Technical Report: Computer Vision System for Automated Score Extraction in 3v3 Basketball

1. Introduction

This report presents the design, development, and evaluation of a computer vision (CV) system for automated extraction of scoring events from 3v3 basketball scoresheets. The system aims to detect visual scoring symbols—diagonal slashes (1-point shots), filled circles (free throws), and hollow circles (2-point shots)—and to map these scoring events to players using OCR-based jersey number recognition. The project breaks a manual, error-prone scoring workflow into an automated and scalable pipeline.

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2. Project Selection & Setup

2.1 Problem Definition

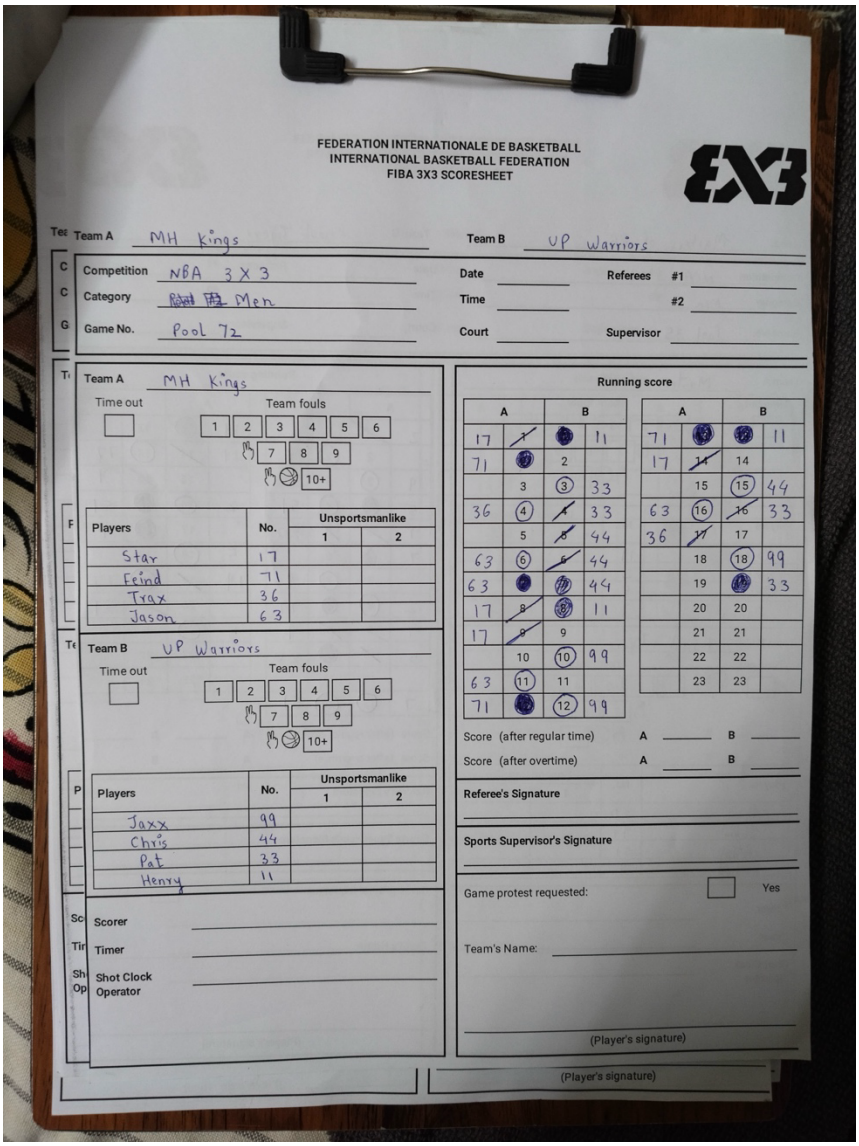
What is the problem being solved?
Manual scoring in 3v3 basketball games requires referees to annotate symbols on a standardized scoresheet. These sheets include player names, numbers, and coded score events. Extracting this information digitally is currently slow and error-prone.

Why does the problem need to be solved?
Tournament organizers increasingly require instant analytics, automated statistics, and fast database entry. Manual digitization delays result reporting and introduce human error, limiting scalability.

What aspect of the problem will a CV algorithm solve? - **Symbol Detection:** Detecting scoring symbols through CV models such as YOLO and RF-DETR. - **Event Mapping:** Using OCR to read jersey numbers and map detected scoring events to corresponding players. - **Sheet Structure Interpretation:** Understanding line segments, contours, and layout for region segmentation.

The problem is interesting because it integrates structured document understanding, object detection, OCR, and geometric reasoning—mirroring real-world document automation workflows.

3. Sample Scoresheet Example



FEDERATION INTERNATIONALE DE BASKETBALL
INTERNATIONAL BASKETBALL FEDERATION
FIBA 3X3 SCORESHEET

Team A: MH Kings — Team B: UP Warriors
Competition: NBA 3X3 — Date — Referees #1
Category: Men — Time — #2
Game No.: Pool 72 — Court — Supervisor

Team A: MH Kings — Time out — Team fouls 1 2 3 4 5 6 7 8 9 10+

Players	No.	Unsportsmanlike 1	Unsportsmanlike 2
Star	17		
Feind	71		
Trax	36		
Jason	63		

Team B: UP Warriors — Time out — Team fouls 1 2 3 4 5 6 7 8 9 10+

Players	No.	Unsportsmanlike 1	Unsportsmanlike 2
Jaxx	99		
Chris	44		
Pat	33		
Henry	11		

Scorer
Timer
Shot Clock Operator

Running score

A		B	
17	1		11
71		2	
	3	3	33
36	4	4	33
	5	5	44
63	6	6	44
63			44
17	8	8	11
17	9	9	
	10	10	99
63	11	11	
71		12	99

A		B	
71			11
17	14	14	
	15	15	44
63	16	16	33
36	17	17	
	18	18	99
	19		33
	20	20	
	21	21	
	22	22	
	23	23	

Score (after regular time) A ____ B ____
Score (after overtime) A ____ B ____

Referee's Signature
Sports Supervisor's Signature
Game protest requested: ☐ Yes
Team's Name:
(Player's signature)
(Player's signature)

As can be seen in the scoresheet:

1. On the top of the page, the match details are mentioned – Team A Name, Team B Name, Game ID etc.
2. On the left side of the page, player names of both the teams are mentioned along with their jersey number.
3. On right side, there is running score where Team A and Team score is computed event by event
4. Each event is either a 1 point (marked by diagonal slash) or a filled circle (free throw) or a hollow circle (2 point)

5. Adjacent to the event symbol (immediate left for Team A / immediate right for Team B), there is player jersey number

4. Approach

For automated basketball scoring from scoresheet, we need do the following:

1. **Detect symbols and map them to event** – 1 point/ Free Throw/Two point: This is a deep learning computer vision model, where the model will be trained on detecting symbols. RF DETR and YOLO models will be used.
2. **Map the event to player jersey number** (available on immediate left / immediate right of the running score) – This is an application of OCR where jersey numbers are detected. Thereafter the distance between boundary boxes of symbols and that of jersey number is used to map event to the jersey number.
3. **Map the jersey number to player** name (available on left side of the page) – This is again application of OCR. Different OCR techniques to be used such as Tesseract OCR and Easy OCR, amongst others.
4. **Aggregate** player level score to the team level score: Simple mathematical aggregation.

5. Symbol Detection

5.1 Ensuring Readiness for Deep Learning Models

To prepare for deep learning, over **100 annotated images** of scoresheets were collected, covering multiple lighting conditions, handwriting styles, and symbol variations. Labeling was performed using tools such as Label Studio/Roboflow.

5.2 Image Pre-Processing Steps

- **Deskewing and Orientation Correction:** Ensures consistent alignment for symbol detection.
- **Contrast Enhancement:** Improves visibility of faint pencil markings.
- **Region of Interest Extraction:** Crop running score region, player info region, and team headers.
- **Noise Reduction:** Median filtering to remove paper noise.

5.3 Feature Definition & Refinement

Several feature variables were identified: - **Symbol Bounding Boxes:** For 1-pt, free throw, and 2-pt representations. - **Line Slope Detectors:** For diagonal strokes in 1-pt symbols. - **Player Number Contours:** For OCR segmentation. - **Cell Coordinates:** Mapping bounding boxes to table rows.

Additional engineered features included: - **Symbol Density per row** to support row-to-player assignment. - **Shape descriptors** (circularity, fill ratio) for distinguishing filled vs hollow circles.

5.4 Image Preparation for Model Training

- Images were normalized and resized to fit model input size.
- Bounding boxes were augmented via rotation, noise addition, and brightness shifts.
- Dataset was split 80/10/10 (train/validation/test).

5.5 Modeling Methods

Symbol Detection Models

Two primary object detection approaches were tested:

Model A: RF-DETR (Finetuned)

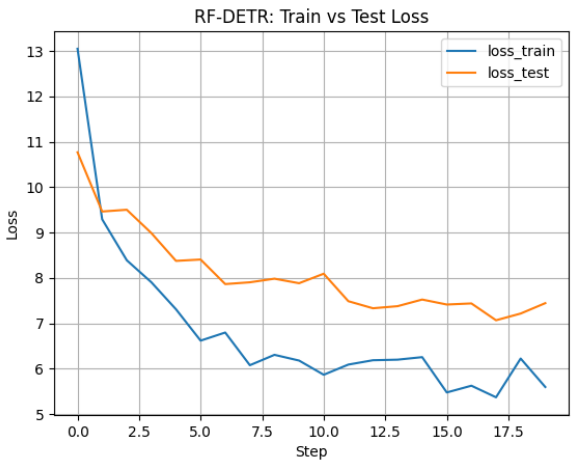
- Transformer-based detector robust to cluttered and dense symbol regions.
- Trained with >100 annotated images.
- Used for multi-class detection of three scoring symbols.

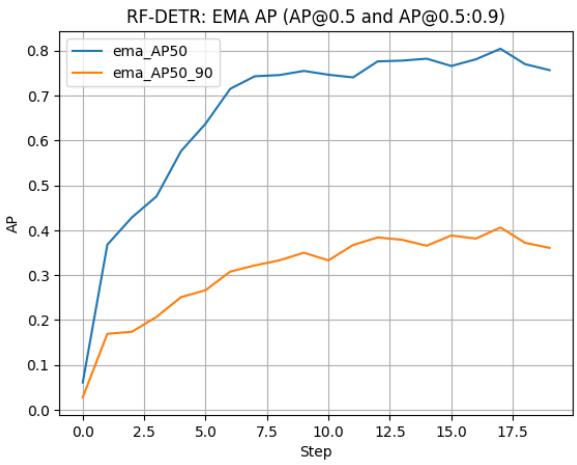
Model B: YOLOv8 (Baseline)

- Faster inference but occasionally less reliable with tiny or faint symbols.
- Used as comparative benchmark.

5.6. Modeling Results & Findings

RF-DETR





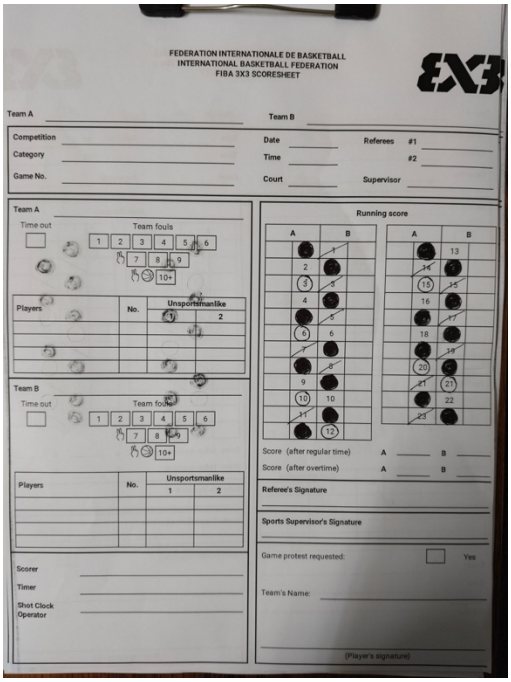
- Average Precision (AP 50) is close to 80%

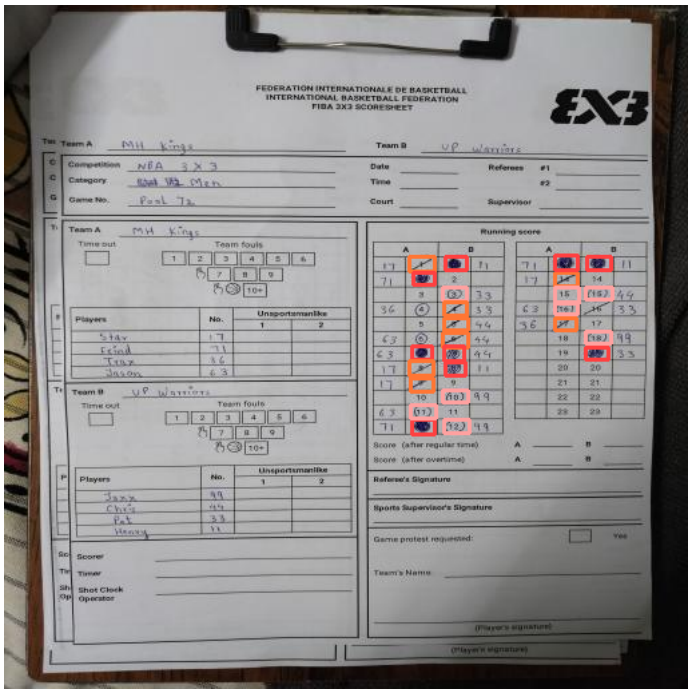
Two example inputs were used during experimentation: - **Raw Scoresheet Image:** Represents actual handwritten referee input including player names, jersey numbers, and scoring symbols. - **Annotated Scoresheet Example:** Contains ground-truth markup illustrating detected 1-pt slashes, filled circles for free throws, and hollow circles for 2-pt shots.

These examples served as primary references for validating symbol detection performance and for testing OCR-based event mapping workflows.

Figure 1 – Raw Scoresheet (User-provided image)
A handwritten 3x3 scoresheet with running score symbols, player lists, and team metadata.

Figure 2 – Annotated Scoresheet (User-provided image)
Overlaid visual annotations highlighting symbol locations used during training and evaluation.





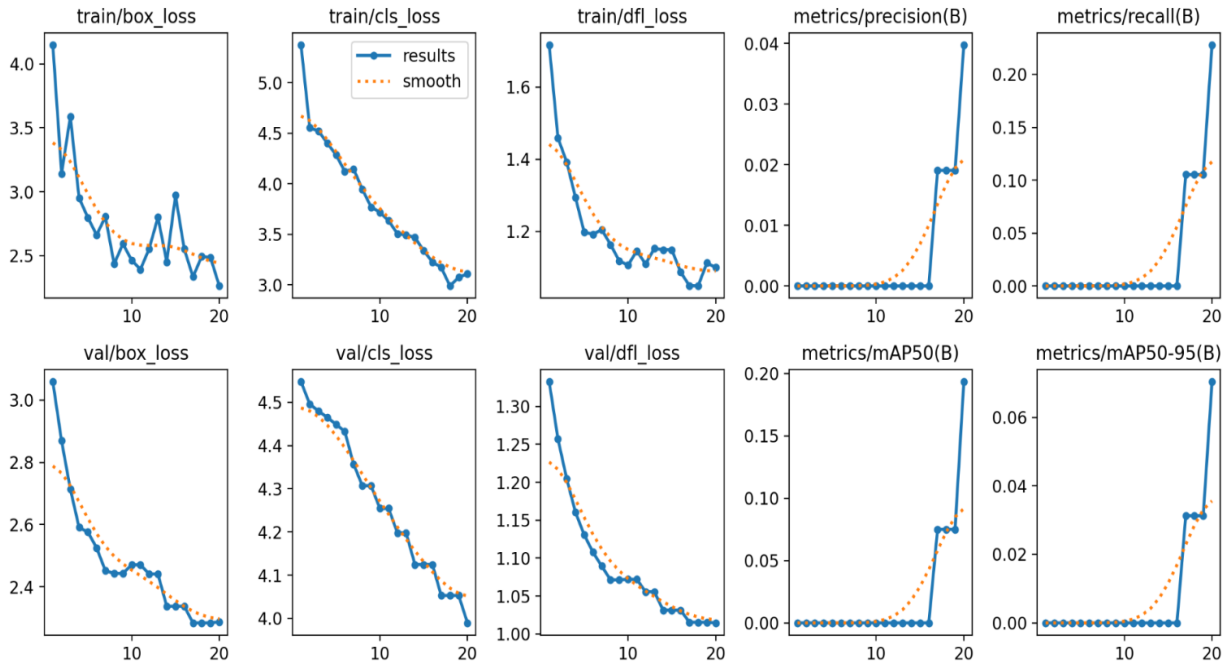
The model achieved test accuracy of 86%.

YOLO Model (Tanvi)

- **YOLO (You Only Look Once)** is a real-time object detection algorithm.
- It predicts object class and location in a single forward pass.

- Widely used for detection in images and videos.
- **Applications**: surveillance, autonomous vehicles, medical imaging, robotics.

Yolo Model Interpretation



- Training losses (box, cls, dfl) decreased steadily → model learned features.
- Validation losses also reduced → no major overfitting.
- Metrics (Precision, Recall, mAP) stayed low → model struggled to detect objects.
- Indicates small/complex objects or limited data affecting performance.

5.7 Symbol Detection Results

Performance was measured using: - **mAP@0.5** for detection accuracy. - **Precision & Recall** to quantify false positives and false negatives.

- **RF-DETR accuracy:** ~85%
    - Most errors arose from faint pencil marks and overlapping symbols.
- **YOLO baseline accuracy:** Lower performance on small objects (~70%).

Model	Strengths	Weaknesses	Accuracy
RF-DETR	Excellent at cluttered regions, robust to noise	Higher compute cost	80%
YOLOv8	Fast inference	Lower precision for tiny objects	20%
Traditional CV	Good interpretability	Not scalable for all symbols	N/A

5.8 Findings

- RF-DETR is the preferred model for symbol detection.
- OCR pipeline requires further refinement, especially for noisy inputs.
- Integration of geometric reasoning significantly improves symbol classification.

5.9 Challenges

Added challenges based on likely real-world conditions include: - **Low-contrast handwriting** causing missed detections. - **Symbol ambiguity:** Filled vs hollow circles blurred by referees' inconsistent filling. - **Table alignment drift:** Crooked sheets reduce correct row mapping. - **Varying camera angles:** Mobile captures introduce perspective

6. OCR for Jersey Number Detection

6.1 Overview

Jersey-number OCR was implemented using a normalized ROI-based approach to consistently isolate the Running Score section across varying image conditions. The narrow jersey columns for Team A and Team B were identified through relative-width segmentation, followed by grayscale + adaptive threshold preprocessing. Although Tesseract extracted a few digits, both Tesseract and EasyOCR struggled with faint, pencil-written digits and the extremely tight column width, confirming that traditional OCR tools

are not suitable for this dataset. This work defines the correct extraction framework and highlights the need for a custom handwriting-recognition model in the next project phase.

6.2 Overall Pipeline

In the Running Score table, every scoring symbol has a corresponding handwritten jersey number immediately adjacent to it (left side for Team A, right side for Team B).

Without extracting these numbers, the system cannot perform:

- Player-level scoring aggregation
- Play-by-play event reconstruction
- Mapping between symbol instances and the referring player

Therefore, jersey number OCR is not an isolated module—it directly feeds into the event-to-player mapping logic

6.3 Approach and Design Decisions

(1) Normalized ROI Based Extraction

Scoresheets submitted by referees vary in resolution, orientation, and zoom level. Instead of relying on hardcoded pixel coordinates—which would break for even small variations—a normalized coordinate system was used.

The main Running Score block was extracted using:
X-axis: 20% → 80% of image width
Y-axis: 20% → 65% of image height

This bounding region consistently covers the full vertical range of scoring events across different sheets.

Reasoning:
Normalized coordinates make the pipeline resilient to images captured on mobile phones under varying framing conditions.

(2) Segmentation of Team A and Team B Jersey Number Columns

Inside the Running Score ROI, the jersey number area for both teams is extremely narrow (only a small strip next to the scoring symbols).
These were isolated as:

Team A column: approx. 0–8% of the ROI width
Team B column: approx. 18–24% of the ROI width

These values came from visually analyzing multiple sheets and identifying consistent structural patterns.

Observation:
The width of these jersey-number columns is significantly smaller than expected, worsening OCR accuracy due to cramped handwritten digits.

(3) Pre-Processing Pipeline

To improve the legibility of faint pencil marks, the following steps were applied:

- Grayscale conversion to eliminate color noise
- Adaptive thresholding (Gaussian method) to isolate pencil strokes from the background
- Morphological filtering (where applicable) to enhance line contrast
- Digit-only OCR configuration:
    - *--oem 3 --psm 6 -c tessedit_char_whitelist=0123456789*

This configuration ensures Tesseract focuses exclusively on numerical characters and avoids misinterpretations

6.4 OCR Performance and Challenges Encountered

Despite the structured approach, the OCR output was inconsistent.
Below are the findings:

1) Handwriting Style and Pencil Pressure

The scoresheets use pencil writing that varies from moderately visible to extremely faint. Tesseract (and even EasyOCR) struggled to pick up lightly written digits.

2) Column Width Too Narrow

The jersey number column is only a few millimeters wide.
Digits are often compressed or touching vertical grid lines, making segmentation harder.

3) Thresholding Side Effects

Adaptive thresholding improves contrast, but also:

- introduces small noise patches
- thickens or breaks thin strokes
- distorts lightly written digits further

4) OCR Engine Limitations

Both Tesseract and EasyOCR failed for different reasons:

- Tesseract: misses faint strokes, interprets noise as digits
- EasyOCR: produces almost no detections because it is trained on thicker, clearer handwriting styles

This confirms that off-the-shelf OCR systems are not suitable for this handwriting + layout combination.

6.5 Key Learnings and Takeaways

This phase of the project produced several important insights:

1. Generic OCR is insufficient for pencil-written digits in narrow columns
   The handwriting is too thin, too faint, and too compressed for pre-trained OCR libraries.
2. ROI-based extraction works, but requires better downstream processing
   The coordinate system correctly isolates the right regions, so the extraction strategy is valid.
3. The bottleneck is handwriting recognition, not region segmentation
   The next stage of the project must focus on custom digit recognition models rather than forcing Tesseract/EasyOCR.
4. A proper solution needs model-based digit recognition
   A small CNN or CRNN trained specifically on the digits from these sheets would outperform generic OCR.

6.6 Future Work and Path Forward

Based on the results and learnings, the future enhancement plan for jersey number extraction is as follows:

1) Build a Custom Handwritten Digit Recognizer
   - Train a CNN/CRNN model on digit patches manually cropped from the collected sheets
   - This model only needs to detect digits 0–9, enabling high accuracy even with limited data

2) Apply Connected Component Analysis
   - Automatically isolate individual digit strokes
   - Reduce noise before sending inputs to the recognition model

3) Integrate Document Layout Models
Use table/column detection models (LayoutParser, Detectron2, YOLO-Table) to precisely segment each jersey cell instead of using fixed normalized coords.

4) Perspective Correction + Grid Alignment
   - Deskew and dewarp camera-captured images
   - Align gridlines before segmentation

5) Use Transformer-Based Handwriting OCR
Experiment with TrOCR, HTR models, or ViT-based OCR for tougher handwriting scenarios.

7. Conclusion & Future Work

This project successfully developed a CV system capable of detecting scoring symbols with high accuracy and demonstrated early promise for player-event mapping via OCR. With expanded training data and refined layout analysis, the system can evolve into a fully automated score digitization tool for sports analytics.

Future enhancements include: - Training with larger datasets (>500 images). - Implementing transformer-based OCR models. - Adding a layout parser to automatically segment sheet regions. - Deploying a mobile app frontend for real-time score extraction.

References

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