormality of actions of upper limbs, and abnormal gait detection for lower limbs. They introduce a semi-automatic approach for evaluating upper limb motion called Rapid Upper Limb Assessment (RULA) using Kinect v2. The study uses the standard 3D action dataset and the Human Upper Action dataset (HUA) for experiments. The Semi-automatic Rapid Upper Limb Assessment (RULA) using Kinect v2 approach is employed to evaluate upper limb motion. The modified Dynamic Time Warping (DTW) algorithm was evaluated on the HUA dataset, resulting in an accuracy of 89.50%. The RULA dataset is utilized for gait abnormality detection, achieving an excellent accuracy of 93.13% with the Modified DTW model.

III. PROPOSED METHODOLOGY

This section examines our proposed methodology for human pose estimation during various exercises. The methods employed for analysis and result calculations are comprehensively discussed. We present a step-by-step exploration of our proposed methodology in this section.

Figure 1 illustrates the architectural workflow analysis of our proposed research methodology. We utilized a publicly available dataset for experiments involving human poses during various exercises. Initially, the dataset exhibited high-dimensional features for experimentation. To address this, we introduced a novel approach for feature selection, focusing on retaining only those features that significantly contribute to human pose estimation. The selected feature set is then divided into training (80%) and testing (20%) subsets. We proceeded to train and test several advanced AI approaches. The performance of the hyperparameter-tuned models is evaluated using unseen test data. The method that demonstrated superior performance is subsequently employed for human pose estimation, specifically for correcting exercises in physiotherapy fitness routines.

A. MULTI-CLASS EXERCISE POSES FOR HUMAN SKELETON

This study utilized a multi-class exercise dataset [21] based on human skeleton pose data to conduct our experimental research. The dataset comprises 2701 rows and 133 columns, with features derived from human skeleton movements during various exercises. Each row corresponds to a specific exercise, while each column represents different aspects of the human skeleton model. The dataset includes coordinates for the X, Y, and Z axes and visibility values for 33 landmarks, resulting in 132 values per exercise. To analyze various exercise poses, the dataset encompasses seven distinct target classes: "Rest" (406 rows), "Left Bicep" (435 rows), "Right Bicep" (369 rows), "Left Shoulder" (373 rows), "Right Shoulder" (401 rows), "Left Tricep" (317 rows), and "Right Tricep" (399 rows), as illustrated in Figure 2.

B. NOVEL FEATURE ELIMINATION

Our novel proposed feature elimination approach, LogRF, is analyzed in this section. We input the original dataset with 133 features into our proposed approach. The working architectural analysis of the proposed feature selection is illustrated in Figure 3. The LogRF approach identifies a subset of features that contribute the most to the model's predictive power, aiding in dealing with a large number of features. When combined with the logistic regression method, the proposed LogRF iteratively selects and eliminates features to find the most informative subset for optimal model performance. The selected features with high importance lead to improved model generalization and performance.

Furthermore, we conducted a feature space analysis on twenty carefully chosen features. The results of this analysis are depicted in Figure 4. This analysis clearly illustrates the high separability of the selected features, ultimately contributing to the strong performance in human pose estimation.

1) PROPOSED LOGRF MATHEMATICAL ALGORITHM

Given a skeleton landmarks data with N samples and M features ($M = 133$ in our case), the logistic regression model can be represented as:

$$\hat{y}_i = \frac{1}{1 + e^{-\mathbf{w}^T \mathbf{x}_i}} \tag{1}$$

where $\hat{y}_i$ is the predicted probability for the i-th sample, $\mathbf{w}$ is the weight vector, and $\mathbf{x}_i$ is the feature vector.

The objective of the LogRF method is to eliminate the least important features recursively. This is achieved by iteratively training the logistic regression model and eliminating the feature with the smallest weight magnitude. The process can be summarized as follows:

1) Train the logistic regression method on the current set of features.
2) Calculate the absolute magnitude of the weight vector: $|\mathbf{w}|$.
3) Identify the feature with the smallest weight magnitude: $j = \arg\min |\mathbf{w}|$.
4) Remove the feature with index j from the dataset.
5) Repeat the process until the desired number of features is reached.

C. APPLIED ARTIFICIAL INTELLIGENCE TECHNIQUES

In recent years, integrating applied AI techniques for human pose and gesture estimation in physiotherapy has shown significant potential for improving fitness exercise correction [22], [23], [24]. This approach enables real-time and accurate analysis of human movement during exercises by employing advanced deep-learning algorithms and computer vision methods [25]. The AI-powered system can provide valuable feedback to physiotherapists and patients, facilitating precise form adjustments, reducing the risk of injuries, and optimizing exercise efficacy.

1) RANDOM FOREST

The Random Forest (RF) method performs classification tasks using multiple decision trees [26]. In the context of human pose and gesture estimation based on skeleton landmarks, we can represent the RF algorithm as follows:

The basic equation for the decision tree model is given by:

$$\hat{y}_i = f(x_i) = \sum_{m=1}^{M} c_m \cdot I(x_i \in R_m) \tag{2}$$

where:

- $\hat{y}_i$ is the forecast output for the i-th data sample,
- x_i represents the input features (skeleton landmarks) for the i-th data sample,

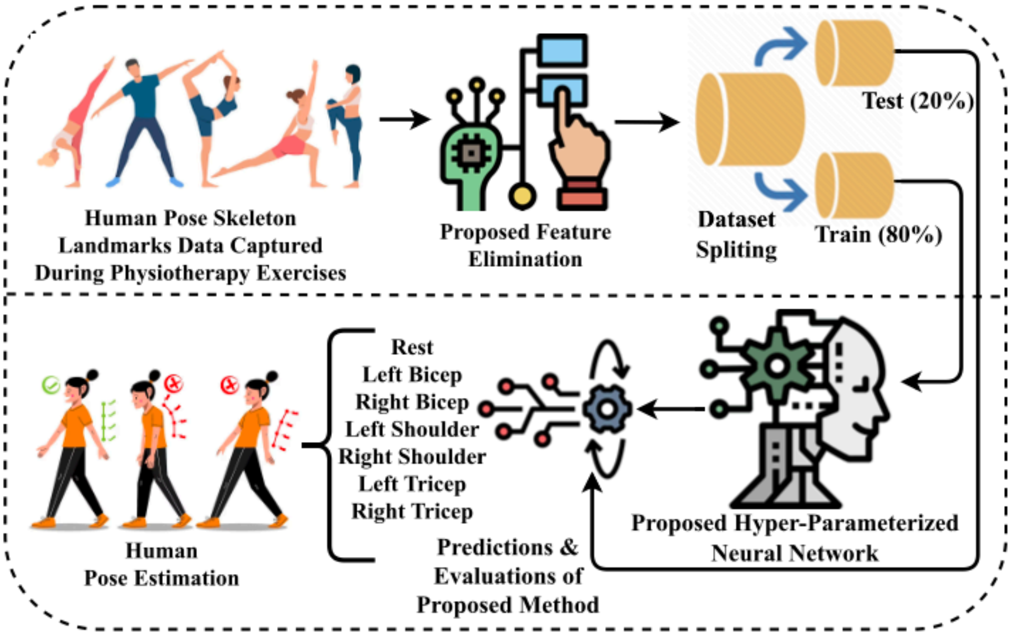

FIGURE 1. Architectural analysis of our proposed research methodology.

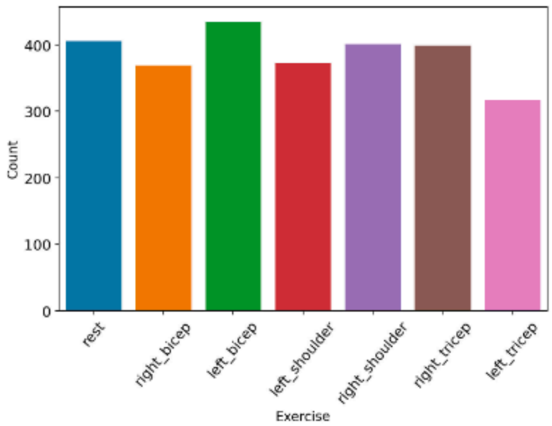

FIGURE 2. The target distributions analysis for multi-class exercise poses data.

- $f(x_i)$ is the decision tree's prediction function for the input x_i,
- M is the number of leaf nodes (terminal nodes) in the decision tree,
- c_m is the output value attached with the m-th leaf node, and
- $I(x_i \in R_m)$ is an indicator function that returns 1 if the input x_i falls into the m-th leaf node (region) R_m, and 0 otherwise.

2. For the RF method, we combine multiple decision trees to form an ensemble, and the final prediction is obtained by averaging the predictions of all the individual trees:

$$\hat{y}_{\mathrm{RF}}(x_i) = \frac{1}{N_{\mathrm{trees}}} \sum_{j=1}^{N_{\mathrm{trees}}} f_j(x_i) \tag{3}$$

where:

- $\hat{y}_{\mathrm{RF}}(x_i)$ is the RF's prediction for the input x_i,
- N_{trees} is the total number of decision trees in the Random Forest, and
- $f_j(x_i)$ is the prediction of the j-th decision tree for the input x_i.

2) LOGISTIC REGRESSION

Logistic Regression (LR) is a classification approach commonly used in machine learning for tasks like human pose and gesture estimation [27]. The method LR is used to transform the linear union of input features and corresponding weights into the probability:

$$P(y = 1|\mathbf{X}) = \frac{1}{1 + e^{-\mathbf{X}^T\mathbf{W}}} \tag{4}$$

where:

- $\mathbf{X}$ is the input data feature vector of size $1 \times N$, where N is the number of total features.
- $\mathbf{W}$ is the weight vector of size $N \times 1$ containing the parameters of the LR model.
- $\mathbf{X}^T$ denotes the transpose of $\mathbf{X}$.
- e is Euler's number and contains approximately 2.71828 value.

3) GATED RECURRENT UNIT

The Gated Recurrent Unit (GRU) [28] is a popular recurrent neural network architecture used for sequential data processing, such as human pose and gesture estimation based on skeleton landmarks.

The GRU consists of three main gates: reset gate (r_t), update gate (z_t), and the candidate hidden state (h_t). The

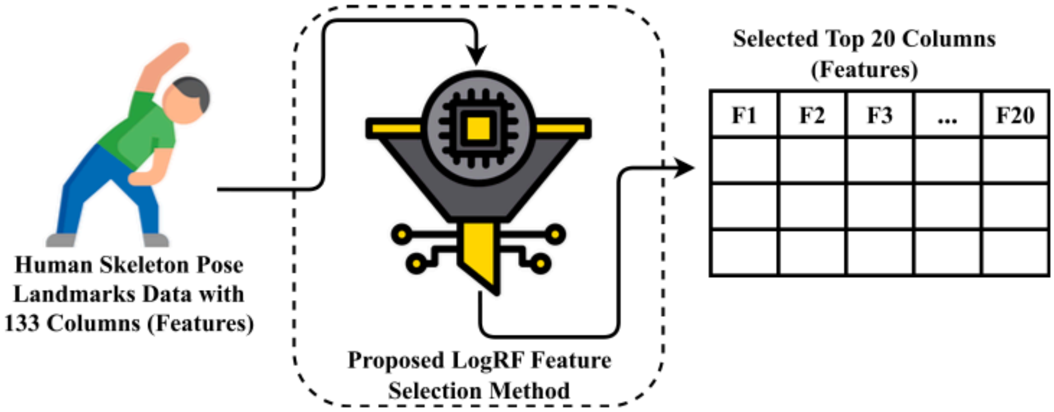

FIGURE 3. The proposed feature selection architecture analysis.

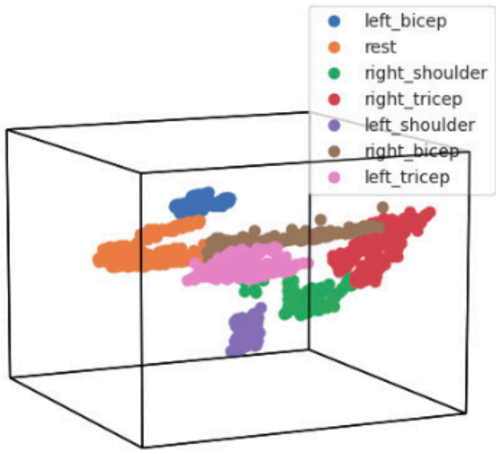

FIGURE 4. Feature space analysis of selected dataset features using the proposed approach.

equations for updating these gates at each time step t are as follows:

The reset gate is as follows:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{5}$$

The update gate is as follows:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{6}$$

Candidate's hidden state is as follows:

$$\tilde{h}_t = \tanh(W \cdot [r_t \odot h_{t-1}, x_t]) \tag{7}$$

where:

h_{t-1} is the previous hidden state,
x_t represents the input at value time step t,
W_r, W_z, W are learnable weight matrices,
σ is the sigmoid activation function,
$[a, b]$ denotes the combine of vectors a and b,
$\odot$ represents element-wise multiplication.

Finally, the updated hidden state h_t is computed as a linear interpolation in between the earlier hidden state h_{t-1} and the candidate hidden state $\tilde{h}_t$ using the update gate z_t:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{8}$$

This recurrent updating process is applied iteratively over the entire sequence of skeleton landmarks, allowing the GRU to capture temporal dependencies and extract meaningful pose and gesture information.

4) LONG SHORT-TERM MEMORY

The Long Short-Term Memory (LSTM) network [29] is a kind of recurrent neural network that can effectively model sequential data such as human pose and gesture information based on skeleton landmarks. In an LSTM unit, the following equations govern its operation:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{9}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{10}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{11}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{12}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{13}$$

$$h_t = o_t \odot \tanh(C_t) \tag{14}$$

where:

i_t, f_t, o_t are the input, forget, and output gate at a time step t,
$\tilde{C}_t$ is the candidate cell state at time step t,
C_t is the cell state value at time step t,
h_t is the hidden state value at time step t,
x_t is the input value at time step t,
$[h_{t-1}, x_t]$ denotes the combination of h_{t-1} and x_t,
σ is the sigmoid activation function, and
$\odot$ represents element-wise multiplication.

The LSTM network's ability to capture temporal dependencies and handle long-term memory makes it suitable for human pose and gesture estimation tasks based on sequential skeleton landmarks data.

TABLE 2. Hyperparameter setting analysis of applied method in this study.

Method	Hyperparameter Description
RF	n_estimators=4, max_depth=2, random_state=0, criterion='entropy'
LR	random_state=0, max_iter=12, multi_class='auto', C=1.0
GRU	Dropout=0.2, activation='softmax', loss = 'categorical_crossentropy', optimizer = 'adam' , metrics='accuracy'
LSTM	Dropout=0.2, activation='softmax', loss = 'categorical_crossentropy', optimizer = 'adam' , metrics='accuracy'

D. HYPERPARAMETER OPTIMIZATION

The most appropriate parameters for the applied deep learning and machine learning algorithms are selected using a recursive testing and training process [30]. Table 2 demonstrates the best-fit selected parameters for our applied human pose and gesture assessment models.

IV. RESULTS AND DISCUSSIONS

This section provides a thorough analysis of the outcomes obtained from employing machine learning techniques in the field of human pose estimation. Within this section, we examine the empirical findings derived from our experiments and thoroughly explore their implications. The results presented highlight the precision and effectiveness of each algorithm, as measured by various performance metrics.

A. EXPERIMENTAL SETTING

To conduct our research experiments on human pose estimation, we have developed advanced AI approaches using the Python 3.0 programming language. We employed an open-source environment called Google Colab to implement our experiments. This environment features a GPU backend, 13 GB of RAM, and 90 GB of disk space. We evaluated the performance of the applied pose estimation method using metrics such as precision, accuracy, recall, f1 score, standard deviations, and runtime computation.

B. RESULTS WITH ORIGINAL FEATURES

This section comprises the performance analysis using all features. Each applied machine learning and deep learning model undergoes evaluation by utilizing all dataset features, as illustrated in Table 3. The parameters employed to assess the results of the applied methods include accuracy, recall, and F1 score. Additionally, the classification report is analyzed. The analysis reveals that machine learning models outperform deep learning methods. Among all dataset features, the LSTM method yields the lowest performance score, followed by the GRU approach. The machine learning-based RF achieves an acceptable performance score of 87%. Conversely, the LR approach attains the highest accuracy score of 95% in comparison to the others. This analysis concludes that the method exhibits low performance for human pose and gesture estimation when all dataset features are applied. Consequently, there exists a requirement for an advanced feature selection mechanism to mitigate dimensionality and enhance performance.

TABLE 3. Performance metrics analysis results with original features.

Method	Accuracy	Target class	Precision	Recall	F1
RF	0.87	left_bicep	1.00	1.00	1.00
		left_shoulder	1.00	1.00	1.00
		left_tricep	0.00	0.00	0.00
		rest	1.00	1.00	1.00
		right_bicep	0.53	1.00	0.69
		right_shoulder	1.00	1.00	1.00
		right_tricep	1.00	1.00	1.00
		Average	0.80	0.87	0.83
LR	0.95	left_bicep	1.00	0.90	0..95
		left_shoulder	0.89	0.98	0.93
		left_tricep	1.00	1.00	1.00
		rest	1.00	1.00	1.00
		right_bicep	0.80	1.00	0.89
		right_shoulder	1.00	0.77	0.87
		right_tricep	1.00	1.00	1.00
		Average	0.96	0.95	0.95
GRU	0.64	left_bicep	0.52	0.99	0.68
		left_shoulder	0.53	0.85	0.65
		left_tricep	0.64	0.28	0.39
		rest	0.88	0.49	0.63
		right_bicep	0.96	0.84	0.90
		right_shoulder	0.60	0.70	0.65
		right_tricep	0.90	0.40	0.55
		Average	0.71	0.64	0.63
LSTM	0.22	left_bicep	0.10	0.35	0.15
		left_shoulder	0.00	0.00	0.00
		left_tricep	0.28	0.31	0.29
		rest	0.00	0.00	0.00
		right_bicep	0.00	0.00	0.00
		right_shoulder	0.38	0.82	0.52
		right_tricep	0.00	0.00	0.00
		Average	0.11	0.22	0.14

C. RESULTS WITH NOVEL PROPOSED APPROACH

Using the proposed LogRF approach, the twenty selective features are utilized to assess the performance of the applied methods as described in Table 4. The deep learning-based LSTM method achieved an accuracy score of 0.829, which is acceptable and significantly improved compared to the results with the original features. The GRU approach also performs well, with a performance accuracy of 0.974. The machine learning models demonstrate strong performance with the selected features. The highest performance accuracy of 0.998 is achieved by the proposed RF approach. Additionally, the classification report results for each method show significant improvement. This analysis concludes that all applied methods enhanced their performance accuracy with these highly important selective features. Our proposed approach proves to be beneficial in enhancing human pose estimation performance.

The performance analysis of applied neural network techniques based on time series is presented in Figure 5. The training loss, validation loss, training accuracy, and validation accuracy are the performance metrics evaluated during the training process of GRU and LSTM models. The analysis indicates that in the initial five epochs, loss scores are high, and accuracy scores are low due to the random weight initialization of the neural network at the start layer. After achieving optimal weights in the sixth epoch, both deep learning methods improve their performance scores and reduce the loss. This analysis concludes that the deep learning models

TABLE 4. Performance metrics analysis results with selective features.

Method	Accuracy	Target class	Precision	Recall	F1
RF	**0.998**	left_bicep	1.00	1.00	1.00
		left_shoulder	1.00	0.98	0.99
		left_tricep	1.00	1.00	1.00
		rest	0.99	1.00	0.99
		right_bicep	1.00	1.00	1.00
		right_shoulder	1.00	1.00	1.00
		right_tricep	1.00	1.00	1.00
		Average	**1.00**	**1.00**	**1.00**
LR	0.990	left_bicep	1.00	1.00	1.00
		left_shoulder	1.00	0.98	0.99
		left_tricep	0.99	1.00	0.99
		rest	1.00	1.00	1.00
		right_bicep	0.99	0.96	0.97
		right_shoulder	0.96	0.99	0.98
		right_tricep	1.00	1.00	1.00
		Average	0.99	0.99	0.99
GRU	0.974	left_bicep	0.96	1.00	0.98
		left_shoulder	0.98	1.00	0.99
		left_tricep	0.99	0.90	0.94
		rest	1.00	1.00	1.00
		right_bicep	1.00	0.97	0.98
		right_shoulder	0.90	0.95	0.93
		right_tricep	1.00	1.00	1.00
		Average	0.97	0.97	0.97
LSTM	0.829	left_bicep	0.62	1.00	0.76
		left_shoulder	0.99	0.99	0.99
		left_tricep	0.89	0.37	0.53
		rest	1.00	0.90	0.94
		right_bicep	0.83	0.92	0.87
		right_shoulder	0.80	0.84	0.81
		right_tricep	0.85	0.83	0.84
		Average	0.86	0.83	0.82

attained commendable scores of 90 and above when trained on selected dataset features.

The performance validation analysis, based on the confusion matrix, of the applied methods with selective features is depicted in Figure 6. The analysis reveals that machine learning techniques exhibited a lower error rate during classification compared to deep learning approaches. Specifically, the LSTM model produced 65 incorrect predictions, indicating a significant error rate. In contrast, the proposed RF approach yielded only 1 incorrect prediction in the context of human pose estimation, thereby confirming the exceptional performance of the proposed model.

D. K-FOLD CROSS VALIDATIONS ANALYSIS

We utilized k-fold cross-validation mechanisms to validate the performance of each applied method, as outlined in Table 5. The cross-validation analysis is based on k-fold accuracy and standard deviations. The dataset of selective features is divided into ten folds and used for evaluation. The analysis reveals that deep learning models exhibited low-performance scores with high standard deviations during validations. In comparison, the machine learning method achieved favourable validation scores. This analysis concludes that the proposed RF method attained a high k-fold accuracy score of 0.99 with a minimal standard deviation of 0.0042. Our proposed method has been successfully validated in a generalized manner for human pose estimations during fitness exercise corrections.

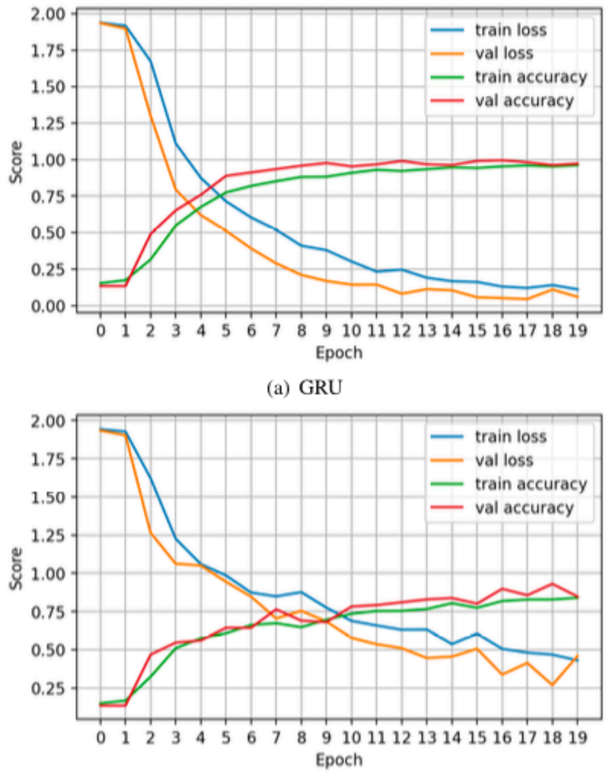

FIGURE 5. Time series-based performance comparison analysis of applied neural network approaches during training.

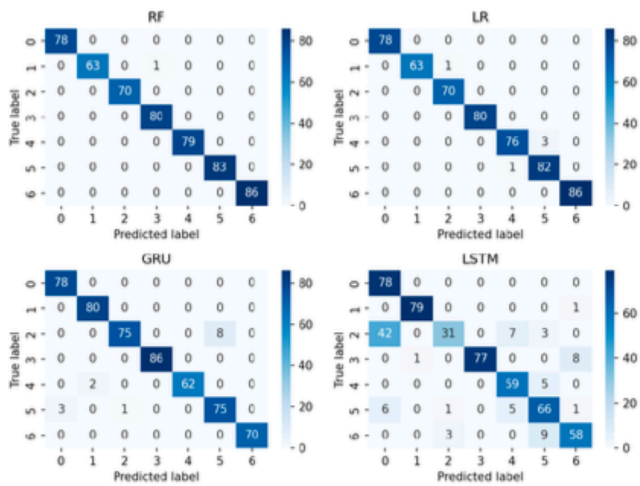

FIGURE 6. Confusion matrix analysis of the applied approaches.

TABLE 5. Performance validation analysis results with proposed features.

Method	k-fold	Accuracy	Standard deviations (+/-)
RF	**10**	**0.99**	**0.0042**
LR	10	0.98	0.0054
GRU	10	0.84	0.1259
LSTM	10	0.68	0.2149

E. COMPUTATIONS COMPLEXITY ANALYSIS

The computational complexity analysis of the applied methods is presented in Table 6. We calculated the runtime computation scores in seconds for each applied method during dataset construction. Upon comparison, it was found

TABLE 6. Computations complexity analysis with proposed features.

Method	Runtime Computations (seconds)
RF	**0.033**
LR	0.062
GRU	10.47
LSTM	12.62

TABLE 7. Performance comparisons with pose estimation based state of the art studies.

Ref	Proposed Technique	Performance Accuracy
[31]	Ensemble Model	0.93
[32]	Scalable Neural Network	0.95
[33]	Two Stream Bilinear C3D	0.84
Our Study	**LogRF+RF**	**0.99**

that deep learning models exhibit the highest complexity, which subsequently results in lower performance. The machine learning-based LR achieved lower complexity when compared to the deep learning methods. The analysis demonstrates that the proposed RF method achieved the minimum computation score of 0.033 seconds for human pose estimation.

F. STATE OF THE ART COMPARISON

The performance of the proposed method was compared with state-of-the-art pose estimation studies, as outlined in Table 7. We selected advanced pose estimation studies for this comparison. The analysis demonstrates that the state-of-the-art studies achieved moderate performance scores. In contrast, our proposed approach outperformed these studies, achieving a high accuracy score of 0.99 for human pose estimation.

V. CONCLUSION AND FUTURE WORK

This research proposes an efficient artificial intelligence method for human pose estimation during physiotherapy fitness exercises. We utilized a multi-class exercise dataset based on human skeleton movement points to conduct our experimental research. The dataset has high feature dimensionality, which affects the performance of human pose estimation with machine learning and deep learning methods. In this research, we have introduced a novel LogRF method for feature selection. We employed four advanced machine learning and deep learning approaches for performance comparison. Extensive experiments demonstrate that the RF method outperformed state-of-the-art studies using the top twenty selected features with a high-performance score of 0.998. The results of each applied method are validated through a k-fold approach and further enhanced using hyperparameter tuning.

A. FUTURE WORK

For future directions, we plan to create an interactive graphical user interface. This interface will incorporate our proposed backend system and connect to a real-time camera. The intended interface aims to accurately estimate human poses for the purpose of correcting physiotherapy fitness exercises.

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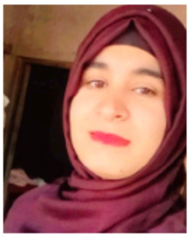
ALI RAZA received the Bachelor of Science degree in computer science from the Department of Computer Science, Khwaja Fareed University of Engineering and Information Technology (KFUEIT), Rahim Yar Khan, Pakistan, in 2021, and the M.S. degree in computer science from KFUEIT. He has published several articles in reputed journals. His current research interests include data science, artificial intelligence, data mining, natural language processing, machine learning, deep learning, and image processing.

AZAM MEHMOOD QADRI received the master's degree in information technology from the Department of Computer Science and Information Technology, Virtual University, Lahore, Pakistan, in 2017. He is currently pursuing the M.S. degree in computer science with the Khwaja Fareed University of Engineering and Information Technology (KFUEIT), Rahim Yar Khan, Pakistan. His research interests include machine learning, deep learning, and artificial intelligence.



IQRA AKHTAR received the Bachelor of Science degree in physics from the Institute of Physics, Khwaja Fareed University of Engineering and Information Technology (KFUEIT), Rahim Yar Khan, Pakistan, where she is currently pursuing the M.S. degree in electronics with the Department of Electrical and Biomedical Engineering. Her current research interests include artificial intelligence, physics applications, and physical science.

NAGWAN ABDEL SAMEE received the B.S. degree in computer engineering from Ein Shams University, Egypt, in 2000, and the M.S. degree in computer engineering and the Ph.D. degree in systems and biomedical engineering from Cairo University, Egypt, in 2008 and 2012, respectively. Since 2013, she has been an Assistant Professor with the Information Technology Department, CCIS, Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia. Her research interests include data science, machine learning, bioinformatics, and parallel computing. Her awards and honors include the Takafull Prize (Innovation Project Track), Princess Nourah Award in innovation, the Mastery Award in predictive analytics (IBM), the Mastery Award in Big Data (IBM), and the Mastery Award in Cloud Computing (IBM).

MAALI ALABDULHAFITH was born in Saudi Arabia, in September 1985. She received the Doctor of Philosophy (Ph.D.) degree in computer science from Dalhousie University, Halifax, Canada, in 2017. In 2014, she joined the College of Computer and Information Science (CCIS), Princess Nourah bint Abdulrahman University (PNU), as a Lecturer. She was promoted to an Assistant Professor, in 2018. Currently, she is the Director of Data Management and Performance Measurement with CCIS, PNU, overlooking and managing the strategy of the college. Her research interests include machine learning, data analytics, emerging wireless technology, and technology applications in health care.

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APPENDIX C
Published Paper and Certificate

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PHYSIOTHERAPY POSE DETECTION MODEL

Prof.Saurabh Paradh, Chaitanya Pathak, Atharv Chormale, Jay Patil
Savitribai Phule Pune University, Sinhgad College of Engineering Warje
E-mails: ithod.rmdssoe@sinhgad.edu,chaitanyapathak218@gmail.com,
jaydpatil1102@gmail.com, atharvchormale27@gmail.com

Abstract

Human pose recognition has become an important focus in computer vision, particularly for applications in physiotherapy and self-assessment. In this work, we present an approach for accurate physiotherapy pose assessment using deep learning algorithms. The proposed system utilizes pose detection to facilitate the self-guided learning of physiotherapy exercises. Specifically, our approach employs multi-part pose detection through a standard PC camera to capture and analyze physiotherapy poses in real-time. We introduce an enhanced scoring algorithm capable of assessing various poses, which ensures adaptability across different pose types and environments. Additionally, a hybrid machine learning model is implemented using Linear Regression to extract features from key points identified in each frame, leveraging the Open Pose framework. The robustness of this system is evaluated across multiple physiotherapy poses in diverse settings, demonstrating its potential for effective, real-time physiotherapy

assessment Keywords:
Physiotherapy Pose Assessment
Deep Learning Algorithms
Pose Detection

INTRODUCTION

The physiotherapy pose detection model leverages advancements in computer vision and deep learning to enhance the effectiveness of physiotherapy exercises. Its primary goal is to monitor and assess patients' posture and movements in real-time, providing feedback to ensure accurate exercise execution, which is essential for successful rehabilitation.

The system is built upon human pose estimation techniques, using pose detection algorithms to capture and analyze body movements accurately. It operates via a standard PC camera, allowing users to perform exercises in any setting, making it particularly useful for home-based rehabilitation and self-guided physiotherapy. By detecting and assessing posture through key points on the body, the model ensures that patients maintain proper form, reducing the risk of injury and improving therapeutic outcomes

His model also incorporates machine learning algorithms, such as logistic regression, to analyze the relationship between different posture variables and assess pose accuracy. Additionally, the use of frameworks like OpenPose enhances the precision and adaptability of the model, enabling it to work effectively across various environments and pose types.Ultimately, this physiotherapy pose detection model provides a valuable tool for accessible, reliable, and private physiotherapy support, promoting better recovery outcomes and empowering patients to manage their rehabilitation independently.

LITERATURE REVIEW

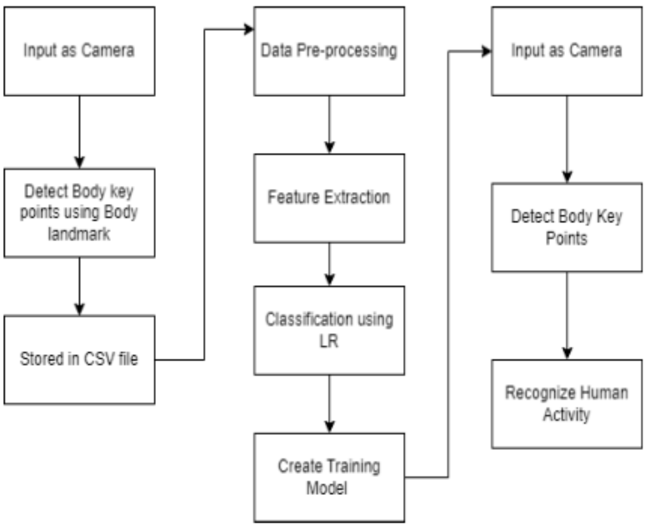
Pose detection for physiotherapy is an emerging field within computer vision, aimed at improving patient rehabilitation by assessing exercise accuracy and providing real-time feedback. This literature review synthesizes key research contributions and identifies ongoing challenges and future directions.Recent studies have focused on developing algorithms that can accurately assess physiotherapy poses in real-time. For instance, Agrawal, Shah, and Sharma's work highlights the importance of dataset diversity and the challenges posed by limited data. They created a specialized dataset of over 5,500 images covering ten distinct physiotherapy poses to train and test their model, which achieved a high accuracy of 99.04% using a Random Forest Classifier. The success of this model is attributed to the use of TensorFlow's pose estimation framework, which allows precise skeletal structure extraction and joint angle calculation, essential for pose assessment

Despite advancements in pose recognition algorithms, challenges such as real-time feedback, generalizability, and dataset limitations persist. Real-time feedback is critical for physiotherapy applications but remains difficult to implement effectively without significant computational resources. Additionally, the limited diversity of existing datasets hinders model adaptability across varied poses, exercises, and user environments. Addressing these issues is crucial for the effectiveness of physiotherapy pose detection systems in clinical and home settings.

Future research may explore methods to diversify datasets, enhance real-time feedback capabilities, and integrate wearable sensor data to improve accuracy and responsiveness. Studies also suggest that combining machine learning models with Internet of Things (IoT) technologies could provide a more robust framework for pose recognition, extending its utility in physiotherapy and self-guided rehabilitation applications.

DESIGN AND IMPLEMENTATION

The physiotherapy pose detection system leverages a stationary camera to capture continuous video input of individuals performing exercises. Key body points, such as elbows, knees, and shoulders, are identified to assess posture, with the coordinates stored in a structured CSV file for efficient data access. Pre-processing steps, including data cleaning and alignment, enhance the data quality, reducing noise and improving consistency. Essential features, like joint angles and distances between key points, are extracted for precise posture representation. The system then employs Logistic Regression for pose classification by calculating probabilities based on these features. Following training, the model accurately assesses new poses by comparing them to learned patterns, enabling real-time feedback to ensure correct form and support effective physiotherapy and rehabilitation.



Functionalities: Video Input and Capture: The system initiates by capturing continuous video input from a stationary camera, recording individuals performing physiotherapy exercises. This video feed serves as the primary source of data, enabling real-time pose detection and analysis for immediate feedback.

Body Key Point Detection: Specific body landmarks, including major joints such as elbows, knees, shoulders, and ankles, are detected and tracked. This process allows the system to create a skeletal model of the person, essential for analyzing posture and identifying correct or incorrect alignment.

Data Storage: After detecting key points, their coordinates are stored in a CSV file, providing a structured format for data management. This organized storage allows for efficient retrieval and use of the data in later stages of processing and model training.

Data Pre-processing: The raw key point data undergoes cleaning and normalization to remove noise and ensure consistency. This pre-processing step includes aligning data points, filtering out irrelevant frames, and standardizing data, which optimizes it for feature extraction and model training.

Feature Extraction: The system calculates critical features, such as joint angles, distances between key points, and relative limb positions. These features capture the essentials of body posture, forming a detailed representation that can differentiate between correct and incorrect physiotherapy poses.

Pose Classification: Using the extracted features, the system applies Logistic Regression to classify physiotherapy poses by assigning probabilities to each pose type. This classification step enables the model to label each pose based on the likelihood of its correctness, which is crucial for pose assessment.

Model Training and Evaluation: With labeled data and extracted features, a machine learning model is trained to recognize specific poses. Through training, the model learns to accurately classify poses, improving its performance over time to ensure reliable assessment when applied to new data.

Real-time Pose Assessment: Once trained, the system assesses physiotherapy poses in real-time, comparing observed features against trained patterns to determine posture accuracy. This functionality provides instant feedback, helping users maintain correct form and supporting effective rehabilitation outcomes.

CONCLUSION

In our proposed physiotherapy posture recognition and correction system, we aim to assist learners in accurately performing physiotherapy exercises by providing immediate, targeted feedback. The system operates by first detecting the learner’s pose and then measuring key body angles in comparison with an instructor's reference pose. Any discrepancies in alignment are identified, pinpointing specific areas where the learner's form diverges from the ideal stance. Based on these differences, the system classifies the learner’s posture into four performance levels, offering a structured assessment that guides users toward corrective action and improvement. This approach enhances training effectiveness, supporting precise and reliable physiotherapy practice.

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