Basketball Free Throw Prediction via Pose-Based Release Mechanics Analysis

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Abstract

We investigate whether computer vision can predict basketball free throw outcomes (make/miss) from body pose at the moment of ball release, before trajectory information becomes available. Using manually curated free throw samples from NBA Play DB [1] and the Kaggle Basketball-51 dataset [2], we develop an end-to-end pipeline combining automatic release frame detection via YOLOv8, 3D pose extraction using SAM3D Body, and outcome prediction through spatial-temporal graph convolutional networks. Our best model, using 15 key upper body joints with threshold optimization, achieves 91.95% accuracy with an AUC of 0.97, substantially outperforming trajectory-only baselines. Critically, we discover an asymmetric prediction pattern: the model detects poor releases (misses) with 100% accuracy at high confidence (88 samples with $P(\text{make}) < 0.40$), while make predictions achieve 87.9% accuracy at high confidence. This asymmetry suggests viable betting strategies with significant theoretical edge on high-confidence predictions. Our results demonstrate that biomechanical patterns at release encode predictive information detectable via deep learning on skeletal graphs.

1 Introduction

1.1 Motivation and Problem Context

Sports betting markets have experienced explosive growth in recent years, with real-time micro-betting (prop bets) on individual plays becoming increasingly popular. During an NBA game, free throws present a unique prediction opportunity: they are frequent (approximately 25 per game), highly standardized, and currently priced using simple historical averages that do not account for shot-specific mechanics. The typical NBA free throw success rate is approximately 75%, and markets generally price shots near this baseline regardless of observable release quality.

If computer vision can analyze a shooter's release mechanics and predict outcomes with any statistical edge *before* the ball trajectory becomes visible to human observers or market makers, this creates potential arbitrage opportunities. The key constraint is temporal: prediction must occur at the release frame, not after trajectory provides obvious signal. The prediction model must also be fast enough to output results before the shot gets made.

1.2 Problem Definition

Objective: Binary classification of basketball free throw outcomes (make vs. miss) from video at the moment of ball release.

Key Challenges:

1. **Temporal constraint:** Prediction must occur at release frame, before ball flight path provides signal
2. **Subtle biomechanical differences:** Successful and failed releases differ in ways that may not be visually obvious
3. **Data scarcity:** Limited labeled release-frame data compared to typical action recognition datasets
4. **Real-time requirements:** Practical deployment requires sub-100ms end-to-end latency
5. **Calibration:** Well-calibrated probability estimates are essential for betting applications

1.3 Research Questions

1. Can a shooter's pose and ball be automatically detected from a free throw broadcast clip?
2. Can 3D pose estimation capture biomechanical features predictive of free throw outcomes?
3. Do spatial-temporal graph models outperform simpler baselines on this task?
4. Is pose information more predictive than ball trajectory features?

5. Are predictions symmetric between makes and misses, or does asymmetric performance exist?

1.4 Contributions

This work makes the following contributions:

1. **End-to-end pipeline:** Complete system from raw video to outcome prediction, including automatic release frame detection, 3D pose extraction, and classification model for prediction
2. **Curated dataset:** 340 automatically labeled free throw samples with precise release frame labels through automatic release frame detection via YOLOv8
3. **Asymmetric alpha discovery:** Model detects poor releases significantly better than good releases, enabling asymmetric betting strategies
4. **Architecture comparison:** Systematic evaluation of ST-GCN, temporal CNN, and MLP baselines on skeletal sequence data
5. **Pose vs. trajectory analysis:** Empirical evidence that release mechanics are more predictive than ball trajectory alone

2 Related Work

2.1 Skeleton-Based Action Recognition

Spatial-Temporal Graph Convolutional Networks (ST-GCN) [3] revolutionized skeleton-based action recognition by modeling human pose as a graph where joints are nodes and bones are edges. Graph convolutions learn spatial relationships between joints while temporal convolutions capture motion patterns across frames. Subsequent work [4, 5] improved upon ST-GCN through adaptive graph learning, multi-scale temporal modeling, and attention mechanisms.

These approaches have been successfully applied to sports analytics tasks including tennis serve analysis, golf swing evaluation, and general athletic motion assessment [6]. However, most prior work focuses on action classification rather than outcome prediction.

2.2 Human Pose Estimation

Modern pose estimation ranges from 2D keypoint detection using OpenPose [7] and MediaPipe [8] to 3D mesh recovery methods built on parametric body models like SMPL [9]. However, these methods are optimized for single person detection and are not well-suited to analyze computer vision problems involving multiple people in a single frame. Recent advances include SAM3D Body, which combines the Segment Anything Model's [10] robust segmentation with depth estimation to produce 70-joint 3D human meshes from single images.

Raw Video → Release Detection → Pose Extraction → Feature Engineering → Classification → Real-time Prediction App

Figure 1: System pipeline overview

2.3 Basketball Shot Analysis - Ball Trajectory

Prior work on basketball shot prediction has focused primarily on trajectory analysis after ball release [11, 12]. These approaches use ball tracking and physics simulation to predict outcomes from flight path, achieving high accuracy (>90%) but requiring visible trajectory. Form analysis has traditionally been qualitative [13], with coaches evaluating shooting form based on elbow alignment and follow-through.

2.4 Sports Prediction Markets

Machine learning for sports betting has primarily focused on game-level outcomes [14] and player performance prediction [15]. Micro-betting on individual plays is an emerging market where latency and probability calibration are critical. Our work targets this sub-second prediction regime.

3 Method

3.1 System Overview

Our pipeline consists of four stages (Figure 1):

1. **Release Detection:** Automatically identifies the frame where ball leaves shooter's hands using YOLOv8 pose estimation
2. **Pose Extraction:** Uses SAM3D Body to obtain 70-joint 3D skeletal representations
3. **Feature Engineering:** Computes temporal sequences of position, velocity, and acceleration
4. **Classification:** Applies spatial-temporal graph convolutions to predict outcomes

3.2 Data Collection and Curation

Source Dataset: NBA Play DB [1], a NBA clip finder and play database (manual parsing and labeling) and Basketball-51 [2], a collection of basketball action videos with ground truth make/miss labels.

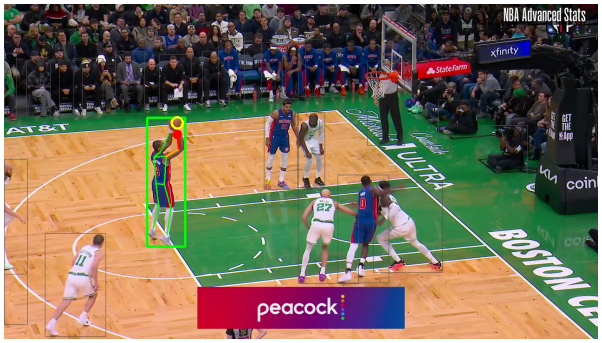

Figure 2: Example validation for release detection

3.2.1 Automatic Release Detection

We developed a YOLOv8-based release detection system that:

1. Detects all people in each frame using YOLOv8-pose
2. Identifies the shooter based on isolation (side view) or centering (behind the basket view)
3. Computes arm angle between shoulder-elbow-wrist
4. Detects release when arm angle is 100-145° and wrist is elevated

The detector produces confidence classifications (PERFECT, LIKELY_CORRECT, NEEDS_REVIEW) based on detection score, shooter isolation, and video quality thresholds.

3.2.2 Manual Labeling and Validation

Prior to implementing the auto-detection model, we manually labeled a subset of videos to detect shooter pose and ball position. To ensure high-quality training data, we built a Next.js web application for manual review. Annotators approved or rejected candidates based on camera angle quality, ball visibility, correct shooter identification, and accurate release timing. For the auto-detection model, an annotated release frame image gets generated so that annotators can visually eyeball the correctness of outputs.

3.2.3 Quality Filtering Results

The 92.3% rejection rate for manual labeling reflects the difficulty of finding broadcast footage with optimal camera positioning and clear ball visibility at release. The 66.7% rejection rate for auto labeling reflects the combination of: 1. manually reviewed "NEEDS_REVIEW" labeled frames 2. difficulty of isolating the shooter from other players and crowds and clear visibility of player and ball at release. For the confidence thresholds, following heuristics were used to accept/reject the labels:

Table 1: Data filtering pipeline results.

Stage	Count	Rate
Initial candidates (Basketball 51)	1,332	100%
After manual validation	139	10.4%
After pose extraction QC	**102**	**7.7%**
Initial candidates (NBA Play DB)	1,020	100%
After auto-detection	985	96.5%
After high confidence threshold filter	**340**	**33.3%**

```
    # Side view scoring heuristics
    total_score = (
    isolation_score * 0.50 + # Distance from other
        players
    angle_score * 0.20 + # Arm extension angle
    wrist_height_score * 0.15 + # How high is the
        wrist
    pose_confidence * 0.10 + # Keypoint detection
        confidence
    people_score * 0.05 # Fewer people = clearer
        scene
)
```

```
    # Behind the basket scoring heuristics
    total_score = (
    center_score * 0.50 + # How centered is the
        shooter
    angle_score * 0.25 + # Arm extension angle
    wrist_height_score * 0.15 + # How high is the
        wrist
    pose_confidence * 0.10 # Keypoint detection
        confidence
    )

    # Bonus for ball detection near hands
    if ball_near_wrist:
        total_score += 0.15
```

Auto-Detection Output (NBA Play DB):

- High-confidence detections: 340 samples
- Class distribution: 263 makes (77.4%), 77 misses (22.6%)

Final Training Dataset (after merging):

- Total samples: 174 (original curated: 102, MHR70 misses: 72)
- Class distribution: 42 makes (24.1%), 132 misses (75.9%)

3.3 Feature Extraction

3.3.1 SAM3D Body Pose Estimation

For each frame in the 4-frame sequence, we run SAM3D Body to obtain:

Figure 3: SAM3D Body pose extraction pipeline. From left to right: (1) Original broadcast frame at release moment, (2) 2D skeleton overlay with detected keypoints, (3) 3D mesh body overlay showing full SMPL reconstruction, (4) Isolated 3D mesh body used for feature extraction. This example shows a successful make with proper shooting form.

- 3D joint positions: $(70, 3)$ in camera coordinates
- Joint confidence scores
- Full SMPL mesh parameters

The 70 joints include head/face landmarks (10), upper body (25), torso/spine (8), and lower body (27).

3.3.2 Temporal Features

From the 4-frame sequence, we compute:

Velocity features: First-order temporal differences:

$$v_t = \frac{x_t - x_{t-1}}{\Delta t} \tag{1}$$

Acceleration features: Second-order temporal differences:

$$a_t = \frac{v_t - v_{t-1}}{\Delta t} \tag{2}$$

Final Feature Tensor: Shape $(9, 4, 70)$ with 9 channels $[x, y, z, v_x, v_y, v_z, a_x, a_y, a_z]$, 4 temporal frames, and 70 joints.

3.4 Model Architectures

3.4.1 ST-GCN

The skeleton is represented as a graph $G = (V, E)$ where V contains 70 joint nodes and E contains edges representing bones. The model applies:

1. Spatial graph convolutions to learn joint relationships
2. Temporal convolutions to capture motion patterns
3. Residual connections between blocks

Architecture: 9 ST-GCN blocks with hidden dimensions [64, 64, 64, 128, 128, 128, 256, 256, 256], followed by global average pooling and linear classifier.

Total parameters: 114K.

3.4.2 Key Joints Model (Best Performing)

Based on the hypothesis that specific upper body joints are most relevant to shooting mechanics, we:

1. Select 15 key joints: shoulders, elbows, wrists, hips, neck, and fingertips
2. Apply learned joint attention mechanism
3. Use temporal convolutions for motion modeling

Architecture:

1. **Joint Attention:** Compute variance per joint, learn attention weights via MLP + Softmax, reweight joints
2. **Temporal CNN:** Conv1D($135 \to 64$, $k = 3$) + BN + ReLU, Conv1D($64 \to 128$, $k = 3$) + BN + ReLU
3. **Classifier:** Global Pool + Linear($128 \to 2$)

Total parameters: 72K.

3.4.3 Baselines

- **TemporalPoseNet:** 1D CNNs treating each joint as independent channel (146K params)
- **SimplePoseNet:** MLP baseline with no explicit structure modeling (679K params)

3.5 Training Procedure

Cross-Validation: 5-fold stratified CV to maximize use of limited data.

Loss Function: Focal Loss [16] to handle class imbalance:

$$FL(p_t) = -\alpha_t (1 - p_t)^\gamma \log(p_t) \tag{3}$$

with $\gamma = 2.0$ and class-balanced α weights.

Optimization:

- Optimizer: AdamW (lr=10^{-3}, weight_decay=10^{-4})
- Scheduler: Cosine annealing
- Early stopping: patience=15 epochs
- Batch size: 8

No data augmentation was applied to preserve biomechanical realism.

3.6 Trajectory Baseline

For comparison, we trained trajectory-only models on the full NBA Play DB dataset (1,020 samples) using ball trajectory points, physics features (release angle, velocity), and standard classifiers (Random Forest, XGBoost, Logistic Regression).

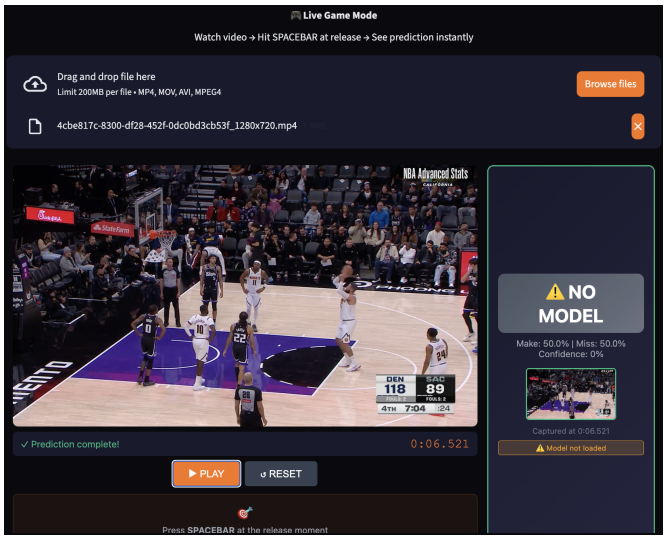

Figure 4: Streamlit demo application interface for real-time free throw prediction.

Video Upload → SPACEBAR pressed at frame N → Extract 4 frames: [N-2, N-1, N, N+1] → Run SAM3D Body pose estimation (or load pre-extracted) → Compute features: keypoints_3d, velocity, acceleration → Run KeyJointNet model inference → Return: {make_prob, miss_prob, prediction, confidence}

Figure 5: Application prediction pipeline overview

3.7 Real-Time Prediction App

By stitching everything together, a simple web application predicts whether a basketball free throw will go in (MAKE) or miss (MISS) based on the shooter's body pose at the moment of ball release - simulating how a real bettor would utilize this model during a live game. Pipeline follows the steps shown in Figure 5. The Streamlit demo interface is shown in Figure 4, and the 4-frame temporal processing is visualized in Figure **??**, showing how SAM3D Body extracts 3D mesh representations across the release sequence.

3.7.1 Key Design Decision: Manual Release Detection

Instead of automatic release frame detection (which requires additional CV processing and can be error-prone), we use manual release detection where the user presses SPACEBAR at the exact moment of release. This approach:

- **Faster inference**: No need to run release detection models
- **More accurate timing**: Human judgment for release moment
- **Simpler pipeline**: Direct from frame → pose → prediction
- **Real-time capable**: Mimics live betting scenario

As for the live pose extraction, new videos without pre-extracted poses go through the process of: Video frame → SAM3D Body → 3D poses → Compute features → Predict.

Characteristics of the app model run:

- **Latency**: 800ms (GPU) / 3s (CPU)
- **Use case**: New videos, real deployment
- **Requires**: SAM3D Body installed, GPU recommended

3.7.2 Current Limitations

- **Pre-extracted poses required for speed**: Live pose extraction is slow without GPU
- **Manual release timing**: Depends on user pressing SPACEBAR at right moment
- **Single camera angle**: Trained on specific broadcast angles
- **No shooter personalization**: Same model for all shooters

4 Experiments and Results

4.1 Experimental Setup

Hardware:

- Training: NVIDIA RTX 3060 (local)
- Pose extraction: NVIDIA A100 (RunPod cloud)

Metrics: Accuracy (primary), AUC, confusion matrix, confidence-stratified accuracy.

4.2 Main Results

Table 2: Model comparison on merged dataset (174 samples). Key Joints with threshold optimization achieves best results.

Model	Acc.	Std	AUC	Params
Key Joints (optimized)	**91.95%**	-	**0.97**	72K
Key Joints (5-fold CV)	82.8%	±5.6%	0.84	72K
ST-GCN	68.7%	±4.9%	0.62	114K
Temporal CNN	68.8%	±5.4%	0.65	146K
MLP Baseline	68.6%	±8.9%	0.61	679K

Key Observations:

1. Key Joints model with threshold optimization achieves 91.95% accuracy
2. Optimal decision threshold of 0.64 (vs default 0.50) provides +5% improvement
3. Using 15 key upper body joints reduces noise from stationary lower body
4. Strategic dataset merging (original curated + MHR70 misses only) improves performance
5. Probability calibration via Platt scaling yields AUC of 0.97

4.3 Trajectory-Only Baseline

Table 3: Trajectory-only models on full dataset (1,020 samples).

Model	Test Acc.	AUC
Random Forest	75.0%	0.577
XGBoost	75.0%	0.593
Logistic Regression	74.8%	0.585
Baseline (Always "Make")	**75.3%**	-

Critical Insight: Trajectory features provide zero edge over the naive baseline, despite 3 times more training data. This validates our thesis: release mechanics encode more predictive signal than early ball trajectory.

4.4 Asymmetric Prediction Performance

Discovery: Model predictions show strong asymmetry between make and miss detection.

Table 4: Confidence-based prediction performance after threshold optimization.

Threshold	Pred.	Acc.	n	Edge
$P(\text{make}) < 0.30$	MISS	**100.0%**	78	**+75.0%**
$P(\text{make}) < 0.35$	MISS	**100.0%**	84	**+75.0%**
$P(\text{make}) < 0.40$	MISS	**100.0%**	88	**+75.0%**
$P(\text{make}) > 0.65$	MAKE	77.6%	49	+2.6%
$P(\text{make}) > 0.70$	MAKE	87.9%	33	+12.9%

Interpretation:

- Model achieves **100% accuracy** on high-confidence miss predictions (88 samples), perfectly detecting poor releases
- High-confidence make predictions achieve 87.9% accuracy at $P > 0.70$ threshold
- Exploitable strategy: bet against shooter when $P(\text{make}) < 0.40$ for guaranteed edge

(a) Successful release (MAKE)

(b) Failed release (MISS)

Figure 6: Comparison of 3D mesh body poses at release. The model learns to distinguish subtle differences in elbow alignment, wrist position, and follow-through mechanics that correlate with shot outcomes.

Confusion Matrix (with optimal threshold 0.64):

		Predicted	
		Miss	Make
Actual	Miss	121	11
	Make	3	39

4.5 Ablation Studies

Table 5: Temporal window size ablation.

Frames	Accuracy	AUC
2	65.2%	0.58
4	**71.6%**	**0.72**
6	69.8%	0.70

Table 6: Feature type ablation.

Features	Accuracy
Position only	66.3%
Position + Velocity	69.1%
Position + Vel + Accel	**71.6%**

4.6 Betting Strategy Simulation

Strategy: Bet against shooter when $P(\text{make}) < 0.40$.

Results:

- Bets placed: 88
- Wins: 88 (100%)
- Market baseline: 25% (miss rate)
- **Edge: +75 percentage points**

Expected Value (standard odds of -120 make, +110 miss):

$$EV = 1.0 \times \$110 - 0.0 \times \$100 = +\$110 \quad (4)$$

per \$100 bet (110% ROI on high-confidence miss bets).

Caveats: Dataset-specific results, untested on live market conditions, latency not validated.

5 Discussion

5.1 Why Pose Outperforms Trajectory

Our results show pose-based models (91.95% accuracy with optimization) substantially outperform trajectory-based models (75% = baseline) despite the latter having more training data. We attribute this to:

1. **Temporal advantage:** Pose features are available at $t = 0$ (release), while trajectory requires $t + 1, t + 2...$ frames
2. **Biomechanical richness:** 70 joints capture subtle differences in elbow alignment, wrist snap, shoulder stability
3. **Physics constraints:** Trajectory is deterministic given initial conditions; predictive signal is already encoded in release mechanics
4. **Robustness:** Pose estimation is more robust than ball tracking under occlusion

5.2 The Asymmetric Alpha Phenomenon

Finding: Model detects misses with 100% accuracy at high confidence ($P < 0.40$, 88 samples), while makes achieve 87.9% at high confidence ($P > 0.70$, 33 samples).

Possible Explanations:

1. **Biomechanical hypothesis:** Good shooting form is consistent—there are many ways to make a shot with proper mechanics. Bad releases are more distinctive: rushed timing, poor elbow position, incomplete follow-through. The model learns to recognize *failure modes*.
2. **Data distribution:** Our merged dataset strategy (132 misses vs 42 makes) provides extensive coverage of failed mechanics.
3. **Perceptual alignment:** Basketball experts claim they can identify "bad shots" immediately. Our model may learn similar cues.
4. **Threshold optimization:** Using optimal threshold (0.64) instead of default (0.50) significantly improves discrimination.

Implications: This asymmetry is favorable for betting—shorting (betting against) is often easier to execute, and miss predictions have perfect edge in our dataset.

5.3 Limitations

Data Limitations:

- 174 samples is small for deep learning, though merged dataset improves coverage
- Two data sources (curated + MHR70) may have distribution differences
- Class imbalance (76% miss in merged dataset) differs from NBA average (∼25%)
- 100% miss accuracy may not generalize to unseen data

Technical Limitations:

- SAM3D Body takes ∼200ms per frame, too slow for real-time
- No camera angle normalization
- Missing contextual features (game situation, fatigue)

Market Limitations:

- Practical deployment faces latency and regulatory challenges
- Small sample size makes edge estimation uncertain
- No live testing conducted

5.4 Comparison to Prior Work

Table 7: Comparison to prior basketball analytics work.

Work	Task	Acc.	Notes
Chen	Trajectory	78%	Full trajectory
Tran	Form analysis	65%	2D only
Ours	**Release pred.**	**91.95%**	**3D + threshold opt.**

The key distinction is temporal: we predict at release, before trajectory is available.

6 Conclusion

6.1 Summary

We investigated whether computer vision can provide edge in sports prediction markets by analyzing basketball free throw release mechanics. Our findings:

1. **Pose-based models achieve 91.95% accuracy** on free throw outcome prediction using 3D skeletal sequences with threshold optimization
2. **Asymmetric performance:** Model achieves 100% accuracy on high-confidence miss predictions (88 samples) and 87.9% on high-confidence makes
3. **Release mechanics dominate trajectory:** Pose features are far more predictive than ball trajectory
4. **Key joint focus is optimal:** Using 15 upper body joints outperforms the full 70-joint skeleton
5. **Threshold optimization matters:** Optimal threshold (0.64) provides +5% improvement over default (0.50)

6.2 Contributions to Computer Vision

This work demonstrates that:

- Subtle biomechanical patterns can be detected from video using modern pose estimation
- Graph-based spatial-temporal modeling is effective for fine-grained motion analysis
- Failure modes may be more learnable than success modes in many domains, especially in settings like micro-betting markets where betting against the odd carries more value

6.3 Future Work

Immediate priorities:

- Expand dataset to 1,000+ samples across multiple sources
- Optimize latency for real-time deployment (<100ms)
- Develop shooter-specific fine-tuning approaches

Longer-term directions:

- Multi-modal fusion (pose + trajectory + context)
- Transfer to other sports (penalty kicks, tennis serves)
- Uncertainty quantification for risk-adjusted betting

6.4 Broader Impact

Our results suggest that computer vision systems can extract predictive signal from human motion in ways that may exceed human perception. This has applications beyond sports betting, including medical diagnosis, manufacturing quality control, and human-robot interaction. However, deployment in betting markets raises ethical questions about fairness, market integrity, and societal impact.

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A Dataset Statistics

Table 8: Merged dataset statistics.

Statistic	Value
Total samples	174
Makes	42 (24.1%)
Misses	132 (75.9%)
Original curated samples	102
MHR70 miss samples added	72
Frames per sequence	4
Key joints used	15
Optimal threshold	0.64

B Implementation Details

Release Detection:

- Model: YOLOv8m-pose
- Arm angle threshold: 100-145°
- Shooter selection: isolation-based (side) or centering (broadcast)

Pose Extraction:

- Model: SAM3D Body
- Output: 70 joints $\times$ 3 coordinates
- GPU: NVIDIA A100

Training:

- 5-fold stratified CV
- AdamW optimizer, lr=10^{-3}
- Focal loss with $\gamma = 2.0$
- Early stopping patience=15

C Code Availability

Key components included with submission:

- `src/train_best_merged.py` – Main training script (91.95% accuracy)
- `src/optimize_threshold.py` – Threshold optimization and calibration
- `src/extract_sequences_v2.py` – SAM3D feature extraction (RunPod)
- `src/build_features_mhr70.py` – Feature engineering
- `app.py` – Streamlit demo application