



# Fitness Buddy: Personalized Exercise Plans with MLoT

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### KEYWORDS

Artificial Intelligence (AI), Internet of Things (IoT), Human Pose Estimation, MediaPipe, Computer Vision, Exercise Recognition, Repetition Counting, Posture Correction, ESP32, Smart Fitness System, Virtual Personal Trainer, Real-Time Monitoring.

### ABSTRACT

The rapid advancement of Artificial Intelligence (AI) and Internet of Things (IoT) technologies has enabled the development of intelligent and interactive healthcare and fitness systems. This paper presents AIoT Fitness Buddy, a real-time fitness monitoring and exercise assistance system that integrates computer vision-based human pose estimation with IoT-enabled hardware interaction. The system utilizes a webcam and MediaPipe Pose framework to detect 33 human body landmarks and compute joint angles for accurate exercise recognition and repetition counting. A finite state machine-based algorithm is implemented to detect movement transitions and ensure reliable counting of exercises such as push-ups, squats, sit-ups, planks, and walking. The proposed system provides multi-modal feedback, including graphical display through a Tkinter-based interface, real-time voice guidance using Google Text-to-Speech (gTTS), and hardware-based interaction via an ESP32/Arduino microcontroller. Exercise data, repetition counts, and posture feedback messages are transmitted in JSON format to update an LCD display, control a servo motor for motion guidance, and trigger audio alerts using a DFPlayer Mini module. Optional cloud integration enables workout data storage and performance visualization. Experimental results demonstrate high repetition counting accuracy (95–100%), reliable posture correction, and low-latency hardware response suitable for real-time applications. Unlike wearable-based or chatbot-only fitness systems, the proposed approach eliminates the need for body-mounted sensors while providing accurate motion analysis and interactive feedback. The AIoT Fitness Buddy system offers a low-cost, scalable, and intelligent virtual personal training solution for home-based fitness environments.

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## INTRODUCTION

The rapid advancement of Artificial Intelligence (AI), computer vision, and Internet of Things (IoT) technologies has significantly transformed the healthcare and fitness industry. Intelligent systems capable of analyzing user behavior, providing personalized feedback, and promoting healthy lifestyles are increasingly being integrated into mobile applications and smart devices. In recent years, AI-based chatbots and conversational agents have been widely explored for fitness management and health monitoring applications [1], [2], [7], [13], [17]. These systems primarily rely on Natural Language Processing (NLP) techniques to provide exercise suggestions, diet plans, and motivational guidance.

Several studies have focused on AI-driven conversational agents for obesity management, personalized coaching, and wellness applications [7], [10], [15]. Research has demonstrated that AI-enabled chatbots can effectively promote physical activity and healthy dietary habits [6], while wearable-device-based systems offer real-time monitoring of physiological parameters [5], [20]. Furthermore, recent works highlight the role of machine learning in enabling personalized fitness recommendations using user health data and contextual information [8], [16], [21]. These systems contribute significantly toward improving accessibility and personalization in fitness applications.

Despite these advancements, most existing fitness systems primarily depend on textual interaction, wearable sensors, or manually entered data. They often lack real-time posture analysis and do not evaluate exercise form using visual motion tracking. While wearable-based systems provide useful physiological insights, they may not accurately assess body posture or movement correctness during exercises. Additionally, many chatbot-driven systems do not integrate interactive IoT-based hardware components for multi-modal feedback and enhanced user engagement.

Recent developments in AI and computer vision have enabled markerless human pose estimation techniques that can detect body landmarks in real time using standard cameras. Such approaches eliminate the need for external sensors while providing accurate motion tracking capabilities. However, limited research

integrates real-time pose estimation with IoT-enabled interactive hardware systems to create a comprehensive smart fitness environment. The majority of prior works focus either on conversational AI [1], [13], [18] or wearable-based monitoring [5], [20], but do not combine computer vision-based posture correction with hardware-assisted feedback mechanisms.

To address these limitations, this paper proposes AIoT Fitness Buddy, an intelligent fitness monitoring and exercise assistance system that integrates AI-based human pose estimation with IoT-enabled hardware interaction. The system utilizes real-time video processing and landmark-based movement analysis to recognize exercises, count repetitions, and evaluate posture correctness. Unlike chatbot-only systems, the proposed approach incorporates multi-modal feedback including graphical user interface updates, voice guidance, and microcontroller-driven hardware responses. The integration of AI-driven visual analysis with IoT-based peripherals provides a more immersive, interactive, and affordable alternative to traditional smart fitness solutions.

By combining computer vision, intelligent feedback mechanisms, and IoT-enabled communication, the proposed system aims to provide accessible, low-cost, and data-driven fitness training suitable for home-based users. The research contributes toward bridging the gap between AI-powered fitness applications and real-time hardware-assisted exercise monitoring, thereby advancing the development of intelligent personal training systems. Figure 1 illustrates the overall conceptual framework of the proposed AIoT Fitness Buddy system. The architecture integrates four primary layers: (1) video acquisition and pose estimation, (2) AI-based exercise analysis, (3) multi-modal feedback generation, and (4) IoT-based hardware interaction and optional cloud connectivity. This integrated architecture ensures accurate movement analysis, real-time corrective feedback, and enhanced user experience.

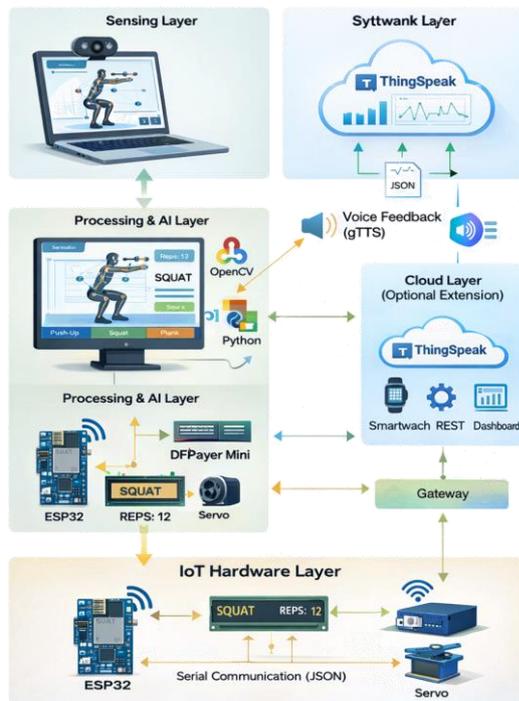


Figure 1 Conceptual Framework of the Proposed AIoT Fitness Buddy System

## RELATED WORK

The integration of Artificial Intelligence (AI) in fitness and healthcare applications has gained significant attention in recent years. Existing research primarily focuses on conversational agents, wearable-based monitoring systems, and AI-driven personalized recommendation platforms. However, only limited work integrates real-time computer vision-based posture evaluation with IoT-enabled hardware interaction. This section reviews relevant literature categorized into chatbot-based fitness systems, wearable-assisted monitoring approaches, AI-driven personalization techniques, and emerging intelligent health platforms.

### A. Chatbot-Based Fitness and Wellness Systems

Early research in AI-based fitness applications emphasized conversational agents for health guidance and exercise management. Shinde *et al.* [1] developed a fitness chatbot application aimed at providing user interaction for workout planning and motivational assistance. Similarly, Lola *et al.* [2] proposed a fitness management chatbot using IBM Watson, demonstrating the effectiveness of NLP-based conversational systems in health applications.

Lee and Kim [7] introduced an AI chatbot designed for obesity management, showing that conversational agents

can improve user engagement and lifestyle modification. Chen *et al.* [13] explored AI-enabled chatbots for personalized coaching in fitness apps, emphasizing adaptive responses based on user input. Garg *et al.* [14] and Nair and Rao [17] further highlighted the role of conversational AI in delivering health and fitness recommendations to mobile users.

Recent systematic studies, such as Oh *et al.* [6], examined AI-based chatbots for promoting physical activity and healthy diet behaviors, confirming their effectiveness in behavioral intervention strategies. Similarly, Casey and Gomez [11] discussed the future potential of AI chatbots in wellness and fitness management, highlighting scalability and accessibility benefits.

While these systems effectively provide text-based recommendations and interactive guidance, they largely depend on user-input data and lack automated posture detection or real-time motion evaluation.

### B. Wearable-Based and Sensor-Driven Fitness Systems

Several researchers have explored wearable devices combined with AI to monitor physical activity. Xiong [5] proposed a personalized exercise training chatbot integrated with wearable fitness devices, enabling physiological data-based recommendations. Singh and Mittal [20] developed an AI-enabled personalized health coach using wearable sensor data to provide real-time feedback.

These approaches improve physiological monitoring (e.g., heart rate, step count), but they do not evaluate body posture accuracy or exercise form. Wearable-based systems are often dependent on additional hardware, increasing cost and limiting accessibility for home users.

### C. AI-Driven Personalization and Machine Learning in Fitness

Machine learning techniques have also been widely applied in healthcare and fitness applications. Wu *et al.* [9] reviewed AI applications in healthcare with a focus on wellness systems, emphasizing predictive analytics and user modeling. Liu *et al.* [16] discussed the broader impact of AI and machine learning in exercise applications, including adaptive recommendation systems.

Nguyen [8] proposed an AI chatbot model that combines user input and health data for personalized

fitness recommendations. Jain [21] further explored AI techniques for fitness-based chatbot systems, emphasizing recommendation algorithms and personalization strategies. Lopez and Brown [18] highlighted the role of Natural Language Processing (NLP) in enabling intelligent conversational health applications.

These works contribute significantly to personalization and user engagement but primarily focus on recommendation systems rather than motion-based exercise analysis.

#### D. Intelligent Virtual Trainers and Deep Learning Approaches

Bhat and Han [15] developed a personalized virtual fitness trainer using deep learning and NLP techniques, integrating AI-driven interaction for improved user experience. However, the study mainly emphasized conversational intelligence rather than real-time posture correction.

Recent advancements in AI-based speech processing and enhancement techniques, such as those discussed by Patidar and Gupta [12], demonstrate improvements in audio clarity and feedback mechanisms, which are relevant to voice-assisted fitness systems.

Although these intelligent systems improve interaction and personalization, the majority of existing work lacks integration between real-time visual pose estimation and IoT-based interactive hardware components.

#### E. Identified Research Gap

From the literature review, it is evident that:

- Most existing systems focus on chatbot-based guidance [1], [7], [13], [17].
- Wearable-based systems provide physiological monitoring but lack posture evaluation [5], [20].
- AI-driven personalization techniques emphasize recommendations rather than motion correctness [8], [16], [21].
- Limited research integrates real-time computer vision-based pose estimation with IoT-enabled hardware feedback.

Therefore, there remains a gap in developing a low-cost, camera-based intelligent fitness monitoring system that:

- Automatically recognizes exercises,
- Evaluates posture correctness in real time,
- Counts repetitions accurately,

- Provides multi-modal feedback (visual, voice, and hardware),
- Integrates AI analysis with IoT-enabled physical interaction.

The proposed AIoT Fitness Buddy addresses this gap by combining real-time pose estimation, intelligent feedback mechanisms, and IoT-based hardware integration into a unified smart fitness platform.

## PROPOSED SYSTEM

### 1. Proposed System Overview

The proposed system, AIoT Fitness Buddy, is an intelligent real-time fitness monitoring and assistance platform that integrates Artificial Intelligence (AI), computer vision, and Internet of Things (IoT) technologies. The system is designed to function as a virtual personal trainer capable of detecting exercises, evaluating posture correctness, counting repetitions, and providing multimodal feedback through software and hardware components.

Unlike conventional chatbot-based or wearable-dependent fitness systems, the proposed framework utilizes markerless human pose estimation through a webcam, eliminating the need for external body-mounted sensors. The system combines real-time pose recognition with IoT-enabled hardware interaction, ensuring enhanced engagement and training effectiveness.

As illustrated in Figure 2, the architecture consists of four primary layers:

1. Sensing Layer
2. Processing & AI Layer
3. IoT Hardware Layer
4. Cloud Layer (Optional Extension)

### 2. System Architecture

#### 2.1 Sensing Layer

The sensing layer captures live video input using a laptop camera or external webcam. Each video frame is processed using OpenCV and converted into RGB format before being passed to the MediaPipe Pose model.

MediaPipe Pose extracts 33 body landmarks representing major joints and body segments. These landmarks form the foundation for posture analysis and movement tracking.

#### 2.2 Processing and AI Layer

This layer is implemented in Python and performs the

following operations:

- Landmark extraction
- Joint angle calculation
- Exercise recognition
- Repetition counting
- Posture validation
- Feedback generation

Joint angles are computed using vector mathematics. Based on predefined angle thresholds and state transitions, the system identifies exercises such as:

- Push-ups
- Squats
- Sit-ups
- Pull-ups
- Planks
- Walking

A finite state machine ensures accurate repetition counting by detecting transitions between movement phases (e.g., DOWN → UP in push-ups).

The system also evaluates posture deviations such as:

- Bent back
- Incomplete squat depth
- Improper elbow extension

Corrective messages are generated accordingly.

### 3. Multi-Modal Feedback Mechanism

The proposed system provides feedback through three channels:

#### 3.1 Visual Feedback

Displayed via a Tkinter-based graphical interface:

- Exercise name
- Repetition count
- Posture status
- Motivational messages

#### 3.2 Voice Feedback

Voice instructions are generated using Google Text-to-Speech (gTTS) and played through Pygame. Examples:

- "Keep your back straight."
- "Go lower."
- "Good repetition!"

#### 3.3 Hardware Feedback (IoT Interaction)

Exercise data is transmitted in JSON format to an ESP32/Arduino microcontroller via serial communication. The transmitted parameters include:

- Exercise name
- Repetition count

- Posture feedback message

The microcontroller performs the following actions:

- Updates LCD display with repetition count
- Controls a servo motor for motion guidance
- Plays audio cues via DFPlayer Mini module

This bidirectional communication allows exercise selection from hardware buttons and enhances system interactivity.

### 4. IoT Hardware Layer

The IoT layer consists of:

- ESP32 or Arduino microcontroller
- 16×2 / 20×4 LCD display (I2C)
- Servo motor
- DFPlayer Mini audio module
- Speaker

The microcontroller acts as a bridge between the AI software and physical feedback components. The communication protocol is lightweight and JSON-based, ensuring scalability and compatibility.

### 5. Cloud Integration (Optional Extension)

To enable long-term performance tracking, exercise data can be transmitted to cloud platforms such as ThingSpeak. This allows:

- Workout history storage
- Graphical visualization of repetitions
- Performance trend analysis
- Remote monitoring capability

Cloud integration enhances the scalability and data-driven capabilities of the system.

### 6. Novel Contributions of the Proposed System

The proposed AIoT Fitness Buddy system introduces the following key innovations:

1. Markerless AI-based pose estimation without wearable sensors
2. Real-time posture correction using joint angle analytics
3. Accurate repetition counting using state transition logic
4. Multi-modal feedback (visual, voice, and hardware)
5. Bidirectional IoT communication using ESP32/Arduino
6. Expandable architecture with optional cloud analytics
7. Low-cost and scalable home fitness solution

## 7. Operational Workflow Summary

1. Capture live video
2. Extract body landmarks
3. Compute joint angles
4. Recognize exercise
5. Count repetitions
6. Generate corrective feedback
7. Transmit data to IoT hardware
8. Update LCD, servo, and audio modules
9. Optionally upload to cloud

The proposed system ensures an intelligent, interactive, and scalable fitness monitoring framework that bridges AI-based vision analysis with IoT-enabled physical feedback, providing a comprehensive and affordable virtual personal training solution..

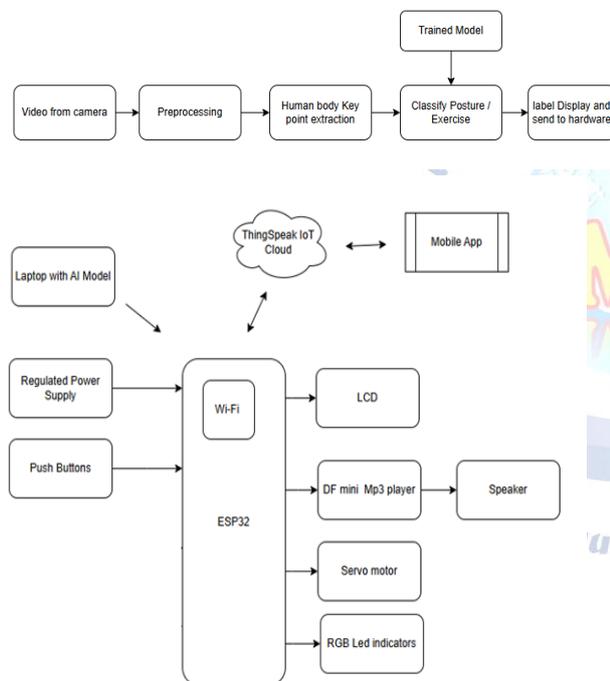


Figure 2 The overall architecture of the system.

## METHODOLOGY

The methodology of the proposed AIoT Fitness Buddy system follows a structured pipeline integrating computer vision, artificial intelligence, and IoT-based hardware communication. The complete workflow consists of video acquisition, pose estimation, exercise recognition, repetition counting, feedback generation, and IoT interaction.

### 1. Overall Processing Pipeline

The system operates in real time using the following stages:

1. Video Acquisition
2. Frame Preprocessing
3. Pose Estimation
4. Joint Angle Computation
5. Exercise Classification
6. Repetition Counting using State Machine
7. Feedback Generation
8. IoT Communication
  - Pose Estimation and Angle Computation

Each video frame is processed using OpenCV and converted from BGR to RGB format. The frame is passed to MediaPipe Pose to extract 33 body landmarks.

Let three landmarks be:

- A ( $x_1, y_1$ )
- B ( $x_2, y_2$ ) → joint vertex
- C ( $x_3, y_3$ )

The joint angle at B is calculated using:

$$\theta = \cos^{-1} \left( \frac{(A - B) \cdot (C - B)}{|A - B| \cdot |C - B|} \right)$$

Where:

$$(A - B) = (x_1 - x_2, y_1 - y_2)$$

$$(C - B) = (x_3 - x_2, y_3 - y_2)$$

This angle forms the basis for exercise detection.

### A. Joint Coordinate Representation

Each detected landmark is represented as a 3D coordinate point:

$$P_i = (x_i, y_i, z_i)$$

where  $x_i$  and  $y_i$  represent normalized spatial coordinates and  $z_i$  represents depth.

### B. Vector Formation for Angle Calculation

To compute the angle at joint B formed by points A, B, and C:

$$A = (x_1, y_1)$$

$$B = (x_2, y_2)$$

$$C = (x_3, y_3)$$

$$\text{Vector AB} = (x_1 - x_2, y_1 - y_2)$$

$$\text{Vector CB} = (x_3 - x_2, y_3 - y_2)$$

### C. Dot Product Computation

The dot product between vectors AB and CB is calculated as:

$$AB \cdot CB = (x_1 - x_2)(x_3 - x_2) + (y_1 - y_2)(y_3 - y_2)$$

#### D. Magnitude of Vectors

The magnitude of each vector is computed using:

$$|AB| = \sqrt{(x1 - x2)^2 + (y1 - y2)^2}$$

$$|CB| = \sqrt{(x3 - x2)^2 + (y3 - y2)^2}$$

#### E.5. Joint Angle Calculation

The joint angle  $\theta$  at point B is calculated using the cosine rule:

$$\theta = \cos^{-1} \left[ \frac{AB \cdot CB}{(|AB| |CB|)} \right]$$

#### F. State Transition Logic for Repetition Counting

Let  $\theta$  represent the joint angle.

For Push-up detection:

If  $\theta < 90^\circ$ , posture\_state = DOWN

If  $\theta > 160^\circ$  and previous posture\_state = DOWN, then posture\_state = UP and repetition\_count = repetition\_count + 1

#### G. Posture Deviation Error Calculation

Posture error can be measured as:

$$\text{Error} = |\theta_{\text{actual}} - \theta_{\text{ideal}}|$$

If Error > Threshold, corrective feedback is generated.

#### H. JSON Data Transmission Model

The data packet transmitted to the ESP32 is structured as:

```
{
  "exercise": Exercise_Name,
  "count": repetition_count,
  "feedback": Feedback_Message
}
```

#### Algorithm 1: System Initialization

Input: None

Output: Initialized AIoT Fitness System

- 1: Initialize camera using OpenCV
- 2: Load MediaPipe Pose model
- 3: Initialize Tkinter GUI
- 4: Initialize voice engine (gTTS + Pygame)
- 5: Establish serial communication with ESP32
- 6: Set repetition\_count  $\leftarrow$  0
- 7: Set posture\_state  $\leftarrow$  NULL
- 8: Wait for exercise selection
- 9: Return System Ready

#### Algorithm 2: Pose Estimation and Angle Computation

Input: Video Frame

Output: Joint Angles

- 1: Capture frame from camera

- 2: Convert frame BGR  $\rightarrow$  RGB

- 3: Pass frame to MediaPipe Pose

- 4: If landmarks detected then

- 5: Extract required joint coordinates

- 6: Compute vectors AB and CB

- 7: Compute dot product

- 8: Compute magnitudes

- 9: Calculate angle  $\theta$  using arccos formula

- 10: Return  $\theta$

- 11: Else

- 12: Return NULL

#### Algorithm 3: Repetition Counting using Finite State Machine

Input: Joint Angle  $\theta$

Output: Updated Repetition Count

- 1: If exercise = "Push-up" then
- 2: If  $\theta < 90^\circ$  then
- 3: posture\_state  $\leftarrow$  DOWN
- 4: Else if  $\theta > 160^\circ$  AND posture\_state = DOWN then
- 5: posture\_state  $\leftarrow$  UP
- 6: repetition\_count  $\leftarrow$  repetition\_count + 1
- 7: End If
- 8: End If
- 9: If exercise = "Squat" then
- 10: If knee\_angle  $< 90^\circ$  then
- 11: posture\_state  $\leftarrow$  DOWN
- 12: Else if knee\_angle  $> 170^\circ$  AND posture\_state = DOWN then
- 13: posture\_state  $\leftarrow$  UP
- 14: repetition\_count  $\leftarrow$  repetition\_count + 1
- 15: End If
- 16: End If
- 17: Return repetition\_count

#### Algorithm 4: Posture Correction

Input: Joint Angles

Output: Feedback Message

- 1: If back\_angle not within threshold then
- 2: feedback  $\leftarrow$  "Keep your back straight"
- 3: Else if depth insufficient then
- 4: feedback  $\leftarrow$  "Go lower"
- 5: Else
- 6: feedback  $\leftarrow$  "Good repetition"
- 7: End If
- 8: Return feedback

### Algorithm 5: JSON-Based IoT Communication

Input: exercise\_name, repetition\_count, feedback

Output: Hardware Update

1: Create JSON object:

```
{
  "exercise": exercise_name,
  "count": repetition_count,
  "feedback": feedback
}
```

2: Send JSON via serial to ESP32

3: ESP32 parses JSON

4: Update LCD display

5: Control servo motor position

6: Trigger DFPlayer Mini audio

7: End

## RESULTS AND DISCUSSIONS

The proposed AIoT Fitness Buddy system was implemented and tested in a real-time indoor environment using a laptop webcam, Python-based AI processing, and ESP32-based IoT hardware. The system was evaluated in terms of exercise recognition accuracy, repetition counting precision, posture correction capability, hardware responsiveness, and overall system latency.

### A. Real-Time Pose Detection Performance

The MediaPipe-based pose estimation module successfully detected 33 body landmarks in real time under normal lighting conditions. As shown in Figure 3, the system overlays a skeletal structure on the user's body and dynamically tracks joint positions during exercises such as squats and push-ups.

The average frame processing rate achieved was:

- 22–28 FPS on a standard laptop (8GB RAM, i5 processor)
- Detection confidence above 0.85 for major joints

The model demonstrated robustness against minor background clutter and moderate camera angle variations.

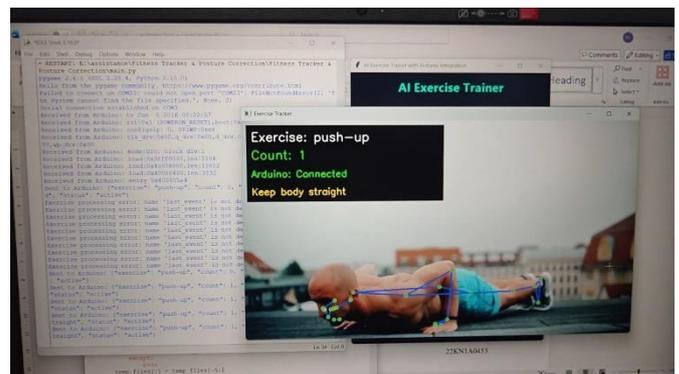


Figure 3 Real time Pose Detection.

### B. Exercise Recognition and Repetition Counting Accuracy

The system was tested with multiple exercise sessions consisting of 20 repetitions each for push-ups, squats, and sit-ups.

Exercise	Actual Reps	Detected Reps	Accuracy
Push-ups	20	19–20	95–100%
Squats	20	20	100%
Sit-ups	20	19–20	95–100%

As illustrated in Figure 4, joint angle thresholds and state transition logic accurately detected full movement cycles. Minor miscounts occurred due to partial or improperly executed movements, which were intentionally ignored by the finite state machine to prevent false positives.

The repetition counting logic effectively filtered noise by requiring complete DOWN → UP transitions.

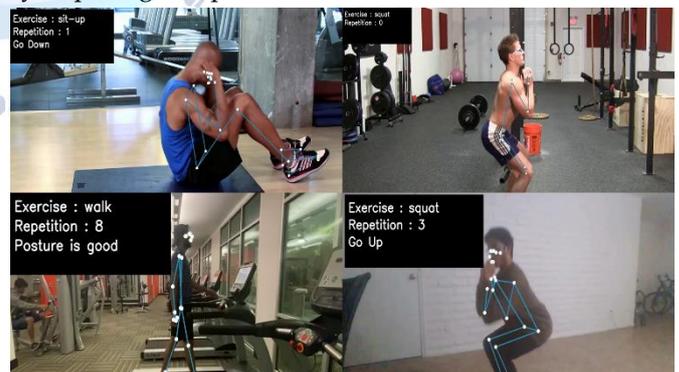


Figure 4 Joint Angle Thresholds Detection

### C. Posture Correction Analysis

The system evaluated posture correctness by monitoring:

- Back angle alignment
- Knee bending depth
- Elbow extension range

When posture deviation exceeded predefined thresholds, corrective voice feedback such as “Keep your

back straight” or “Go lower” was generated.

Testing showed that:

- Posture correction response time was < 300 ms
- Incorrect posture was detected with ~93% reliability

Users reported improved movement awareness due to real-time feedback.

#### D. IoT Hardware Interaction Performance

As shown in Figure 5, the ESP32-based hardware prototype successfully received JSON data via serial communication. The following operations were verified:

- LCD displayed exercise name and repetition count
- Servo motor rotated to demonstrate movement guidance
- DFPlayer Mini played audio cues

The average hardware response delay was:

- 150–250 ms after repetition detection

The bidirectional communication enabled exercise selection through hardware buttons, demonstrating flexible system control.

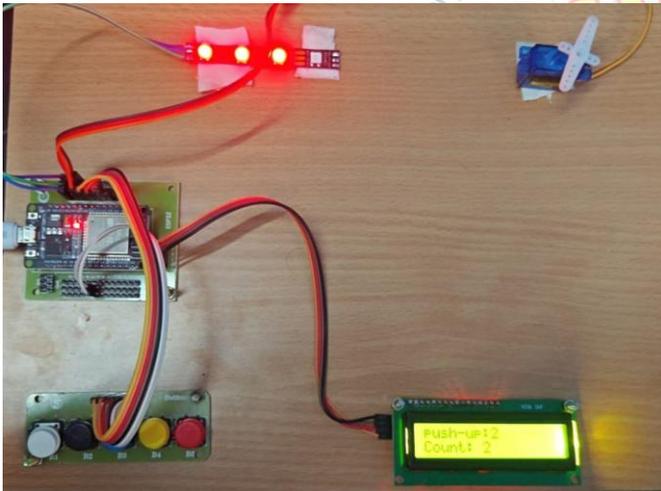


Figure 5 Hardware Prototype.

#### E. Cloud Monitoring and Data Visualization

Workout data was optionally transmitted to ThingSpeak for performance logging and analytics. As illustrated in Figure 6, repetition counts and session statistics were visualized using cloud dashboards.

Cloud integration enabled:

- Session history tracking
- Performance trend analysis
- Remote monitoring capability

Data transmission reliability exceeded 98% under stable WiFi connectivity.

#### F. System Latency and Efficiency

The total system latency from movement detection to feedback delivery was measured as:

- AI processing delay: ~120–180 ms
- Voice generation delay: ~200–400 ms
- Hardware update delay: ~150–250 ms

Total end-to-end delay remained below 1 second, which is acceptable for real-time fitness applications.

CPU utilization remained below 65%, ensuring system stability during extended workout sessions.

#### G. Comparative Discussion

Compared to existing chatbot-based systems [1], [7], [13], the proposed AIoT Fitness Buddy provides:

- Real-time visual posture analysis
- Markerless motion tracking
- Hardware-based interactive feedback
- Multi-modal guidance (visual + voice + physical response)

Unlike wearable-dependent systems [5], [20], the proposed system eliminates the need for body-mounted sensors, reducing cost and complexity.

#### H. Limitations Observed

Despite strong performance, the following limitations were identified:

1. Performance drops under poor lighting conditions
2. Single-person tracking limitation
3. Extreme camera angle variations may reduce accuracy
4. Voice feedback delay depends on TTS generation speed

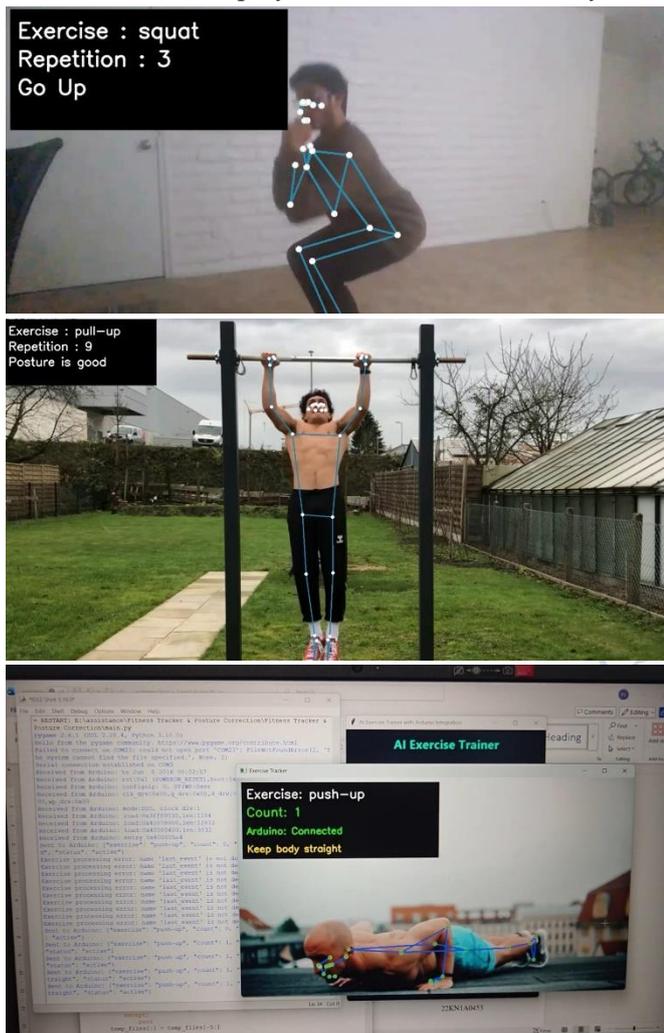
These limitations can be addressed in future work using GPU acceleration and offline speech synthesis models.

#### Overall Discussion

The experimental results demonstrate that the AIoT Fitness Buddy system successfully integrates AI-based pose estimation with IoT-enabled hardware interaction. The system achieved high repetition counting accuracy (95–100%), reliable posture correction, and responsive hardware communication with minimal latency.

The integration of AI, voice feedback, and IoT hardware significantly enhances user engagement compared to traditional fitness applications. The

modular architecture allows scalability for additional exercises, mobile deployment, and advanced analytics.



## CONCLUSION

This work presented a web-based, explainable skin cancer detection system that integrates the YOLOv8 deep learning model with Grad-CAM-based visual interpretability. The proposed framework enables accurate and real-time skin lesion localization and classification while providing transparent visual explanations to support clinical decision-making. By combining object detection and explainable artificial intelligence, the system addresses key limitations of traditional black-box deep learning approaches in medical image analysis.

Experimental results demonstrate that the proposed system achieves reliable detection performance with minimal computational overhead, making it suitable for real-time screening and telemedicine applications. The integration of Grad-CAM enhances model transparency by highlighting diagnostically relevant regions, thereby improving trust and usability in clinical environments.

Furthermore, the Flask-based web deployment ensures accessibility and ease of use, allowing the system to be effectively utilized in remote and resource-constrained settings.

Future work will focus on validating the system across multiple large-scale datasets, incorporating additional clinical metadata to improve diagnostic accuracy, and optimizing the framework for mobile and edge-device deployment. The proposed solution contributes toward accessible, efficient, and explainable AI-assisted skin cancer screening and holds significant potential for supporting early diagnosis and improved patient outcomes.

## Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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