

A User-Centric AI System for Sports Talent Assessment

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Abstract: *Identifying sports talent at an early stage plays an important role in shaping an athlete's development. In many training environments, however, evaluation still depends largely on manual observation and the personal judgment of coaches. While experience-based assessment is valuable, it can sometimes lead to inconsistent results, especially when dealing with larger groups of athletes. This paper presents a practical AI-based system designed to support talent assessment using simple and widely available tools. The system analyses video recordings of athletic activities to understand movement patterns and generate performance insights. Instead of focusing only on technical accuracy, the design also considers how easily the results can be understood and used by athletes and coaches. The system evaluates key attributes such as coordination, stability, and consistency through automated analysis. Initial testing shows that the results remain fairly consistent across repeated trials and provide useful feedback that aligns with general coaching observations. Overall, the study highlights that combining AI with a user-friendly design approach can make performance evaluation more accessible, consistent, and scalable.*

Keywords: Artificial Intelligence, Sports Analytics, Talent Identification, Computer Vision, User-Centred Design Web Application, Athlete Management, Performance Tracking, Coaching System, MERN Stack, React.js, Node.js, MongoDB, Data Management, Sports Technology

I. INTRODUCTION

The process of identifying sports talent is a fundamental part of athlete development. Whether in schools, academies, or professional training programs, early recognition of ability helps in providing focused guidance and improving long-term performance. Traditionally, this process relies heavily on observation, where coaches evaluate athletes based on their experience and judgment.

Although this method has been used successfully for many years, it comes with certain limitations. Different coaches may interpret the same performance differently, and factors such as fatigue, environment, or time constraints can influence decisions. As the number of participants increases, maintaining consistency in evaluation becomes even more challenging.

With the advancement of artificial intelligence, new possibilities have emerged for improving performance analysis. Technologies such as computer vision and machine learning allow systems to process video data and extract useful information about movement. These methods can capture details that may not always be noticeable through manual observation.

Despite these advantages, many existing solutions are not widely used in practical settings. Some require specialized hardware, while others are too complex for everyday use. In addition, the output generated by such systems is not always easy for non-technical users to understand.

This work aims to address these challenges by developing a system that balances functionality with usability. The idea is to create a tool that not only produces reliable performance insights but also presents them in a way that users can



easily interpret. The system is designed to work with standard devices such as smartphones or webcams, making it accessible in a variety of environments.

The main objectives of this study are:

To develop a video-based system for evaluating athletic performance

To generate consistent and understandable performance metrics

To design an interface that is easy to use for both athletes and coaches

By focusing on both technical capability and user experience, the system attempts to bridge the gap between advanced research and practical application.

II. LITERATURE REVIEW

Research in sports performance analysis has changed significantly over time. Earlier methods focused mainly on physical tests and statistical evaluation. While these approaches provided a general idea of an athlete's ability, they were limited in capturing detailed movement patterns.

A. Traditional Methods

Conventional talent identification techniques are usually based on observation and structured testing. Coaches assess athletes through drills, fitness tests, and match performance. These methods rely heavily on expertise, which can be useful in identifying certain qualities such as decision-making or game awareness.

However, subjectivity remains a major concern. The same performance may be judged differently depending on the evaluator. Additionally, these methods are not always practical when large numbers of athletes need to be assessed.

B. Sensor-Based Approaches

To improve objectivity, researchers introduced wearable sensors that track movement and physiological data. Devices such as accelerometers and heart rate monitors provide continuous information about performance.

While these systems offer detailed insights, they also come with drawbacks. The cost of equipment can be high, and maintaining these devices requires additional effort. In some cases, wearing sensors may also affect natural movement, which can influence results.

C. Vision-Based Techniques

Recent developments in computer vision have made it possible to analyze human movement using video data. Pose estimation techniques can identify body joints and track how they move over time. This allows systems to study motion without requiring physical sensors.

Vision-based methods are generally more convenient because they rely on simple camera setups. However, many existing systems focus mainly on technical accuracy and do not pay enough attention to usability. As a result, the outputs may be difficult for users to understand.

D. AI Models in Performance Analysis

Machine learning models have been used to evaluate performance and identify patterns in movement data. These models can achieve good accuracy, especially when trained on large datasets.

However, complex models often lack transparency. Users may find it difficult to understand how a particular score or result was generated. This can reduce trust, especially in environments where decisions are important.

E. Research Gap

A common issue across existing work is the lack of balance between technical performance and user experience. Many systems are designed to be accurate but are not easy to use or interpret.

There is a need for solutions that:



- Provide reliable and consistent evaluation
- Are easy to use in real-world environments
- Present results in a clear and understandable way

This study focuses on addressing that gap by combining AI-based analysis with a design approach that prioritizes usability.

III. SYSTEM ARCHITECTURE

The proposed system is designed with a modular structure so that each component can function independently while still contributing to the overall workflow. This approach makes the system easier to manage, update, and scale when needed.

At a basic level, the system follows a client–server model. Users interact with the system through a web-based interface, while the backend handles data processing, storage, and analysis. This separation ensures that the user experience remains smooth even when complex computations are being performed.

The architecture is divided into four main layers:

- User Interface Layer
- Data Acquisition Layer
- Processing and Analysis Layer
- Data Storage Layer

Each of these layers plays a specific role in transforming raw input into meaningful output.

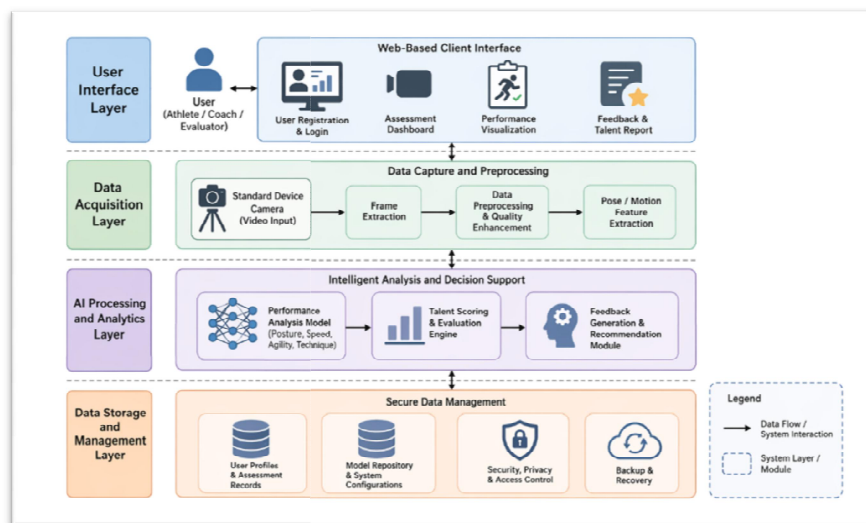


Fig 1. Architectural framework for AI-Integrated Talent Assessment System

A. User Interface Layer

The user interface acts as the main access point for both athletes and coaches. It is designed to be simple and intuitive, avoiding unnecessary technical complexity.

- Athletes can use the interface to:
- Record or upload activity videos
- View their performance results
- Track improvements over time



Instead of presenting raw data, the system uses visual elements such as progress indicators and simple graphs. This helps users understand their performance without needing technical knowledge.

Coaches are provided with additional features such as:

- Comparison between multiple athletes
- Performance summaries
- Trend analysis over time

Access control is implemented to ensure that users can only view relevant data.

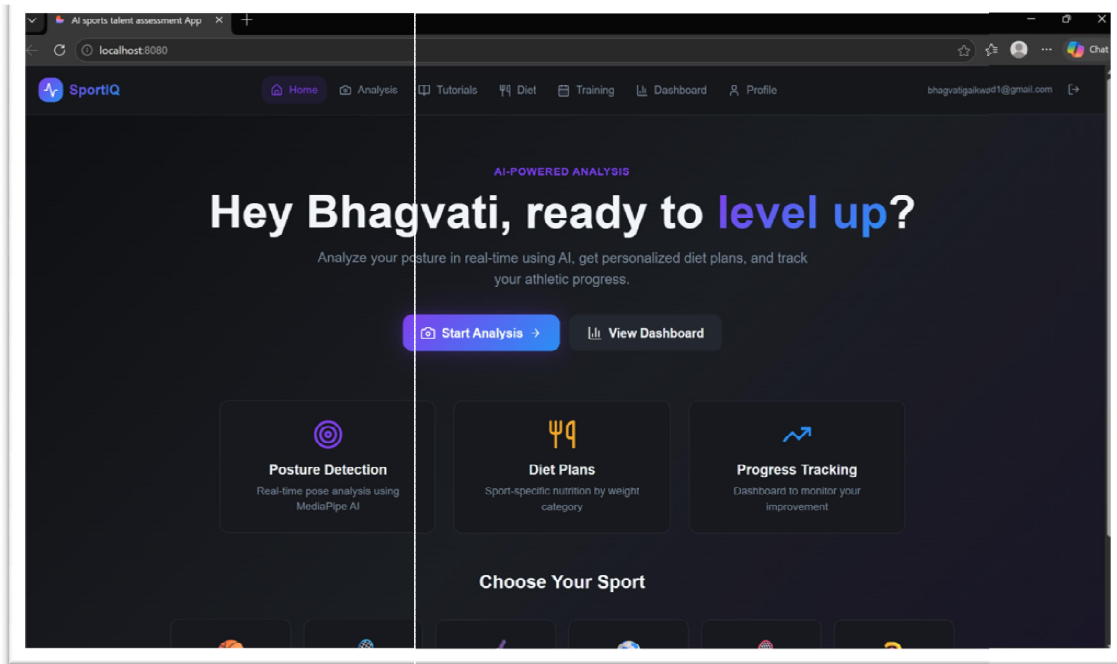


Fig 2. User Dashboard

B. Data Acquisition Layer

This layer is responsible for collecting the input data required for analysis. The system uses standard camera devices such as smartphones or webcams, which makes it easy to deploy in different environments.

To ensure consistency, users are given basic instructions regarding:

- Camera positioning
- Distance from the camera
- Lighting conditions

The system records short video clips rather than long sessions. This approach helps reduce storage requirements while still capturing essential movement details.

Before sending the data for analysis, basic preprocessing steps are applied, including:

- Frame extraction
- Resolution adjustment
- Noise reduction

These steps improve the quality of input data and make further processing more reliable.



C. Processing and Analysis Layer

This is the core component of the system where the actual analysis takes place. The goal here is to convert raw video data into meaningful performance insights.

The process is carried out in multiple stages:

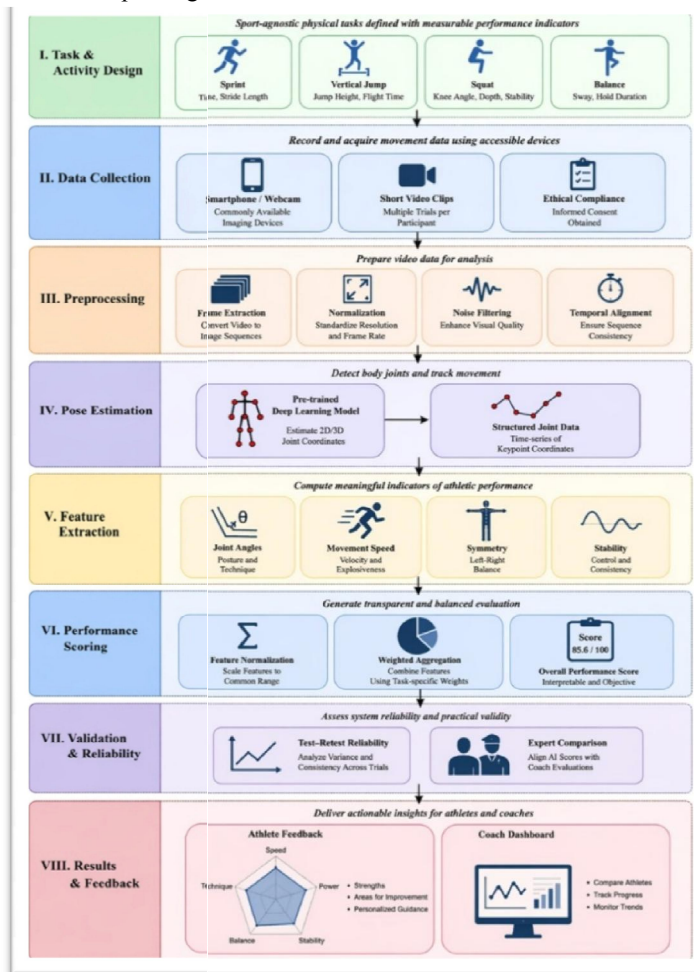


Fig 3. Talent Assessment Pipeline

Pose Detection

The system identifies key body joints such as shoulders, elbows, hips, and knees in each frame. This creates a simplified representation of the human body.

Movement Tracking

The positions of these joints are tracked across frames to understand how the body moves over time.

Feature Extraction

From the movement data, the system calculates useful performance indicators, including:

- Joint angles
- Speed of movement
- Symmetry between left and right sides



Stability and consistency

Performance Evaluation

The extracted features are combined to generate an overall performance score. The focus here is not just accuracy but also consistency and interpretability.

Feedback Generation

The system converts numerical results into simple feedback that users can understand. For example, instead of showing only numbers, it may indicate whether a particular movement needs improvement.

D. Data Storage Layer

The storage layer manages all information generated by the system. This includes:

- User profiles
- Video metadata
- Extracted features
- Performance history

A flexible database structure is used so that new types of data can be added in the future without major changes.

Basic security measures are applied to protect user data. These include controlled access and simple encryption techniques where necessary.

E. Data Flow and Communication

Communication between different components of the system is handled through APIs. This ensures smooth data exchange between the frontend and backend.

Video processing is handled asynchronously. This means users do not have to wait for long periods during analysis. Instead, results are returned once processing is complete.

IV. METHODOLOGY

The methodology is designed to ensure that the evaluation process is consistent, repeatable, and practical for real-world use.

A. Overall Approach

The study follows an implementation-focused approach where a working system is developed and tested. The emphasis is on creating a solution that can be used in actual environments rather than just theoretical analysis.

The system is designed to work with commonly available devices, ensuring accessibility.

B. Activity Design

A set of basic physical activities is defined to evaluate different aspects of athletic ability. These activities are intentionally kept general so that they can be applied across multiple sports.

Each activity is linked to specific performance aspects such as:

- Balance
- Coordination
- Speed
- Consistency

This structured design helps maintain uniform evaluation across users.

C. Data Collection

Participants perform the selected activities while being recorded using a camera. To improve reliability:

Multiple recordings are taken



Conditions are kept consistent as much as possible
 Clear instructions are provided
 Short recordings are preferred to simplify processing and storage.

D. Preprocessing

Before analysis, the recorded video is processed to ensure consistency. This includes:

- Extracting frames
 - Standardizing resolution
 - Removing unnecessary noise
- These steps help improve the accuracy of further analysis.

E. Pose Estimation

Pose estimation is used to identify body joints in each frame.

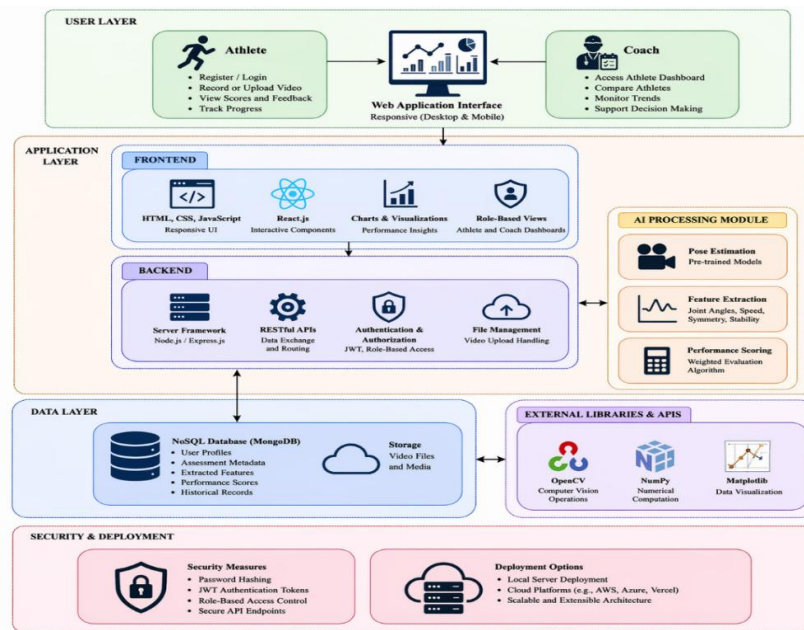


Fig 4. AI-Based Sports

The output is a set of coordinates representing different parts of the body. This allows the system to focus on movement rather than raw video data, making analysis more efficient.

F. Feature Extraction

From the pose data, the system calculates performance-related features such as:

- Joint angle variation
- Movement speed
- Symmetry
- Stability

These features are chosen because they are directly related to athletic performance and are easy to interpret.



G. Scoring Mechanism

The system uses a weighted scoring approach. Each feature contributes to the final score based on its importance. The scoring model is intentionally kept simple to ensure that users can understand how results are generated.

H. Validation

To verify reliability:

Activities are repeated multiple times

Results are compared across trials

The system's output is also compared with general observations to ensure practical relevance.

V. ALGORITHMS AND COMPUTATIONAL MODELS

This section describes the main computational methods used in the system. The focus is on clarity and efficiency rather than complexity.

A. Pose Estimation Algorithm

A pre-trained pose estimation model is used to detect key body joints in each frame. Each frame is processed independently, generating a structured representation of the body.

This representation is used instead of raw video, which reduces storage requirements and simplifies analysis.

B. Temporal Movement Analysis

To understand motion, the system tracks changes in joint positions over time. From this, it calculates:

Displacement

Velocity

Acceleration

Basic smoothing techniques are applied to reduce noise.

C. Feature Engineering

Raw movement data is converted into meaningful indicators such as:

Consistency across repetitions

Symmetry of movement

Stability during activity

These features provide a more useful representation of performance.

D. Scoring Model

All extracted features are combined to generate a final score. Each feature is assigned a weight depending on its relevance.

The goal is to ensure a balanced evaluation where no single factor dominates the result.

E. Efficiency Considerations

The system is designed to run on standard hardware without requiring high-end computational resources. Lightweight processing ensures that the system remains responsive and accessible.

VI. DATASET DESCRIPTION AND EVALUATION METRICS

A. Dataset Collection

Since there is no widely available dataset that perfectly fits this specific use case, a custom dataset was created through controlled recordings. Participants performed predefined physical activities while being captured on camera.



Care was taken to include variation in:

Skill levels (from beginner to moderately trained individuals)

Body types

Movement consistency

This variation helps ensure that the system does not become biased toward a particular group and performs reasonably well across different users.

B. Data Annotation

Instead of manually labelling every frame or movement, a structured approach was used. Performance expectations were defined based on general coaching guidelines and movement standards.

This approach reduces the effort required for manual annotation while still maintaining consistency in evaluation.

C. Evaluation Metrics

To assess how well the system performs, multiple evaluation criteria were used:

Consistency: Measures how stable the results are when the same activity is repeated

Repeatability: Ensures similar inputs produce similar outputs

Alignment with Human Observation: Compares system output with general expert judgment

User Feedback: Evaluates how understandable and useful the results are

Using a combination of these metrics provides a balanced evaluation, covering both technical performance and practical usability.

VII. IMPLEMENTATION OF THE SYSTEM

A. Application Overview

The system is implemented as a web-based application that allows users to interact with it easily. Athletes can upload or record videos and receive feedback, while coaches can review performance data and compare results.

The focus during implementation was to keep the system simple and accessible rather than overly complex.

B. Frontend Design

The frontend is designed to be clean and easy to navigate. Key features include:

Video recording and upload functionality

Display of performance results

Visual indicators such as charts and progress bars

The interface avoids unnecessary complexity so that users can focus on understanding their performance.

C. Backend Functionality

The backend handles:

User authentication

Data processing requests

Communication with analysis modules

Storage and retrieval of results

A structured API system is used to ensure smooth communication between different parts of the application.

D. AI Integration

The AI component processes the video input and generates performance insights. It operates independently from the main application, allowing updates or improvements without affecting the rest of the system.

This separation also makes the system more flexible for future upgrades.



E. Data Management

A flexible database system is used to store:

- User information
- Performance scores
- Activity history

This allows users to track their progress over time and makes it easier to analyze trends.

F. Deployment

The system is designed to run on standard devices and can be deployed either locally or on cloud platforms. This flexibility ensures that it can be used in different environments without requiring specialized infrastructure.

VIII. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

A. Experimental Setup

The system was tested using multiple participants with varying levels of athletic ability. Each participant performed a set of predefined activities several times.

Recordings were made using commonly available devices such as smartphones and webcams to simulate real-world conditions.

B. Consistency of Results

One of the key observations was that the system produced stable results across repeated trials. When the same activity was performed multiple times under similar conditions, the variation in scores remained low.

This indicates that the system is reliable and not overly sensitive to minor changes.

C. Comparison with Human Evaluation

The system's output was compared with general observations made by experienced individuals. While the results were not identical, they showed a reasonable level of agreement.

In simpler activities, the alignment was strong. In more complex movements, small differences were observed, which is expected given the limitations of automated analysis.

D. Performance Tracking Over Time

The system was able to reflect gradual improvements in performance. Users who repeated activities over time showed small but noticeable increases in their scores.

This suggests that the system can be useful not only for evaluation but also for monitoring progress.

E. Robustness

The system performed well under normal conditions. However, certain limitations were observed:

- Poor lighting reduced detection accuracy
- Extreme camera angles affected results
- Very fast movements sometimes caused minor inconsistencies

Despite these issues, the system remained usable in most situations.

F. User Feedback

Feedback from users indicated that:

- The system was easy to understand
- The feedback provided was useful
- Visual representations helped in tracking progress



Coaches found the comparison features helpful, while athletes appreciated the clarity of results.

G. Summary of Results

Overall, the system demonstrated:

Consistent performance

Reasonable agreement with manual evaluation

Practical usability in real-world scenarios

These observations support the effectiveness of the proposed approach.

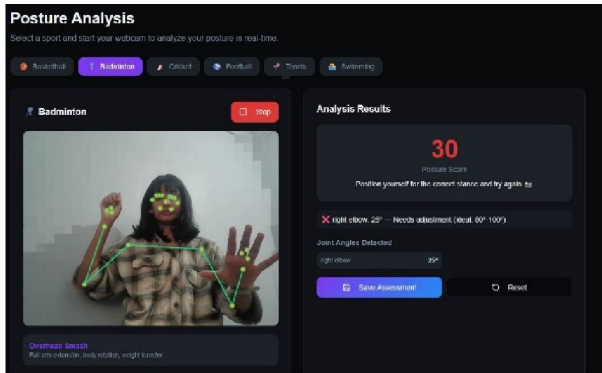


Fig. 5.1 Wrong posture (Posture Analysis)

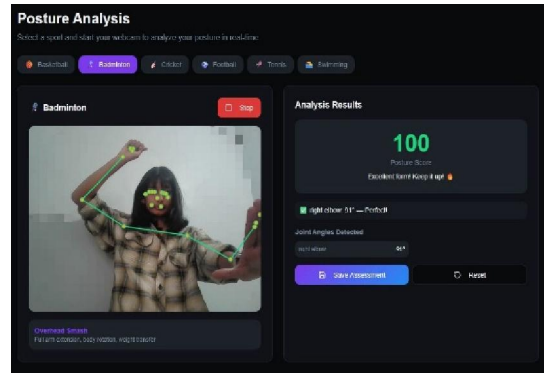


Fig. 5.2 Correct posture (Posture Analysis)

IX. DISCUSSION

The results highlight an important aspect of AI-based systems in sports: usability is just as important as accuracy.

The system successfully reduces subjectivity by relying on measurable indicators rather than personal judgment. At the same time, it avoids unnecessary complexity, making it easier for users to interpret results.

Another key strength is accessibility. Since the system uses standard devices, it can be applied in a wide range of environments, including schools and small training centers.

However, it is important to note that the system is not meant to replace coaches. Instead, it should be viewed as a supportive tool that complements human expertise.

X. USER-CENTRIC DESIGN EVALUATION

To understand how useful the system is in practical scenarios, a separate evaluation focused on user experience was conducted. Since the system is designed for both athletes and coaches, usability was considered just as important as technical performance.

Participants interacted with the system over multiple sessions. Most users were able to navigate the interface without any prior instructions, which indicates that the design is intuitive. Athletes primarily used the system to review their own performance, and many found the visual summaries helpful in identifying gradual improvements.

Coaches approached the system differently. They focused more on comparing athletes and observing trends over time rather than individual scores. This reduced the need for manual tracking and made the evaluation process more efficient.

Another key observation was related to trust. Users were more confident in the results when they could understand how scores were derived. Simple visual indicators and clear feedback played an important role in improving acceptance of the system.



XI. ETHICAL, LEGAL, AND SOCIAL CONSIDERATIONS

The use of AI in performance evaluation introduces certain ethical and legal responsibilities. One of the main concerns is data privacy, especially since the system involves video recordings.

To address this, the system is designed to minimize unnecessary storage of raw data. Wherever possible, processed data is stored instead of full video recordings. Access to user information is restricted, ensuring that only authorized individuals can view it.

User consent is also an essential requirement. Participants must be informed about how their data will be used before they take part in any activity.

From a broader perspective, the system can help reduce bias by relying on measurable factors rather than subjective judgment. However, it is still important to monitor the system regularly to ensure fairness across different users.

XII. LIMITATIONS

Although the system performs reliably in controlled conditions, certain limitations remain.

One of the main challenges is dependence on video quality. Poor lighting, incorrect camera placement, or low-resolution recordings can reduce the accuracy of analysis. While preprocessing helps improve input quality, it cannot fully eliminate these issues.

Another limitation is the generalized nature of the evaluation. Since the system is not tailored to specific sports, it may not capture detailed technical aspects required for specialized training.

Additionally, the scoring model is intentionally simple to maintain interpretability. While this makes results easier to understand, it may not capture more complex performance variations.

XIII. FUTURE WORK

There are several areas where the system can be improved and expanded.

One possible direction is the development of sport-specific modules. This would allow the system to provide more detailed and relevant analysis for different activities such as football, athletics, or basketball.

Another improvement could involve integrating wearable sensor data along with video analysis. This would provide additional insights into performance and improve accuracy.

Improving robustness under challenging conditions, such as low lighting or fast movements, is also an important area for future work.

Finally, deploying the system on a larger scale using cloud-based platforms could make it accessible to a wider range of users.

XIV. CONCLUSION

This study presented a user-centric AI system designed to support sports talent assessment. The system combines video-based analysis with a simple and interpretable evaluation approach, making it suitable for real-world use.

The results demonstrate that consistent and meaningful performance evaluation can be achieved without relying on complex or expensive setups. By focusing on usability along with technical performance, the system becomes more practical and accessible.

While the system is not intended to replace human expertise, it can serve as a valuable support tool for coaches and athletes. Overall, the work highlights the importance of designing AI systems that are both effective and easy to use.

Acknowledgment

The authors would like to thank all individuals who participated in the testing and evaluation of the system. Their feedback contributed significantly to improving the design and functionality of the application.



Declaration of Originality

This work is original and has not been submitted elsewhere for publication. Any external ideas have been used only as general references.

Conflict of Interest

The authors declare that there is no conflict of interest related to this work.

Funding Statement

This project was carried out independently without external funding.

Ethical Approval and Consent

All participants provided informed consent before data collection. Data was handled responsibly, with attention to privacy and security.

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