

TL;DR Thesis

Before ball flight is observed, a pitcher's body already reveals substantial pitch-type information. Broadcast 3D pose captures posture, arm slot, trunk lean, timing, and unintended mechanical tells that are visible from ordinary monocular video. **Bottom line:** body kinematics enable strong pre-release anticipation, while grip-defined variants expose the ceiling of pose-only prediction.

Objectives

Question: how much pitch-type information is visible in a pitcher's body before release?

- Classify eight pitch types from monocular 3D pose alone.
- Identify which joints, events, and biomechanical quantities carry the signal.
- Separate pre-release cues from ball flight.

Dataset

119,561 professional pitches **8** pitch classes **23,913** held-out test pitches

Filtered from 120,471 pitch sequences after minimum length, event-detection, and joint-tracking checks.

Stratified 80/20 train/test split preserves class balance across the eight pitch types.

Pitch	Count	Share
FF	38,560	32.3%
FT	18,570	15.5%
SL	16,221	13.6%
CH	12,170	10.2%
CB	10,456	8.7%
SW	10,225	8.6%
FC	9,743	8.1%
SP	3,616	3.0%

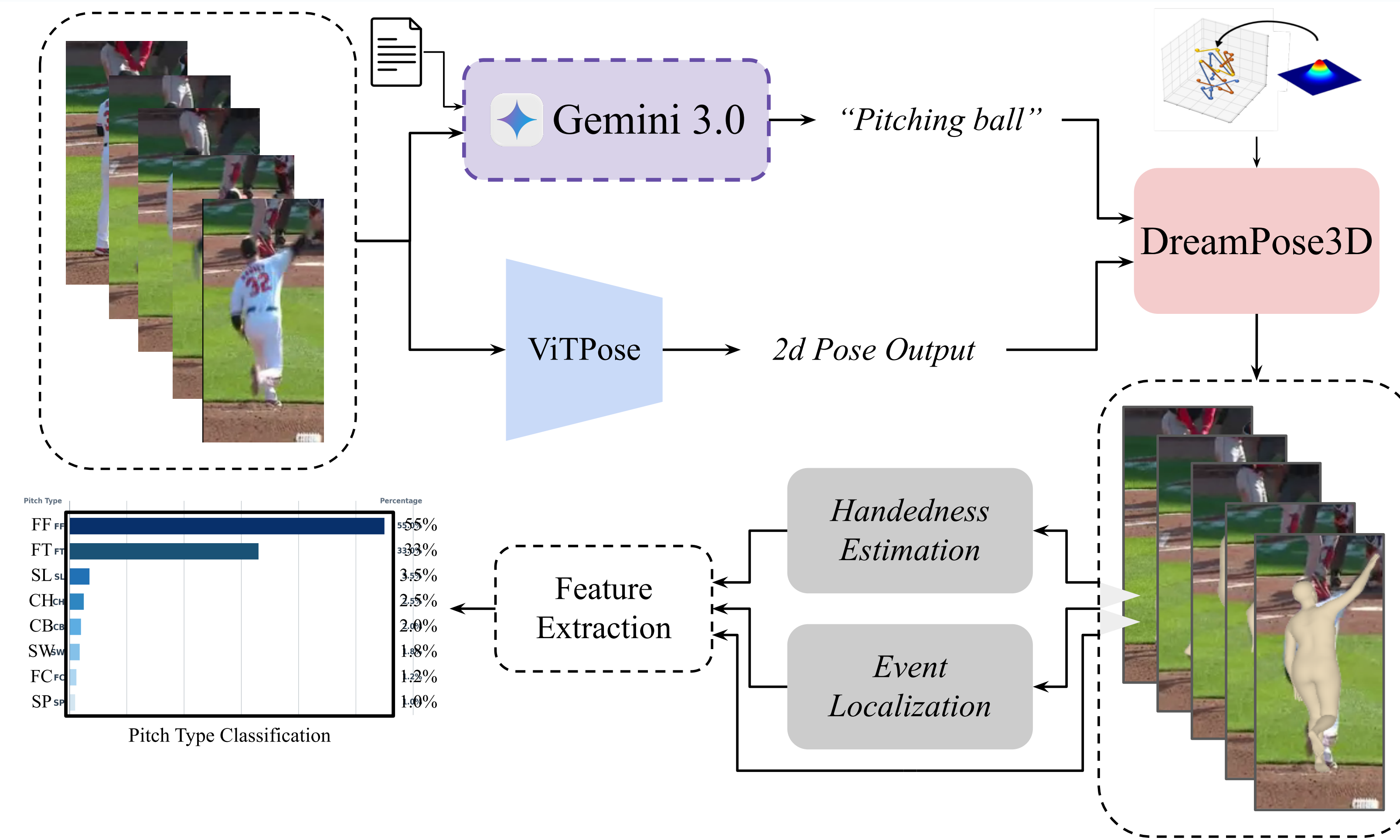
Highlights

- 80.4%** 8-way accuracy from body kinematics alone.
- +3.9%** absolute gain from explicit biomechanical features and temporal deltas.
- 64.9%** of importance lies in upper-body mechanics; lower body contributes 35.1%.
- Wrist position and head/eye orientation dominate joint-level signal.

References

- Bright et al. "PitcherNet: Powering the Moneyball Evolution in Baseball Video Analytics." *CVPRW*, 2024.
- Bright et al. "DreamPose3D: Hallucinatory Diffusion with Prompt Learning for 3D Human Pose Estimation." *arXiv*, 2025.
- Chen and Guestrin. "XGBoost: A Scalable Tree Boosting System." *KDD*, 2016.

Methodology



Pipeline. Broadcast video → 2D pose and action prompt → DreamPose3D sequence → event localization → 229-feature XGBoost classifier. The method converts ordinary broadcast clips into a compact, interpretable pitching signature. A 2D pose estimator and video-language prompt first describe the pitching motion, DreamPose3D lifts the sequence into 3D joints, and a pose-only processing stack aligns handedness, normalizes camera/pitcher variation, and extracts signals only up to release. This keeps the task anticipatory: the model cannot use ball flight, catcher reaction, or post-release trajectory cues.

Pre-Release Feature Design

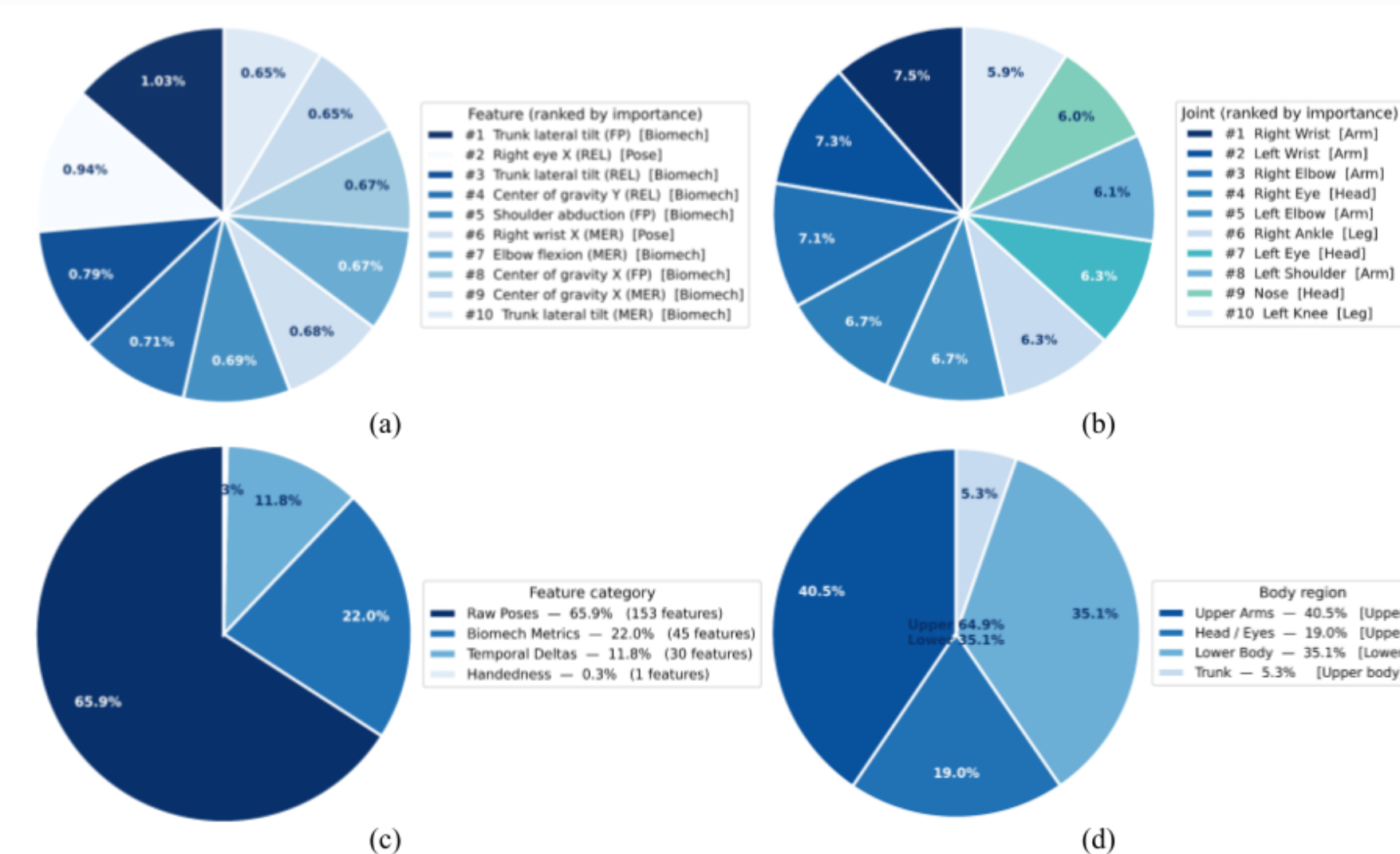
Events. Detect Foot Plant (FP), Maximum External Rotation (MER), and Release (REL) from smoothed lead-ankle and elbow-flexion signals. Event validation reports REL median error of 7.5 ms and FP/MER median errors near 40/34 ms.

Anticipatory constraint. All features are extracted at or before release, so the classifier measures body-kinematic pitch tells rather than downstream ball flight.

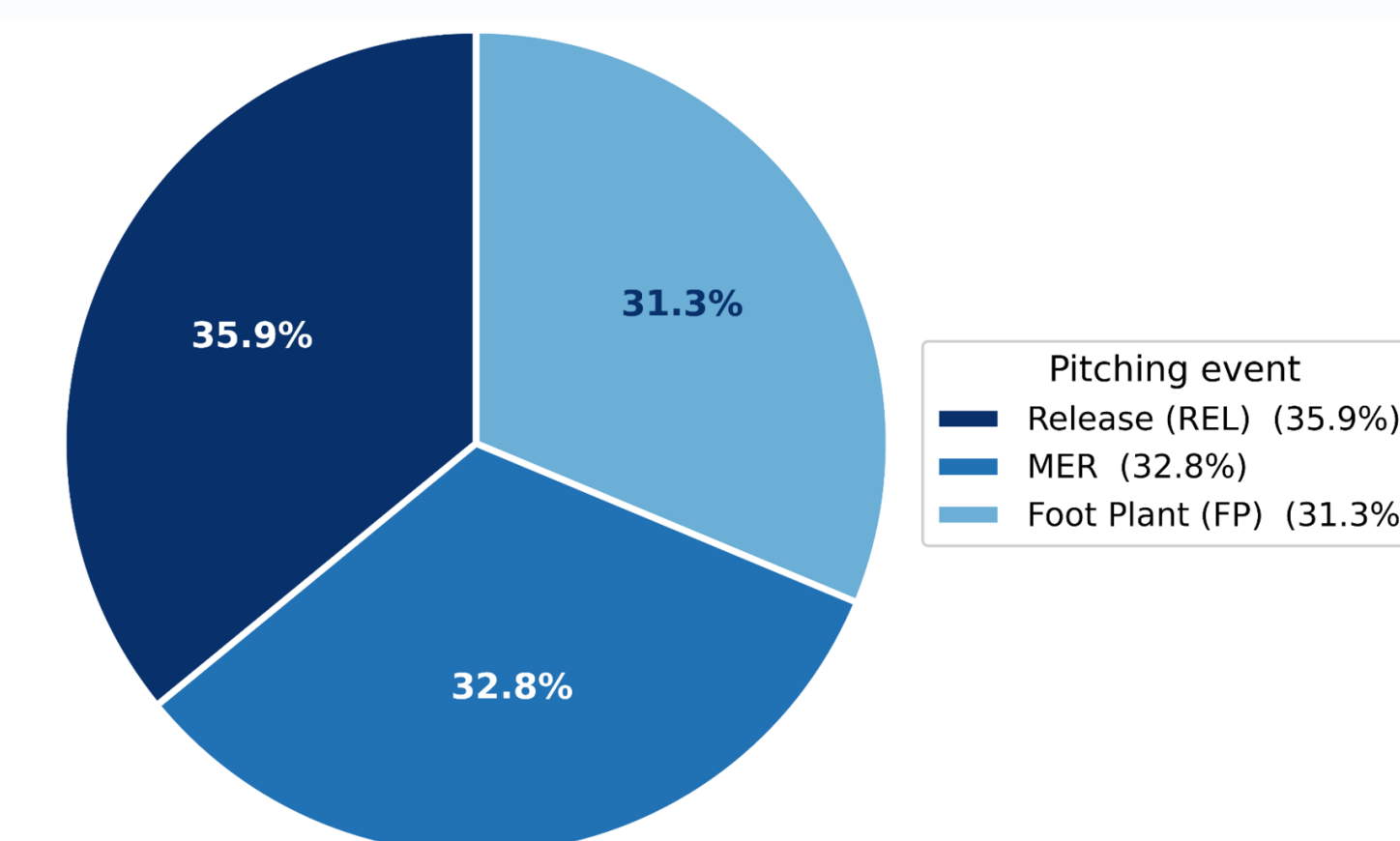
Features. Concatenate normalized 3D joints at FP/MER/REL, 15 biomechanical metrics, 10 temporal deltas, and handedness:

$$\mathbf{x} = [\mathbf{f}_{pose}, \mathbf{f}_{bio}, \mathbf{f}_{\Delta}, \mathbf{h}] \in \mathbb{R}^{229}.$$

Feature Importance



Event Timing



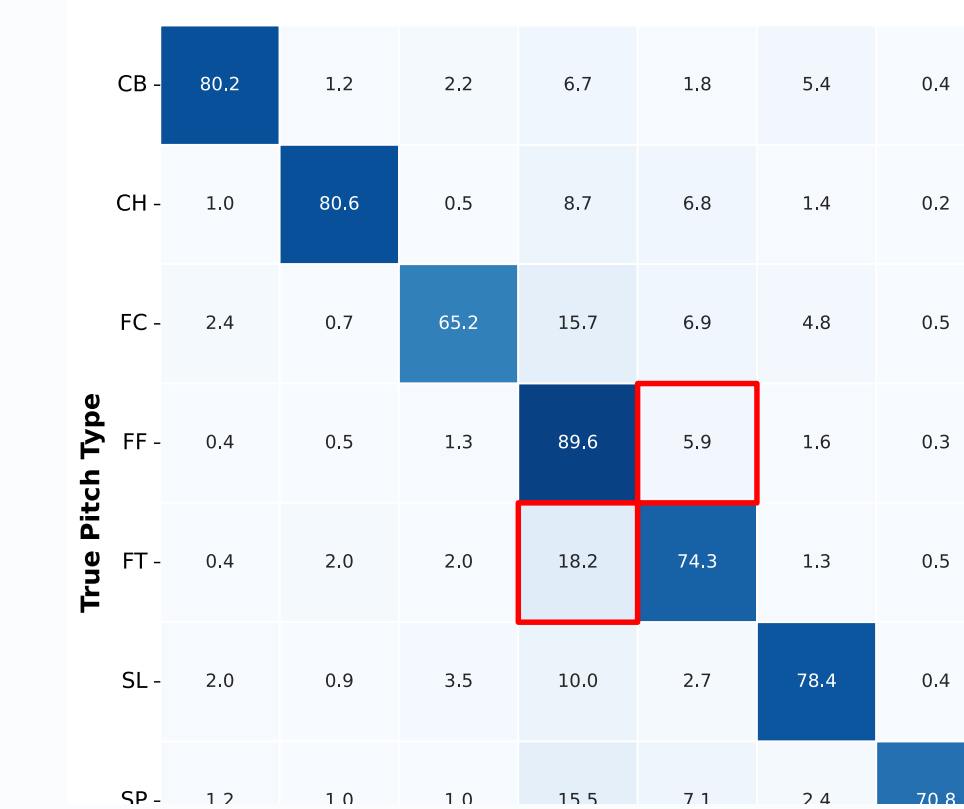
Results

Configuration	Feats.	RF	XGB
Poses only	154	63.1%	76.5%
Poses + biomechanics	229	73.2%	80.4%
Poses + ball flight [†]	166	91.9%	94.0%

[†] Post-release ball-flight data; included only as an approximate upper bound, not a valid anticipatory setting.

Mechanically distinct classes are strongest: CH F1 = 85%, CB F1 = 84%, SL/SW F1 = 81%. Cutters and two-seam fastballs remain hardest because they overlap with fastball and slider mechanics.

Error Mode



Row-normalized confusion matrix. The dominant systematic error is FF↔FT, with 1,133 reciprocal fastball confusions in the test set.

Future Work



Future work will add hand pose, grip, and hand-ball interaction cues to resolve pitch types whose body mechanics are intentionally similar.

Acknowledgements

