

Using AI to Supplement Coaching

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Outline

- Background
 - Machine vs. Human
- Using AI in T&F Today
- Proposed Methodologies
 - Kinematic Analysis
 - Computer Vision & Machine Learning Algorithms
 - Demo – AIMS Toolset
- Performance & Ranking Prediction
 - Statistical & Machine Learning Algorithms
 - Demo – AIMS Toolset
- Conclusion

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“AI is going to take our jobs! We’re being replaced”

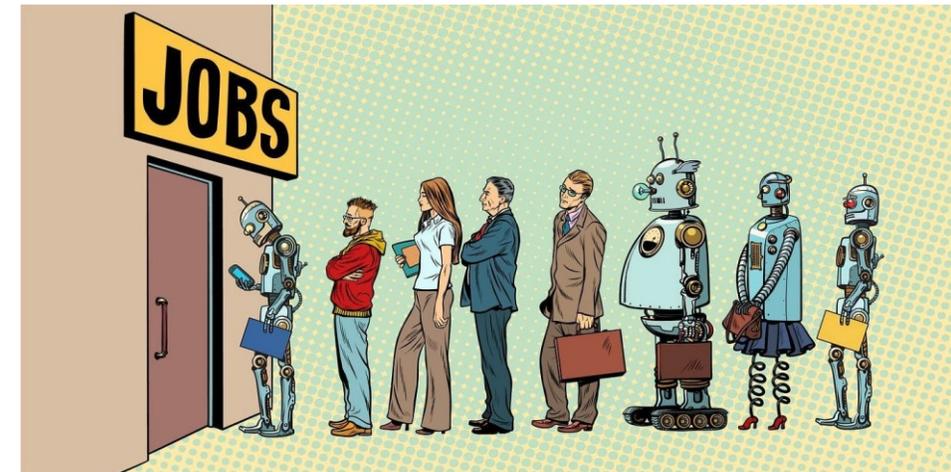
➤ **Valid concern, but we can take advantage**

- Easier than ever to start coaching / get up to speed as a new coach
- Have more tools to make well informed coaching decisions than ever before

➤ **Still no substitute for live, hands-on experience**

- “Might have the recipe, but not the chef”
- Intangibles can never be replaced – Leadership, Emotional intelligence, Discipline, Trust, Motivation, Communication, Relationship building

➤ **If used smartly, AI & Machine Learning can actually enhance our performance as coaches**



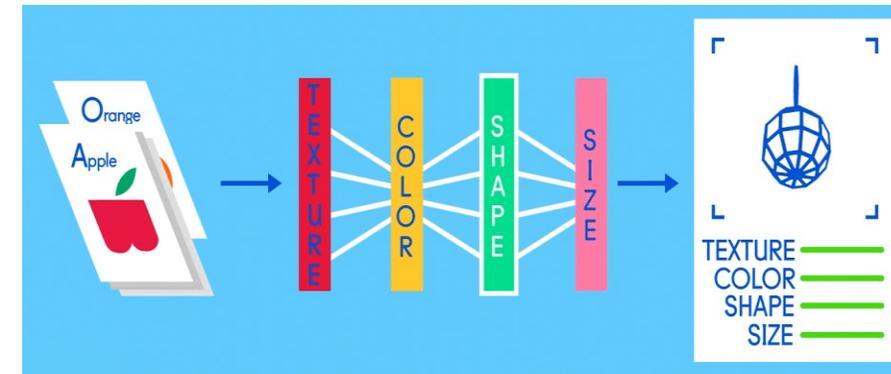
Human Learning vs. Machine Learning

➤ Human Learning

- A lifelong process; sometimes occurs randomly.
- Process of acquiring information and knowledge.
- Requires interactions and activities.
- **Involves the whole personality** – senses, feelings, intuition, beliefs, values, and will.

➤ Machine Learning

- A branch of Artificial Intelligence (AI) that empowers computers to learn from data without explicit programming
- Data is the key.
- **Learning by examples** (data samples).
- Decisions/predictions without being explicitly programmed.



<https://medium.com/co-learning-lounge/what-is-deep-learning-ai-in-simple-words>

Suitability of Machine Learning as Data Volume Grows

➤ ML scales well with data

- Able to handle large volume, learn from it and stay stable.

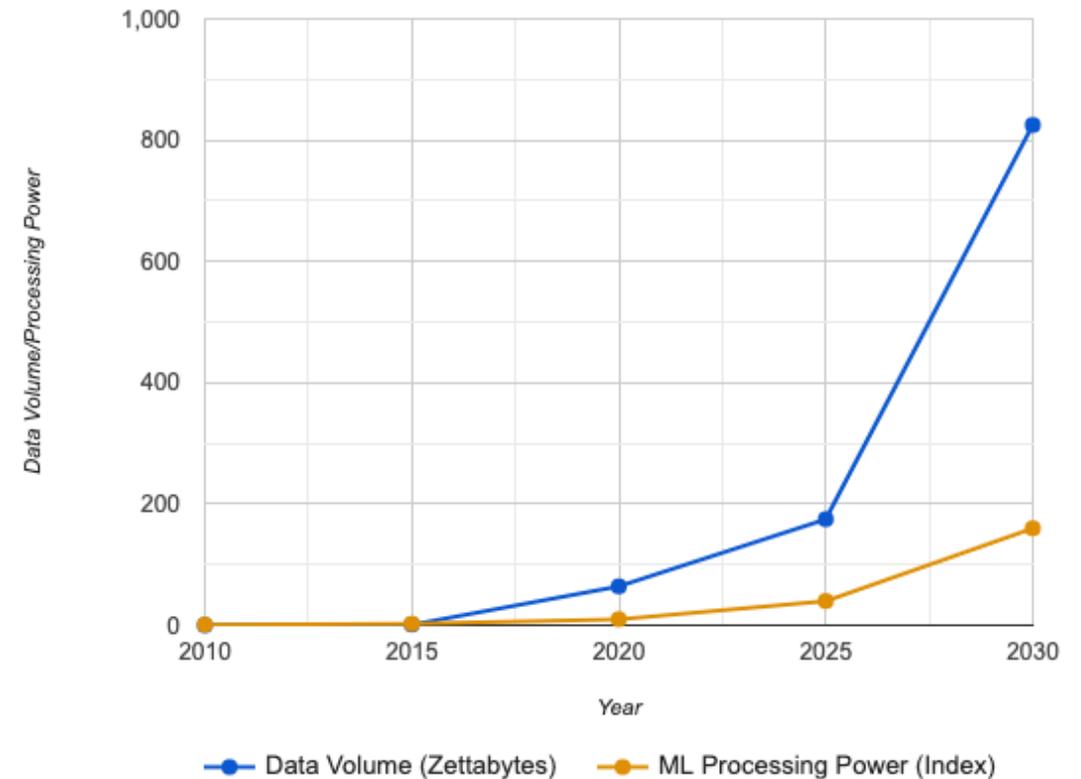
➤ ML thrives on voluminous data

- Can efficiently process large amounts of data and even improve performance.

➤ ML tackles data challenges

- Ambiguities (e.g. noise, variations)
- Biased or imbalanced data
- The curse of dimensionality

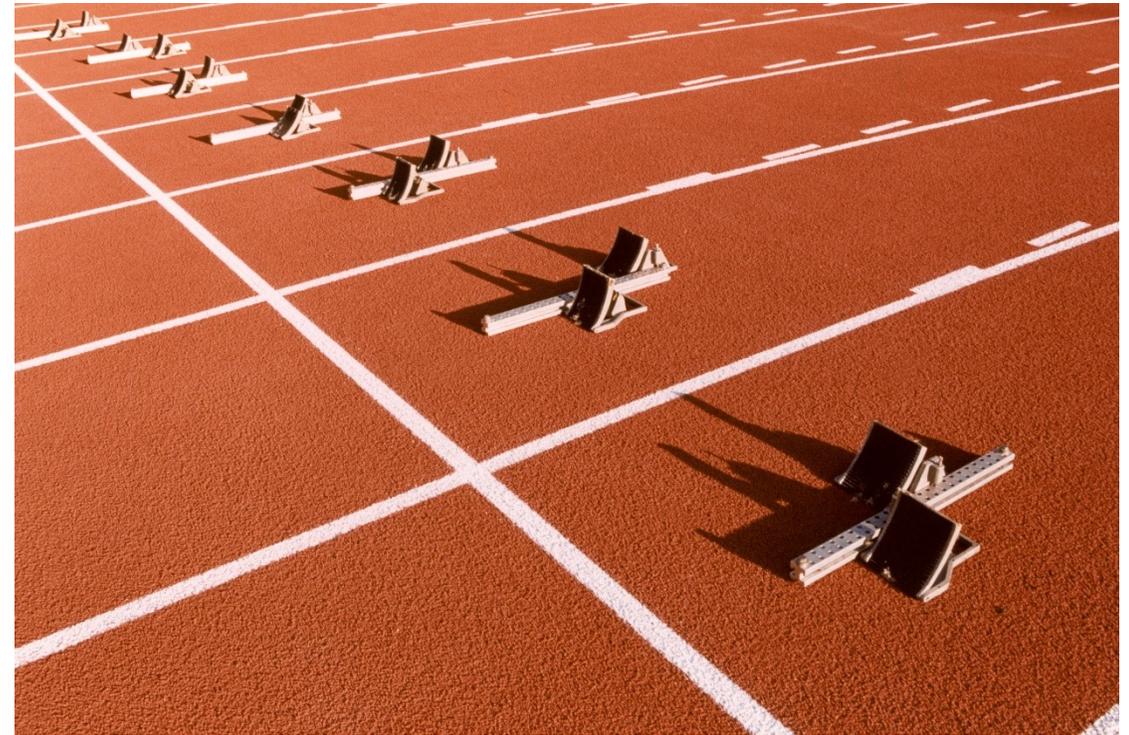
Data Volume Growth vs. Machine Learning Processing Power



<https://www.msystechnologies.com/blog/ai-ml-for-archival-storage-in-quartz-glass/>

ML for Track & Field Evaluation

- Historical and performance data is large, diverse, and continuously updated
- Athletes vary across seasons, events, and conditions
- Technology can identify metrics and patterns that human cannot visually see/measure
 - Biomechanical Analysis
 - Performance Ranking
 - Planning / Periodization



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What Even Is a Coach's Job?

➤ **Teach Event Disciplines**

- Teach optimal technique, strategy, and execution of an athlete's event

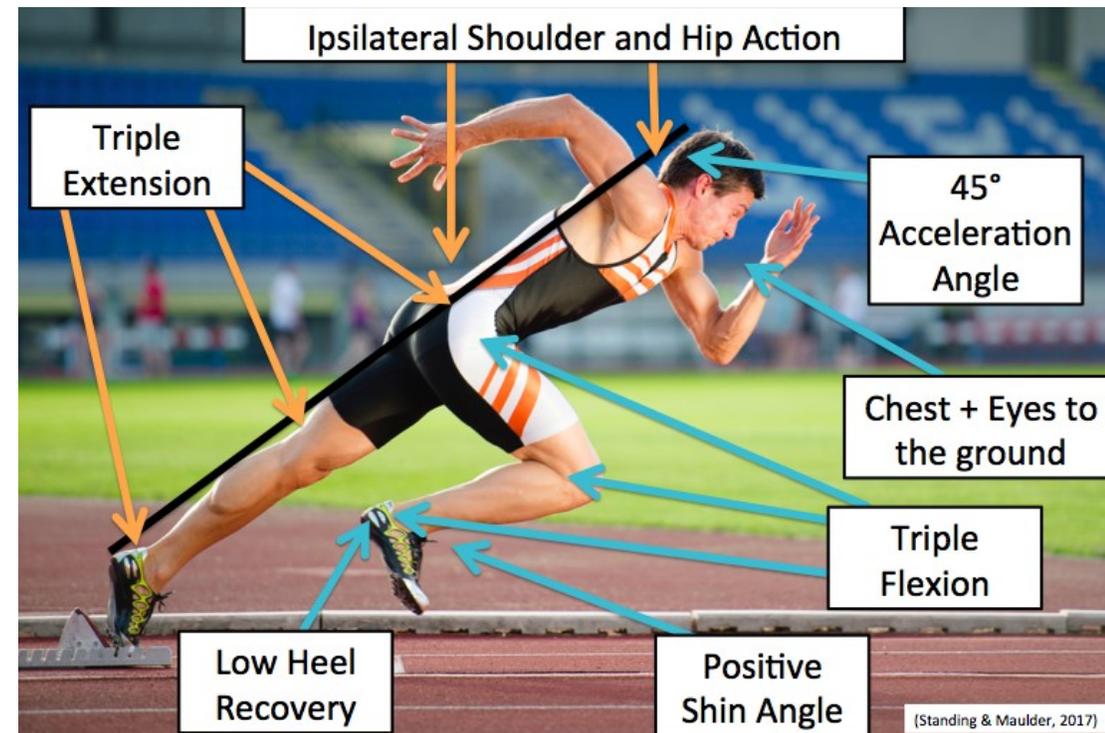
➤ **Plan/Program/Periodize Training**

- Prepare athlete and/or team to perform at their best at the most important time(s) of the season

➤ **Recruiting (Collegiate Coaches)**

Asking the Right Questions

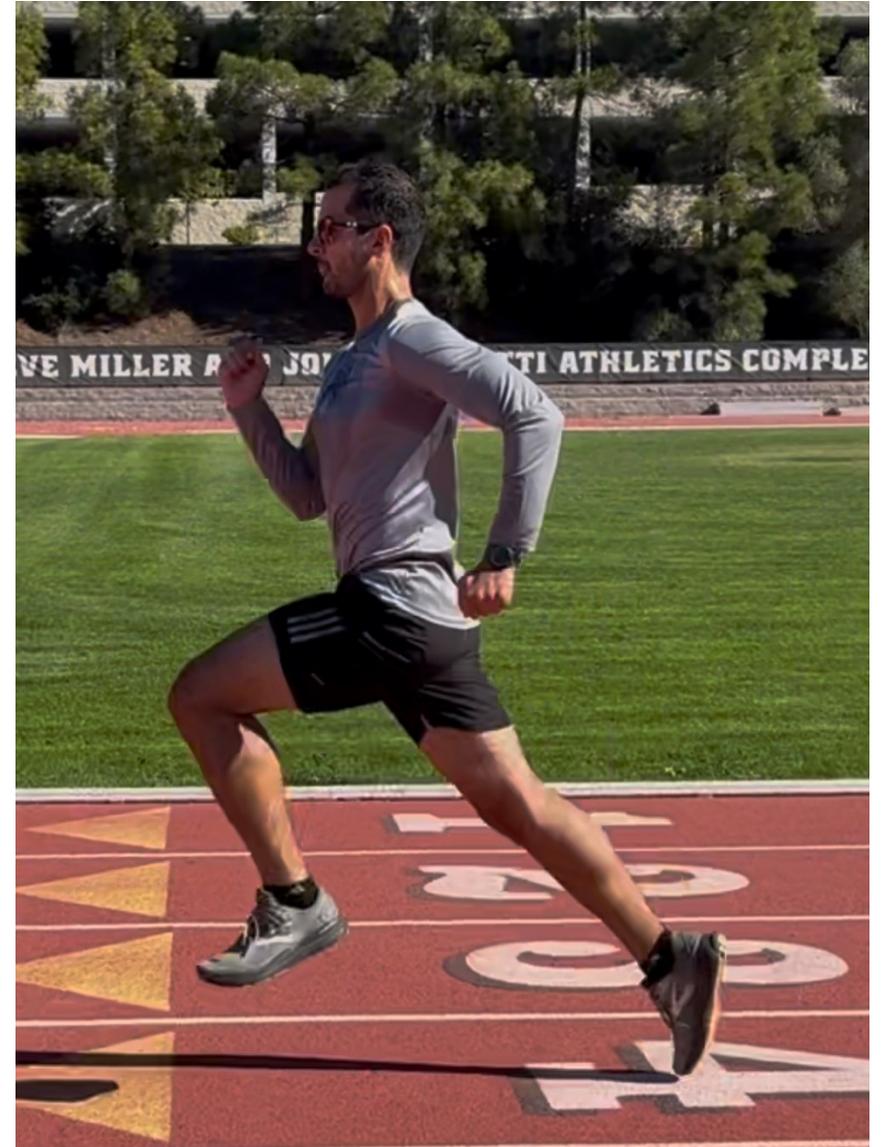
- “How to run faster”
- “How to jump higher”
- “What workouts should a track & field athlete do?”
- ALL will lead to generic / generally unhelpful answers
- Same as searching internet, only difference is faster response times



<https://liamoakeshealthcoach.wordpress.com/2017/03/19/sprint-acceleration-mechanics/>

Asking the Right Questions -- Biomechanics

- “Based on these strides, what can I improve in the toe-off phase of my sprinting mechanics?”



Asking the Right Questions -- Biomechanics

- Pro: Much better than asking basic or vague questions (more data)
- Con: Significant portion of the reply is accurate, but much of it is not, due to complexity of human movement
 - This makes it unreliable for immediate use, due to not knowing what is correct vs incorrect

2. Reduce Excessive Plantar Flexion ("Toe Pointing")

Your ankle appears to linger in plantar flexion slightly after force is already delivered.

Cue:

"Punch the ground, then snap the foot through."



Why it matters:

Over-pushing through the toe increases ground contact time and can slow stride frequency.

Goal:

- Stiff ankle at toe-off
- Quick heel recovery under the glute

Drills:

- Straight-leg bounds
- Ankling / dribble runs
- Wicket drills (short spacing)

ChatGPT

Log in



What You're Doing Well

- **Strong rear-leg extension:** Hip, knee, and ankle are close to full extension—good power production.
- **Neutral head & torso:** Upright posture with no visible over-lean or breaking at the waist.
- **Active arm drive:** Elbow angle and backward arm action are helping balance force.

3. Earlier & Tighter Heel Recovery

Your heel is trailing a bit long behind the body after toe-off.

Cue:

"Heel under the butt, fast."

Why it matters:

A quicker recovery:

- Shortens swing time
- Improves front-side mechanics
- Reduces braking on next contact

Drills:

- B-skips (focus on snap-down)
- Fast cycle drills
- Mini-hurdle sprint runs

Key Improvements at Toe-Off

1. Finish Extension *Through* the Hip (Not Just the Leg)

Your rear leg is extended, but the hip could stay engaged a fraction longer before toe-off.

Cue:

"Push the track back with your glute."

Why it matters:

Incomplete hip extension shifts load to the calf and hamstring instead of the glute, limiting horizontal force.

Drills:



4. Slightly More Front-Side Bias

Your mechanics are still a bit **push-dominant** (back-side heavy).

What to aim for:

- More force applied *before* the hip
- Quicker repositioning of the leg in front

Cue:

"Step over the knee, strike down."

Asking the Right Questions – Recruiting

- “Who were the top division 1 prospects in the high school girl’s Long Jump in Texas last year?”
 - Decent list based on single best results or championship performances, but does not show progressions or reliability of performances

📌 Summary

Here’s a summary of the **top Texas high-school girls long jump prospects from the 2024 season** who stood out nationally **and/or drew NCAA Division I recruiting interest** after their performances last year:

Athlete	School	Highlights	NCAA D-I Status
=====	Prosper Rock Hill	6A state champ; national #1 long jump & triple jump	Committed — Georgia
=====	McKinney North	5A state champ; top U.S. mark	Committed — Alabama
=====	Arlington Martin	6A state medalist; top national mark	Likely D-I interest
=====	Frisco Panther Creek	4A long jump champ	Committed — USC
=====	Houston Memorial	Top mark in Texas	Potential D-I interest

Asking the Right Questions -- Programming

- “What should training look like for a male 800m athlete who has personal records of 1:59 in the 800m, 55 in the 400m, and 4:20 in the 1600m?”
 - Potentially helpful, but fairly vague in key areas and missing lots of context

Given those PRs (1:59 / 55 / 4:20), this athlete profiles as a **speed-leaning 800m runner** with decent but improvable aerobic strength. Breaking 1:59 will come less from raw speed (55 is adequate) and more from **aerobic power, special endurance, and race modeling.**

Below is what **effective training should look like** for this type of 800m athlete.

1 Athlete Profile (What the PRs Tell Us)

- 400m (55) → Enough raw speed to run sub-2:00
- 1600m (4:20) → Aerobic base is *good but not elite*
- 800m (1:59) → Performance is currently limited by:
 - Late-race strength (last 200m)
 - Ability to hold near-400m pace under fatigue

Training priority:

- 👉 Improve aerobic power and special endurance **without losing speed**

2 Weekly Structure (High-School / Developmental Athlete)

5–6 days per week, ~20–35 miles depending on age and season.

Example Weekly Layout

3 Key Training Components

◆ A. Aerobic Development (Foundation)

This is the **biggest growth area.**

◆ B. Aerobic Power / Strength (Critical for 800m)

1× per week during base → 1× every 10 days in season

◆ C. Speed & Mechanics (Maintain, Don't Overdo)

1–2× per week (low volume)

◆ D. Special Endurance (Race-Specific)

This is where 1:59 → 1:55–1:56 happens.

Once per week in season.

4 Strength Training (Highly Recommended)

2× per week in base → 1× in season

5 Mileage Guidelines

Level	Weekly Mileage
Base phase	25–35
Competition	20–30
Peak	18–25

6 Racing Strategy (Based on Current Ability)

With 55 speed:

- Aim for **58–59 first lap**, not 56–57
- Focus on **even aggression**, not front-loading
- Strength = passing ability at 500–600m

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Proposed Methodologies – AIMS Technologies

➤ A dual-module AI system for T&F sport

1. Kinematic Analysis Module

- Uses video + computer vision
- Extracts biomechanical features
- Classifies running posture phases
- Identifies technique issues and injury risks

2. Performance Ranking Module

- Analyzes historical running data
- Measures consistency, versatility, improvement
- Predicts race outcomes
- Assigns cluster-based ranking categories

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Kinematics: Past vs. Present

Past: Lab-Based Analysis

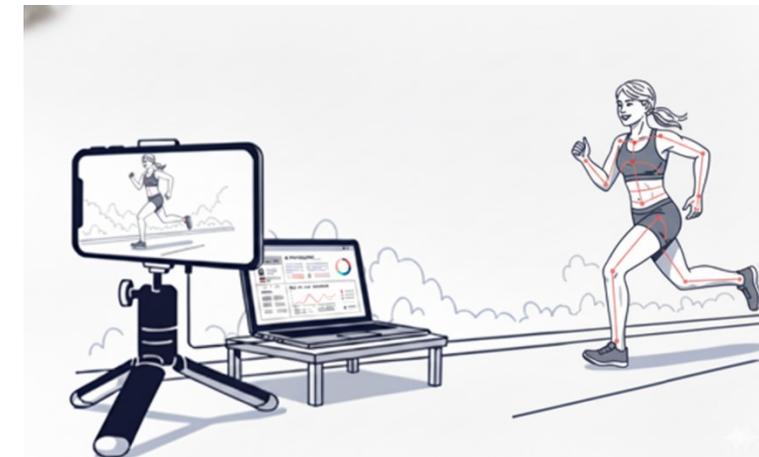
- Traditional biomechanics relied on expensive, customized lab equipment with marker-based systems.
- Disadvantages
 - Intrusive and uncomfortable for the athlete
 - Restricted real-world movements
 - Expensive and time-consuming



<https://animost.com/industry-updates/how-accurate-are-mocap-suits/>

Present: Computer Vision & AI

- Today's technology makes it possible to analyze performance in the field using regular cameras
- Advantages
 - Non-intrusive and transparent
 - Analyzes natural, real-world movements
 - Accessible, fast, and scalable



Kinematic Analysis Module – Flowchart

Video Stream
/ Frame



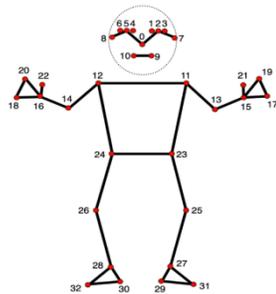
Body Landmarks Estimation

AI-Guided Feature Extraction

AI-Power Posture Classification

Kinematic Analysis & visualization

Visualization & Report



<https://developers.google.com/mediapipe/solutions/vision>

19 Angles and 7 Distances
from body landmarks

Toe-Off
Maximal Vertical Projection (MVP)
Touch-Down
Full-Support



AI-Guided Feature Extraction (Angles & Distances)

- Computer vision and machine learning algorithms automatically extract critical feature points.

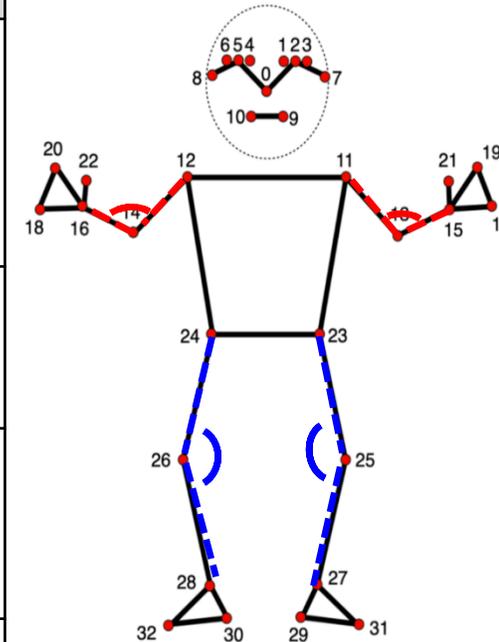
ID	Feature	ID	Feature	ID	Feature
1	Angle Left Foot with x-axis	10	Angle Left Elbow Joint	19	Distance Left Shoulder and Knee
2	Angle Right Foot with x-axis	11	Angle Right Elbow Joint	20	Distance Right Shoulder and Knee
3	Angle Left Knee with x-axis	12	Angle Left Arm with x-axis	21	Angle Left Shoulder and Knee with x-axis
4	Angle Right Knee with x-axis	13	Angle Right Arm with x-axis	22	Angle Right Shoulder and Knee with x-axis
5	Angle Left Thigh with x-axis	14	Angle Left Flexion Joint	23	Distance Left Hip and Ankle
6	Angle Right Thigh with x-axis	15	Angle Right Flexion Joint	24	Distance Right Hip and Ankle
7	Angle Between two Thighs	16	Distance Between two Knees	25	Angle Left Hip and Ankle with x-axis
8	Angle Left Shin with x-axis	17	Distance Left Wrist and Hip	26	Angle Right Hip and Ankle with x-axis
9	Angle Right Shin with x-axis	18	Distance Right Wrist and Hip		



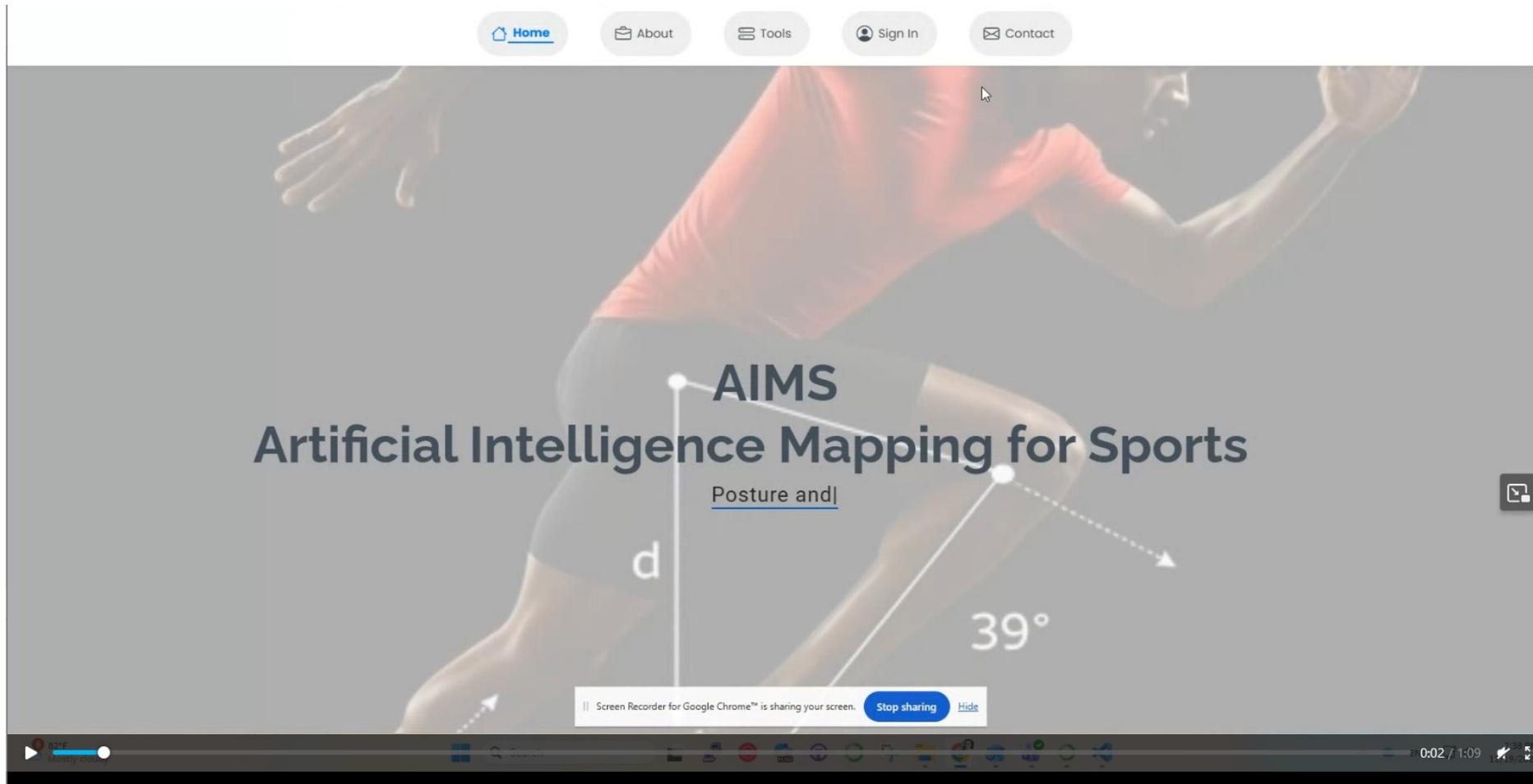
Kinematic Analysis & Visualization – Analysis

➤ Comprehensive kinematic analysis to determine and visualize the metrics for each posture.

Posture	Empirical Metrics (Expert Selected)	Kinematic Metrics (System Analysis)	Landmarks Involved	
			Left	Right
Toe-Off	<ol style="list-style-type: none"> Stance-leg foot perpendicular to the ground. Incomplete extension at knee joint. 90-degree angle between thighs. Swing-leg toe vertical to swing-leg knee. Rear arm open and front arm close. 90-degree flexion of foot. Forearms perpendicular to each other. Front-leg shin parallel to rear-leg thigh. 	<ol style="list-style-type: none"> Foot angle with ground. Knee joint angles. The angle between thighs. Angle of (knee, toe) line with x-axis. Elbow joints angles. The angle of line connects toe, heel, and ankle. Angle of forearm with x-axis. Angle of shins and thighs with x-axis. 	<ol style="list-style-type: none"> 31,32 23, 25, 27 23, 25 25, 31 11, 13, 15 31, 29, 27 15, 13 23, 25, 27 	<ol style="list-style-type: none"> 29, 30 24, 26, 28 24, 26 26, 32 12, 14, 16 32, 30, 28 14, 16 24, 26, 28
MVP	<ol style="list-style-type: none"> 90-degree angle between thighs. Front-leg knee joint angle more than 110-degree. Dorsiflexion of front leg foot. Neutral head carriage. The head and hip should be straight. 	<ol style="list-style-type: none"> Angle between thighs. Knee joint angles. The angle of line connects toe, heel and ankle. Angle of (ears, nose) line with x-axis. Angle (Mid-ears, Mid-hip) line with the x-axis. 	<ol style="list-style-type: none"> 23, 25 23, 25, 27 31, 29, 27 7, 0 7, 23 	<ol style="list-style-type: none"> 24, 26 24, 26, 28 32, 30, 28 8, 0 8, 24
Touch-Down	<ol style="list-style-type: none"> Knees should be together. Front-leg shin should be perpendicular to the ground. Swing-leg foot should be under gluteals. Dorsiflexion of front-leg foot. Hands parallel to each other. Wrist should be after hip. 	<ol style="list-style-type: none"> Distance of knees from each other. Angle of shins with ground. Distance of heel from middle of hip. Angle of line connects toe, heel, and ankle. Elbow joints angle. Distance of wrists from middle of hip. 	<ol style="list-style-type: none"> 25 25, 27 23, 27 31, 29, 27 11, 13, 15 23, 15 	<ol style="list-style-type: none"> 26 26, 28 24, 28 32, 30, 28 12, 14, 16 24, 16
Full-Support	<ol style="list-style-type: none"> Dorsiflexion of front leg foot. Swing-leg foot should be under gluteals. Swing-leg thigh approximately 45-degree. Stance-leg yield from touch down. 	<ol style="list-style-type: none"> Angle of line connecting toe, heel, and ankle. Distance of heel from middle of hip. Thigh angles with x-axis. Knee joint angles. 	<ol style="list-style-type: none"> 31, 29, 27 23, 27 23, 25 23, 25, 27 	<ol style="list-style-type: none"> 32, 30, 28 24, 28 24, 26 24, 26, 28



AIMS Toolset Demo – Kinematic Analysis



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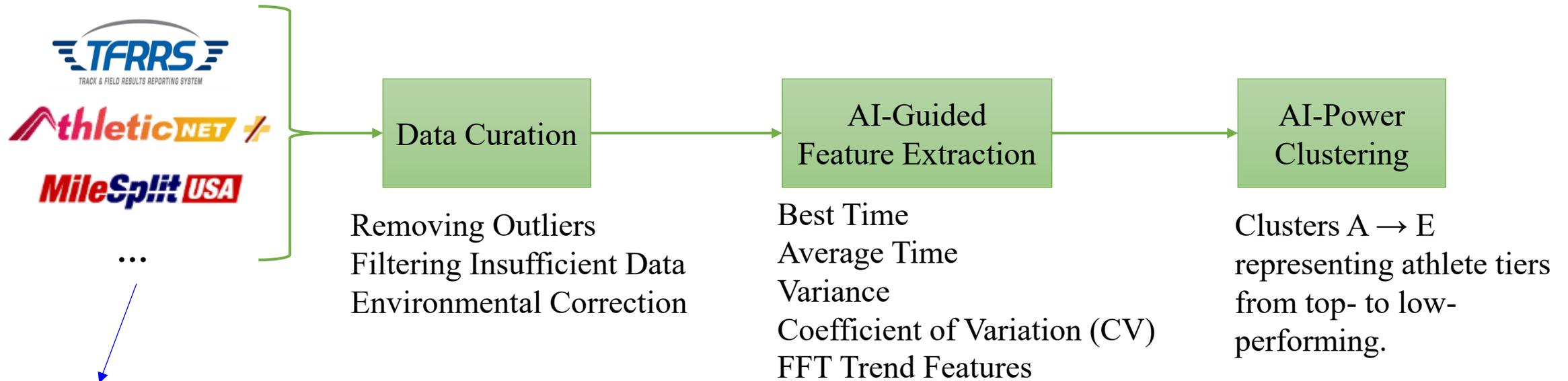
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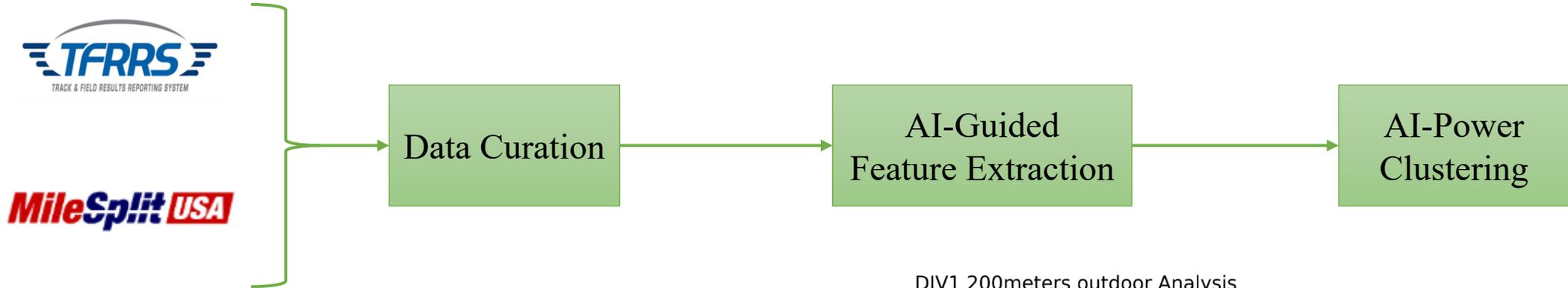
Performance Ranking Module - Flowchart



Examples:

Athlete ID	Year	Team	Field	Types	Score	Competition venue	Date	Wind
1MT	FR-1	Tennessee	200 Meters	Outdoor	20.56	NCAA East First Round	05/22/2024	-0.5
2AS	SO-1	South Florida	200 Meters	Indoor	21.24	American Indoor Track & Field Championship	02/23/2024	-
3OG	JR-3	LSU	200 Meters	Outdoor	20.74	LSU Battle on the Bayou	08/29/2024	2.1
4MK	SR-4	Alabama	400 Meters	Outdoor	45.76	NCAA I Outdoor Track & Field Championships	06/05/2024	0

Performance & Ranking Module – Input & Output



System Message: **Runner with same info was in database.**

Name:

Height: ft in

Gender: Male Female

Kinematic Analysis | **Ranking Prediction**

Season: Indoor Outdoor

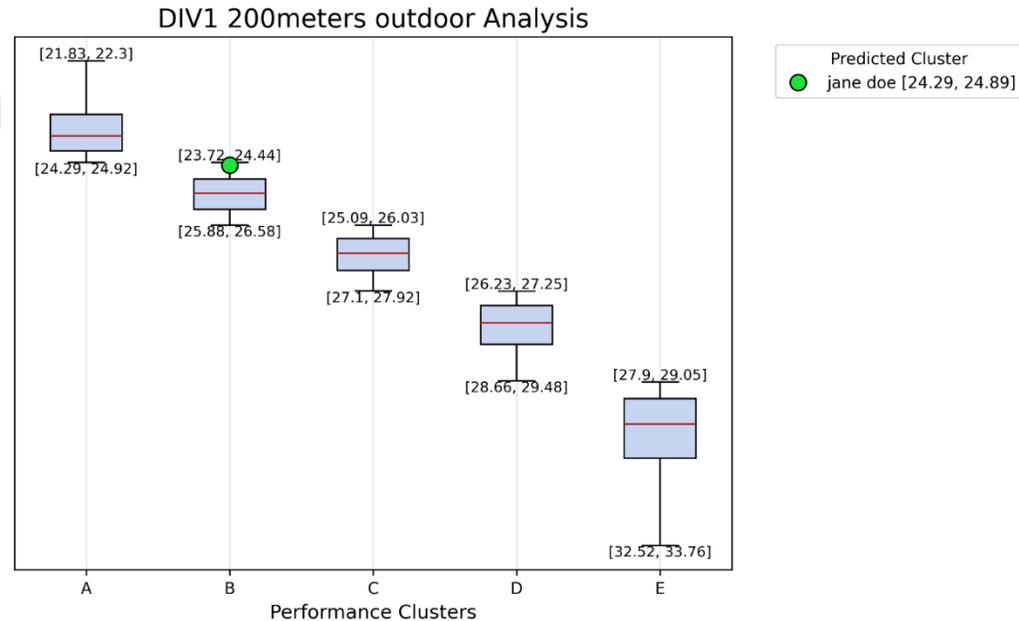
Category Division:

Event:

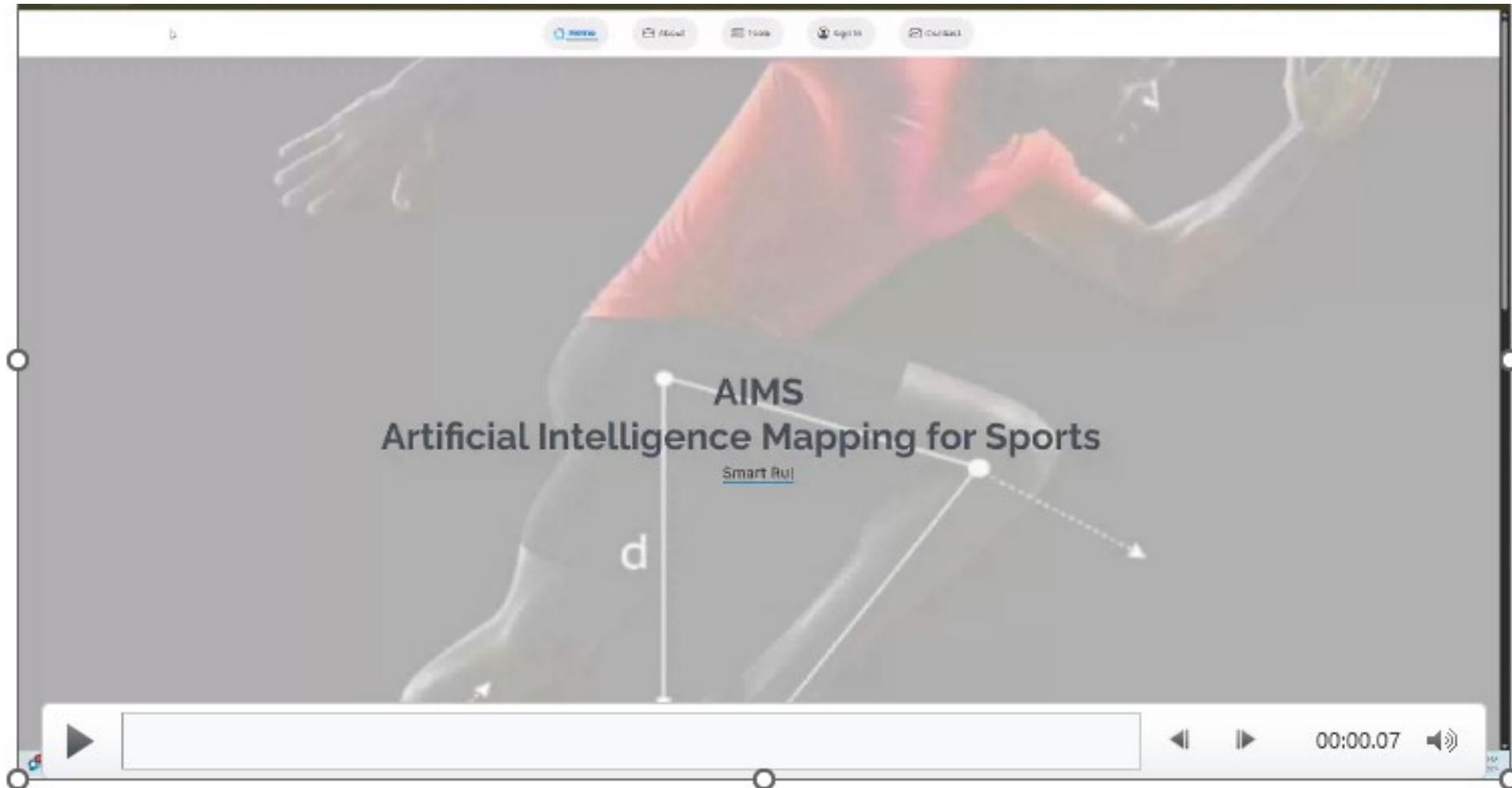
Performance Records (At Least 5 most recent/best):

Scores	Date (optional)	
25.07	08/01/2025	X
24.72	09/01/2025	X
25.23	10/01/2025	X
24.29	11/01/2025	X
25.14	12/01/2025	X

Values:[PR, AVG]



AIMS Toolset Demo – Performance & Ranking Prediction



Conclusions

- AI cannot be a universal solution. To be an effective supporting tool, it must be customized.

- AI technology has potential to enable T&F coaches to
 - Do performance assessment and benchmarking
 - Gain insights on consistency and trends
 - Offer personalized training
 - Identify and recruit talents

- AIMS Toolset provides customized AI technology for
 - Computer-vision-based kinematic analysis
 - Performance & ranking evaluation
 - Accurate, data-driven and actionable insights for coaches and athletes
 - Easy to use yet scalable and practical

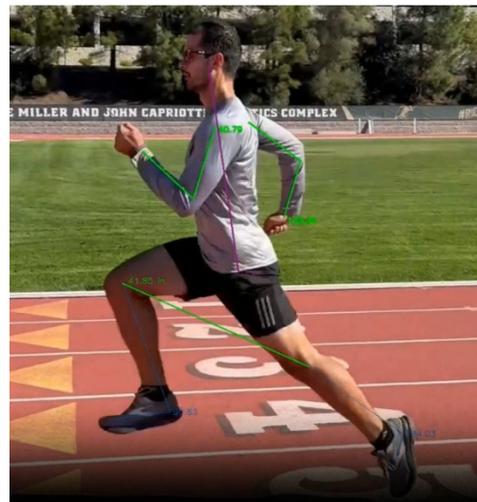
California Polytechnic University & AIMS Technologies, LLC

AIMS Technologies, LLC
Artificial Intelligence Mapping for Sports

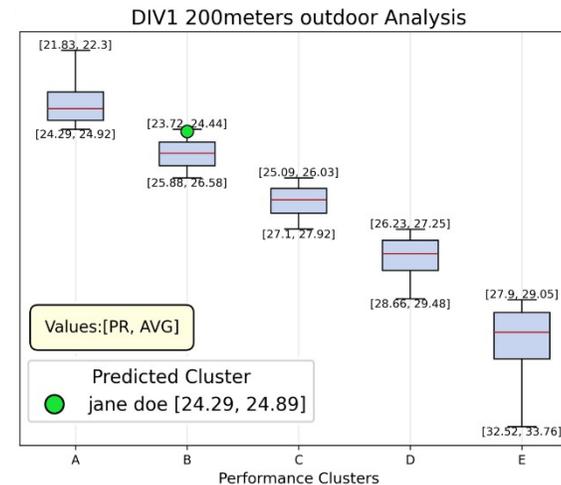
Website: aims-technologies.com
Email: info@aims-technologies.com



Kinematic Analysis



Performance Ranking



Thanks for Your Attention!



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