Artificial Intelligence in Professional Basketball

Miloš Aleksić
Matrikelnummer: 44217
ma143@hdm-stuttgart.de
Computer Science and Media (CS3)
Prof. Dr. Andreas Koch
29. März 2023

Overview

01 Introduction

02 Sports Analytics

03 Implementation of AI in Basketball

03 Application of AI in Basketball

06 Challenges and Limitations

06 Conclusion

07 References

Introduction

Artificial Intelligence (AI) and Machine Learning (ML) have become ubiquitous in various sectors, driving innovation and improving efficiencies. From healthcare to finance, the applications of AI and ML are vast and transformative. These technologies leverage algorithms to process vast amounts of data, learn from it, and make predictions or decisions without being explicitly programmed for the task. The power of AI and ML lies in their ability to analyze complex datasets, identify patterns, and provide insights that were previously unattainable or would take humans an extensive amount of time to derive.

As the capabilities of AI and ML continue to expand, their applications have permeated into areas that were traditionally reliant on human judgment and expertise. One such domain is the world of sports. The field of **sports analytics**, in particular, has seen a significant transformation with the advent of AI and ML. Sports analytics involves the collection, analysis, and interpretation of sports-related data to gain insights and make informed decisions. Whether it's evaluating player performance, predicting game outcomes, or optimizing training regimens, AI and ML are playing an increasingly crucial role in shaping the future of sports.

Transitioning from the broader landscape of AI and ML, let's delve deeper into the realm of sports analytics. Sports analytics have been used to evaluate players, inform coaching decisions, and optimize team performance. The use of machine learning and artificial intelligence in sports analytics has further enhanced the ability to analyze large datasets, identify patterns, and make data-driven decisions. One example of the application of sports analytics in professional sports organizations is the National Basketball Association (NBA), which integrates analytical insights into its core business entities. The organization and its franchises use gathered data to gain valuable insights into several fields of interest [1].

In the following sections, we will delve deeper into the applications of machine learning and artificial intelligence in professional basketball, including case studies, technical foundations, implementations, challenges, and limitations.

Sports Analytics

Sports analytics is a multidisciplinary field that combines data science, statistics, and domain-specific knowledge to extract meaningful insights from sports-related data. It's a rapidly growing field that involves the collection and analysis of relevant historical statistics to provide a competitive advantage to teams or individuals. The use of analytics is pervasive in the professional sports community, as evidenced by the increased role of those practicing front-office management and coaching. The application of analytics in sports is broad, encompassing a variety of methodologies and a wide range of sports, including basketball. The methodologies employed in sports analytics draw from many areas, including optimization, probabilistic modeling, and choice models [2].

The growth of sports analytics has been fueled by advancements in technology that have made data collection more in-depth and accessible. This has led to the development of advanced statistics, machine learning, and sport-specific technologies that allow for game simulations, improved fan acquisition and marketing strategies, and understanding the impact of sponsorship on teams and fans. Sports analytics have also significantly impacted sports gambling, providing bettors with more information to aid their decision-making [2].

In the context of professional basketball, sports analytics have been used to evaluate players, inform coaching decisions, and optimize team performance. The use of machine learning and artificial intelligence in sports analytics has further enhanced the ability to analyze large datasets, identify patterns, and make data-driven decisions. The primary goal of sports analytics is to provide a competitive advantage to teams, athletes, and organizations by making data-driven decisions. The field of sports analytics has two main components: off-field analytics and on-field analytics [3]. The focus of this paper will be on on-field analytics

On-Field Analytics

On-field analytics focuses on improving the performance of teams and individual athletes. It involves the analysis of player statistics, game strategies, and opponent tendencies to gain a competitive edge. On-field analytics can be used for various purposes, which will be elaborated in the following.

Player Evaluation

Player Performance Analytics is a specialized aspect of sports analytics that zeroes in on the intricate analysis of individual player performance. In the context of basketball, this entails the utilization of advanced statistical measures, machine learning methods, and data analysis techniques to comprehend a player's influence on the game, to identify patterns and trends in player performance and comprehend a player's influence on the game, transcending what traditional stats like points, rebounds, and assists can convey [2].

Efficiency Metrics

Metrics such as Player Efficiency Rating (PER), True Shooting Percentage (TS%), and Effective Field Goal Percentage (eFG%) offer a more holistic assessment of a player's productivity on the court, surpassing traditional statistics [3].

Impact Metrics

Metrics like Plus/Minus (PM), Win Shares (WS), and Value Over Replacement Player (VORP) are designed to quantify a player's cumulative contribution to the team's performance, taking into account both offensive and defensive endeavors [4].

Player Tracking

Technological advancements have ushered in player tracking systems like SportVU cameras, which capture data on every player movement during games. This technology facilitates the analysis of patterns, player velocities, shooting locations, defensive efficacy, and much more, providing insights that traditional statistics can't capture [5] [6].

Predictive Modeling

By harnessing historical data coupled with machine learning methodologies, predictive modeling can project a player's forthcoming performance, susceptibility to injuries, and potential career trajectory. Such insights are invaluable for teams when deliberating on drafts, trades, player progression, and contract extensions [7].

Game Strategy Optimization

Game Analytics, within the realm of professional basketball, signifies the application of data analysis methodologies to comprehend and enhance the strategic facets of basketball games. Contrary to focusing solely on individual player performance, game analytics endeavors to discern how various game elements interplay to yield outcomes. Through Game Analytics, teams are empowered to refine their strategies, make judicious in-game decisions, and tailor their game blueprints to augment their winning probabilities. This analytical approach signifies a paradigm shift from intuitive decision-making to an evidence-based strategic framework [3], [4], [5], [6], [7].

Play-by-Play Analysis

In professional Basketball, every play can be the difference between a win or a loss. Machine learning models can analyze each play within a game to discern patterns and trends. For instance, a model might identify that a certain play is more effective against specific defensive setups. By analyzing vast amounts of game data, these models can provide insights on effective play-calling, strategic determinations, and the optimal timing of plays, enabling coaches to make data-driven decisions during crucial game moments [2].

Spatial Analysis

The Basketball Court is a canvas, and player movements paint the picture of the game. With the advent of player tracking technology, teams can dissect player movements and positioning with unprecedented precision. Machine learning models can analyze this spatial data to identify optimal player spacing, prime shooting locales, and effective defensive configurations. For example, a model might determine the best spots on the court for a player to take a shot based on historical success rates and defensive coverage [3].

Lineup Analysis

Basketball is a team sport, and the synergy between players is crucial. Machine learning models can evaluate the performance of different player combinations on the court. By analyzing data from various games, these models can pinpoint the most potent lineups and discern against which opposition lineups they excel. This is invaluable during playoff series, where matchup advantages can be the key to advancing to the next round [4].

Biomechanical Analysis

In the high-paced environment of the NBA, every movement, jump, and sprint counts. Machine learning algorithms are employed to analyze players' movements during games and practices. These algorithms can detect even the slightest deviation from a player's usual biomechanics, which could be indicative of fatigue, an underlying injury, or a change in technique. By identifying these deviations early, NBA teams can take proactive measures, such as adjusting player rotations or recommending rest days, to prevent potential injuries and ensure optimal player performance [1], [8].

Opponent Analysis

Machine learning models can scrutinize vast amounts of game footage to study the strategies and tendencies of rival teams. These models can identify patterns, such as a team's preferred plays in crunch time or defensive vulnerabilities, guiding the formulation of game plans tailored to exploit these insights [5].

Game Pace and Style

The tempo of a basketball game can greatly influence its outcome. Machine learning models can analyze team performance at different paces to discern the optimal game tempo for a particular team. Additionally, these models can evaluate the effectiveness of different styles of play, such as an emphasis on three-point shooting or fast breaks, enabling teams to adapt their strategies based on their personnel and the opposition [6].

In-Game Decision Making

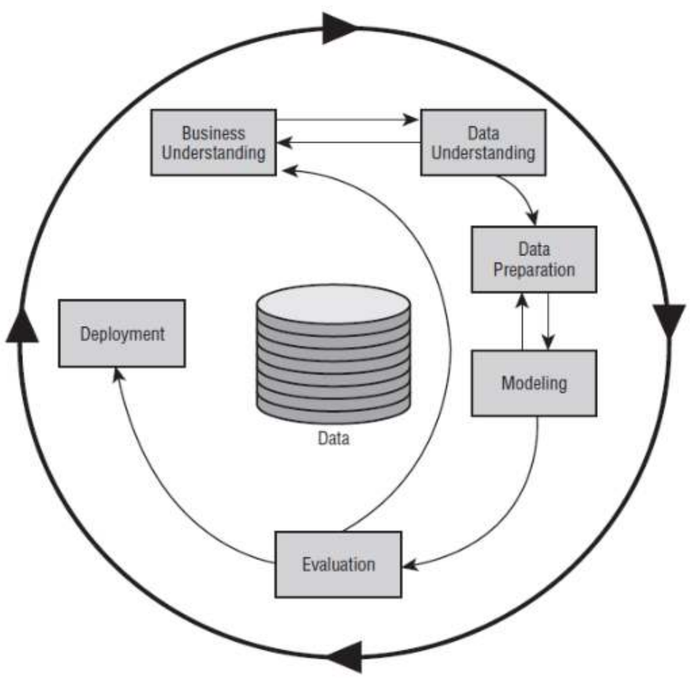
Basketball games are dynamic, and situations can change in the blink of an eye. Machine learning models can support real-time decision-making during games. By analyzing real-time game data, these models can provide recommendations on when to call a timeout, when to make a substitution, or what play to call in a specific scenario, ensuring th.at teams maximize their chances of success [7].

Implementation of AI Systems in professional Basketball

The implementation of AI in professional basketball involves several steps, from data collection to analysis and decision-making. In this section, we will explore the practical implementation of AI in professional basketball, including data collection, preprocessing, model training, evaluation, and deployment. The process of implementing AI or data driven systems in a organization can be described with the Cross Industry Standard Process for Data Mining (CRISP-DM)

Cross Industry Standard Process for Data Mining

The CRISP-DM is a widely recognized and adopted methodology for data mining and analytics projects. It provides a structured approach to planning and executing data-driven projects. It has gained popularity because of its industry-agnostic nature, making it applicable across various sectors and for different types of data-driven projects. The CRISP-DM framework consists of six main phases. Throughout these phases, there's a cyclical process, meaning one might need to go back to earlier phases based on findings in later phases. For example, while modeling, one might realize that additional data preparation is needed, leading to a return to the data preparation phase.



CRISP-DM [9]

Business Understanding

This initial phase focuses on understanding the project's objectives and requirements from a business perspective. It involves defining the problem, determining the project's goals, and assessing the available resources. In terms of understanding the specific objectives of the basketball team or league, the question is, are teams looking to enhance player performance, optimize game strategies or predict player injuries? Stakeholder Involvement is essential. Engaging with coaches, players, sports analysts, and other stakeholders to define the problem and set clear goals for the AI implementation.

Data Understanding

The primary objective is to familiarize oneself with the data, understand its nature, and identify any quality issues In the realm of professional basketball, data collection is an initial and integral step. Fundamental data points, such as player statistics that provide insights into performance metrics like points scored, rebounds, assists, and shooting accuracy, are typically extracted from game records. Game videos, as highlighted in a study by Zhang et al. [11] offer a visual record of matches and can be employed to track player movements, analyze game strategies, and assess overall player performance. Physiological data, such as heart rate, body temperature, and muscle activity, shed light on a player's physical condition and are typically gathered using wearable devices, as explored in depth by Della Vedova et al. [12] Following data collection, it's essential to delve into the data, exploring it to identify patterns, trends, and potential anomalies. This preliminary analysis is crucial, offering a clearer picture of the data's quality and characteristics, and setting the stage for the subsequent phases in the CRISP-DM process.

Data Preparation

Data preprocessing is often the most time-consuming phase in the CRISP-DM methodology, but it's crucial for the success of any AI project. This phase involves cleaning, transforming, and organizing the data to prepare a final dataset suitable for modeling. Data Preparation usually includes the steps of Data Cleaning, Data Transformation and Feature Engineering. Data Cleaning involves removing missing, inconsistent, or erroneous data. For instance, player statistics might need to be cleaned to remove any missing or incorrect entries. Afterwards, raw data, especially from videos, often requires transformation into a format suitable for analysis. This step is coined Data Transformation. Feature extraction techniques are commonly employed. The paper by Kumar et al. [13] provides an exhaustive list of such techniques. An important step is Feature Engineering. This process involves creating new features from the existing data to enhance model performance.

Modeling

With the data prepared, the focus shifts to the modeling phase. This phase involves selecting appropriate modeling techniques, building models, and assessing their quality. Model training is an integral part of this process. It entails choosing a suitable algorithm, configuring the model parameters, and then training the model on the preprocessed data. For instance, a supervised learning model might be trained on player statistics to predict player performance. Neural networks, with their capacity for deep learning, can be employed on game videos to meticulously track player movements. Additionally, reinforcement learning models, which thrive on trial and error, can be trained on various game scenarios to optimize game strategies. Given the complexity and variability of basketball data, it might be necessary to experiment with multiple machine learning algorithms, fine-tuning their parameters to ensure they capture the nuances of the sport and yield the best possible results.

Evaluation

Once the models are built, they transition into the evaluation phase, which is crucial to ensure alignment with the business objectives defined in the initial phase. Model evaluation is a systematic process that involves assessing the performance of the trained model on unseen or validation data. The primary goal is to ensure that the models not only meet the predefined goals but also have the potential to make a significant impact. To achieve this, it's essential to select a suitable evaluation metric that aligns with the nature of the model and the data it was trained on.For instance, a supervised learning model's performance can be gauged using metrics such as accuracy, precision, recall, and F1-score. In contrast, a neural network, which might be dealing with continuous data, can be assessed using metrics like mean squared error, mean absolute error, and R-squared. On the other hand, reinforcement learning models, which operate on a system of rewards and penalties, can be evaluated using metrics that capture their effectiveness, such as cumulative reward, average reward, and the balance between exploration and exploitation.

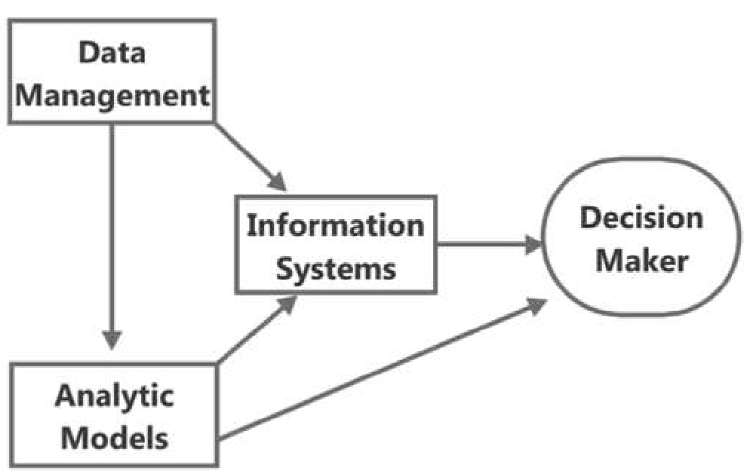
Deployment

The culmination of the AI implementation process in professional basketball is the deployment phase. This phase is not just about moving the trained model into a production environment but ensuring its seamless integration into basketball operations and core business processes. Whether it's building applications around the model, generating insightful reports, or directly influencing game strategies, the model becomes an integral part of the sports analytics workflow. Given the dynamic nature of basketball games, real-time analysis is crucial. Especially during live games, models should be equipped to analyze data in real-time, necessitating a robust infrastructure and efficient algorithms.

However, the deployment phase doesn't end with just integrating the model. Continuous monitoring of the model's performance is paramount to ensure its accuracy, relevance, and adaptability to changing game scenarios. As new data streams in, be it from recent games or evolving player statistics, the models should be agile enough to adapt. Leveraging techniques like online learning or transfer learning can be instrumental in ensuring that the models remain current and continue to provide valuable insights.

Sports Analytics Systems

With the CRISP-DM for sports related data established, organizations usually build a framework around it for further development. In his book, Alamar [14] shows the general structure of such a system. Coincidentally, the respective frameworks complement each other.



Sports Analytics Framework [14]

Alamar's framework emphasizes the seamless integration of these four elements to maximize the benefits of sports analytics. In the following, these four elements will be described and elaborated.

Data Management

This is the foundational step where raw data is collected, cleaned, stored, and organized. Proper data management ensures that this vast amount of data is stored efficiently and can be retrieved quickly for analysis. It ensures that the data is accurate, consistent, and easily accessible. The Data- Understanding and Preparation Phase of CRISP-DM emphasizes the initial exploration to familiarize oneself with its nature and quality and subsequently cleaning and transforming of the data. This dovetails with Alamar's "Data Management" element, which deals with acquiring, verifying, and storing data. In basketball, data can be sourced from various avenues, including player statistics, game videos, player biometrics etc.

Analytic Models

Once the data is managed, analytic models are developed to extract meaningful insights from it. These models can be statistical, mathematical, or computational and are designed to answer specific questions or solve particular problems. This aligns seamlessly with The Modeling phase of CRISP-DM which involves selecting modeling techniques and generating test scenarios. Analytic models in basketball might include predictive models for player performance, optimization models for team strategy, or clustering models to segment players into different playing styles.

Information Systems

Information Systems in Alamar's framework are designed to extract, process, and present the results of data analysis in a manner that's both effective and efficient. This encompasses the presentation of both raw data and the results derived from analytic models. In the context of the CRISP-DM process, the Information Systems component aligns closely with the Evaluation and Deployment phases.

The Evaluation phase of CRISP-DM is pivotal in assessing the quality of the developed models, ensuring they align with the predefined business objectives. This phase resonates with the core purpose of Alamar's "Information Systems", which is to effectively present data or the outcomes of analytic models. Post the modeling phase, the insights and results are often visualized and presented through platforms like dashboards. These tools assist coaches, players, and management in understanding patterns, making informed decisions, and strategizing for upcoming games.

The Deployment phase in CRISP-DM emphasizes the real-world application of the models. This phase is intrinsically linked to Alamar's "Information Systems", as the insights derived from the models are integrated into actionable tools or strategies, making them accessible and actionable for decision-makers. For instance, a predictive model, once validated, might be deployed during live basketball games. This real-time application can provide invaluable insights, such as suggesting optimal player rotations or even predicting game outcomes based on the ongoing performance metrics.

In essence, the Information Systems component of Alamar's framework serves as a bridge, translating the technical outcomes of data analytics into actionable insights for the basketball ecosystem. Through effective evaluation and deployment, as outlined in the CRISP-DM process, these systems ensure that the analytical findings are both relevant and impactful for decision-makers in the realm of professional basketball.

The Decision Maker

Ultimately, the value of analytics is realized when the insights are used to make informed decisions. The decision maker, whether it's a coach or player, uses the information provided to them to make choices that they believe will lead to better outcomes. The initial phase of CRISP-DM, Business Understanding, involves defining the objectives and requirements of the project from a business perspective. This aligns with Alamar's "Decision Makers" element, where the end goal of analytics is to provide relevant information to those making decisions.

In basketball, a coach might use analytics to decide on starting lineups, in-game strategies, or player rotations. Players might use analytics to understand their strengths and weaknesses and focus on specific areas during training.

Application of AI in professional Basketball

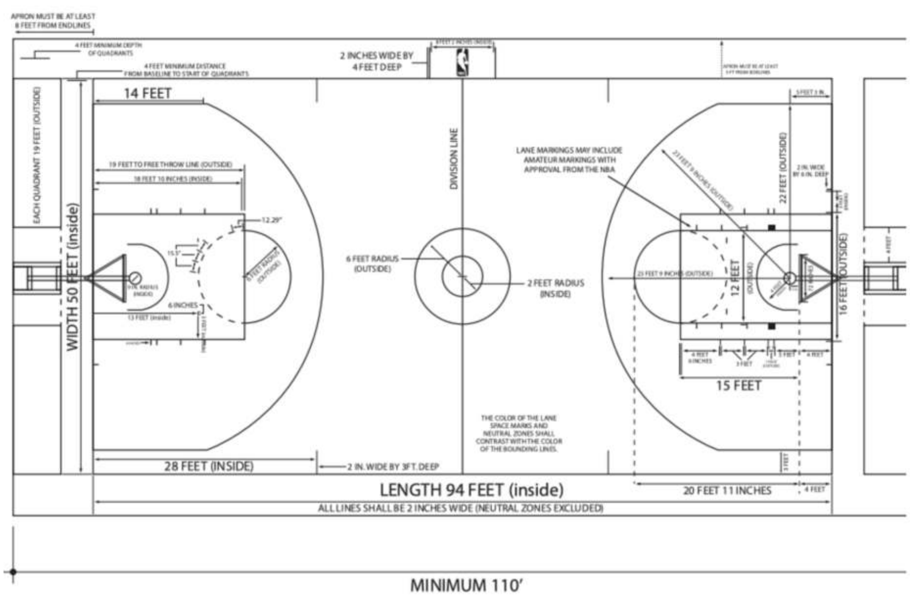
In this section, we will explore the application of of AI applications in professional basketball. This will highlight how AI has been used to analyze players performance.

Computer Vision

At the base of On-Field analytics in Basketball is a Computer Vision system. Computer Vision is necessary to gather data in a fast paced environment like professional Basketball. The NBA's tracking system is predominantly camera-based therefore it is the primary enabler for On-Field Player Performance Analysis and Game Strategy Optimization. In recent years, the NBA has adopted advanced systems to provide a comprehensive understanding of player movements and game dynamics. Central to this initiative is the SportVU system, developed by STATS, which employs a series of six high-definition cameras strategically positioned in the rafters of NBA arenas. These cameras are calibrated to capture the entirety of the court, recording video data at high frame rates, often exceeding 25 frames per second. The high frame rate ensures temporal granularity, facilitating the accurate tracking of rapid player movements and ball trajectories.

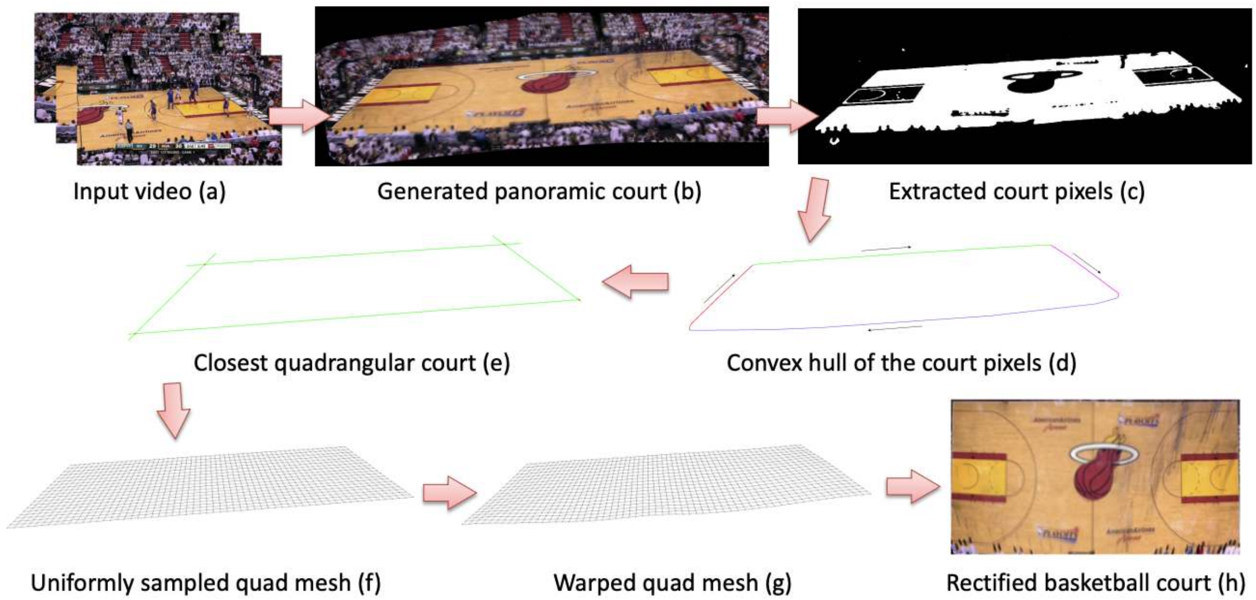
Camera Calibration

Initial system calibration is critical, converting the two-dimensional visual data into real-world spatial coordinates.



NBA Court spatial dimensions [15]

Diving into camera calibration in professional basketball, this essential technique determines intrinsic parameters, such as focal length and lens distortion, and extrinsic parameters, related to camera position and orientation in a 3D space. Essentially, it establishes a link between a 2D image and the actual basketball court through homography, ensuring accurate mapping and analysis of on-court actions. Such calibration is indispensable for activities that utilize positional information within the arena, such as 3D player tracking on the court. Various methodologies have been adopted to manage sport-field registrations in different sports contexts, including basketball [16], [17], [18].

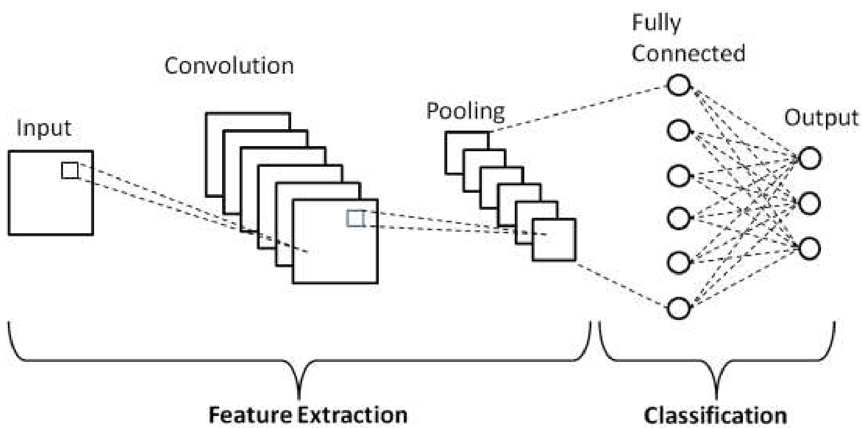


Example Algorithm of Camera Calibration for Basketball [16]

With the advent of deep learning, modern strategies are shifting towards learning a representation of the visible basketball court through semantic segmentation [19]. These methods either directly predict or regress an initial homography matrix, or alternatively, search for the most fitting homography in a reference database [17] that includes synthetic images with known homography matrices or camera parameters [20], [21]. In certain scenarios, a dictionary of camera views is utilized, associating an image projection of a synthetic reference court model to a homography. The segmentation is then connected to the closest synthetic view in the dictionary, offering an approximate camera parameter estimate, which is further refined for the final prediction. This detailed process of camera calibration and field registration is vital in boosting the precision and reliability of player tracking systems, ensuring that the data retrieved is spatially accurate and reflective of the actual on-court movements and strategies.

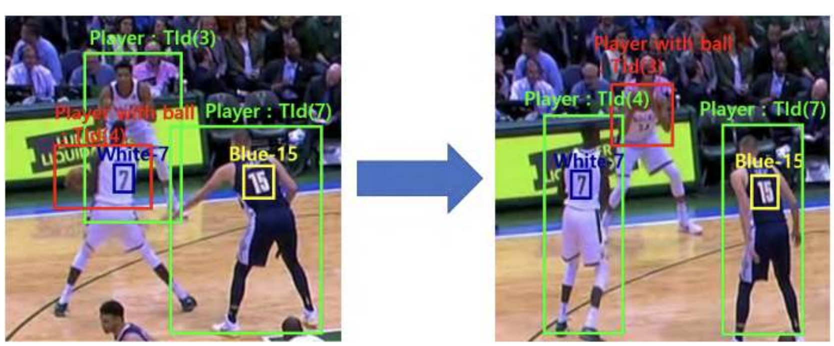
Player- and Ball Localization and Tracking

Computer Vision systems in professional Basketball are mainly responsible for tasks such as player and ball tracking. Player and ball tracking refers to the technological and analytical methods used to capture, record, and analyze the spatial and temporal movements of players and the ball during a basketball game. This involves determining the position of players and the ball in two-dimensional (2D) or three-dimensional (3D) space over time, thereby generating trajectories that represent their movement patterns throughout the game. Additionally, it is necessary to accurately record player statistics.



A general CNN architecture [23]

Central to Image Processing tasks is the application of Convolutional Neural Networks (CNNs) [22]. CNNs are a specialized kind of neural network designed for processing structured grid data, such as images. CNNs are particularly adept at recognizing patterns in visual data due to their hierarchical structure, which allows them to learn spatial hierarchies of features. This hierarchical learning capability has been demonstrated in various applications [24].



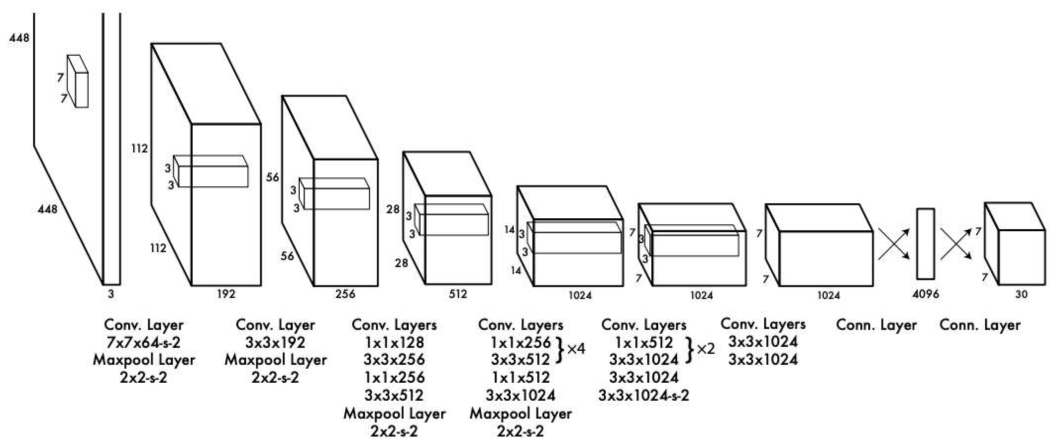
Bounding Boxes around different structures [25]

In the context of the NBA's player tracking, CNNs can be trained to recognize jersey numbers [25], player faces, and even specific postures. For instance, a filter in the initial convolutional layer might learn to recognize sharp color contrasts (useful for identifying jersey boundaries).

Deeper layers might recognize more complex structures like jersey numbers, the player's posture, contours of a player's face or even the basketball [36], [26], helping it to visualize shooting trajectories and optimize players' shooting.

Since Basketball is a fast paced sport, the problems become more difficult to be solved by a trivial CNN. With advances in Machine Learning, multiple algorithms for detection and tracking of objects have been developed. Regarding **Object Detection** which deals with the tasks identifying players in each frame in the context of Basketball, algorithms like **YOLO (You Only Look Once)** found great success. Following from that on, **Object Tracking** wants to keep track of each player's or object's movement across frames. Algorithms like **SORT (Simple Online and Realtime Tracking)** or **DeepSORT** find a lot of applications in our domain.

YOLO



YOLOv1 architecture [27]

The YOLO algorithm takes a unique approach to object detection compared to previous methods. YOLO combines what was once a multi-step process, using a single neural network to perform both classification and prediction of bounding boxes for detected objects. As such, it is heavily optimized for detection performance and can run much faster than running two separate neural networks to detect and classify objects separately. It does this by repurposing traditional image classifiers to be used for the regression task of identifying bounding boxes for objects [27].

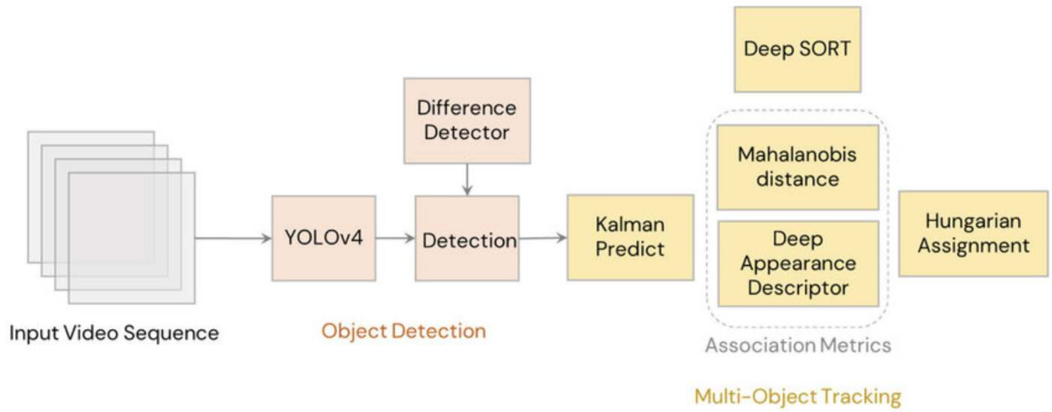
The architecture YOLOv1 consists of 24 convolutional layers, succeeded by two fully-connected layers that predict bounding box coordinates and probabilities. The input image is initially resized to 448x448 before being processed through the convolutional network. YOLO employs 1 × 1 convolutional layers to diminish the number of feature maps and maintain a relatively low parameter count. All layers utilize leaky rectified linear unit activations, with the exception of the final layer which employs a linear activation function [26]. Additional methodologies, such as batch normalization and dropout, are implemented to respectively regularize the model and avert overfitting.

SORT/DeepSORT

The SORT algorithm emerged as a response to the necessity for a computationally efficient and real-time object tracking mechanism. The motivation was to minimize identity switches by predicting the future position of bounding boxes, thus maintaining consistency in object identities across frames [28]. The architecture and functioning of SORT can be dissected into several key technical components:

- **Object Detection:** Prior to tracking, objects within each frame are identified using an independent object detection algorithm, such as YOLO which provides bounding boxes defined by spatial coordinates in the image.
- **Kalman Filtering:** The algorithm employs Kalman filters to predict the future state of a bounding box, utilizing its previous state to estimate the subsequent position and velocity, even amidst temporary occlusions or detection failures. The state here is defined as the bounding box's coordinates and includes both position and velocity.
- **Hungarian Algorithm for Data Association:** The Hungarian algorithm is utilized to associate bounding boxes between consecutive frames, minimizing the overall assignment cost, such as the distances between predicted and newly detected bounding boxes.

Despite its efficiency, SORT grapples with handling occlusions and maintaining object identities in crowded scenes due to its lack of a memory mechanism and appearance model.



DeepSort architecture [31]

DeepSORT was developed to address the limitations of SORT, particularly in handling occlusions and maintaining identities in crowded scenes. It introduces a neural network to extract features and utilizes a Mahalanobis distance metric learning approach to manage associations.

Incorporation of an Appearance Model

DeepSORT integrates an appearance model, which is typically a pre-trained Convolutional Neural Network (CNN), to extract features from detected objects, thereby encoding their appearance into a descriptor. This descriptor aids in distinguishing between different objects and assists in managing occlusions more effectively than SORT.

Matching Metric with Motion and Appearance Information

A sophisticated matching metric is defined, which amalgamates both motion information (derived from the Kalman filter) and appearance information (extracted from the CNN). This metric is employed to compute a cost matrix, which is subsequently resolved using the Hungarian algorithm to associate bounding boxes across frames, maintaining object identities.

Track Management Mechanism

DeepSORT introduces a mechanism to manage tracks, initiating new ones and terminating obsolete ones, based on a set of heuristics, such as a minimum number of detections to confirm a track and a maximum number of missed detections to terminate it.

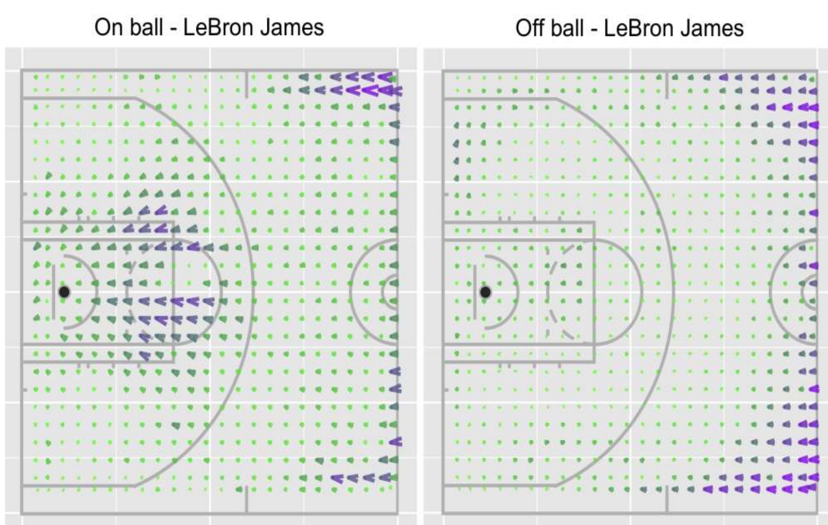
In the realm of basketball player detection and tracking, both SORT and DeepSort have been pivotal in providing real-time tracking capabilities [11], [29], [30], [32], [33]. With its minimalistic approach, it offers a computationally efficient method. DeepSORT enhances tracking accuracy by incorporating appearance information, albeit with increased computational demands.

Player Performance Analysis

It is paramount to realize that Player Performance Analysis is indeed tightly connected to game strategy optimization since one would derive an adequate strategy in regards to what skills the basketball players provide.

The resultant data of the computer vision tasks yields a myriad of metrics, ranging from basic measures such as player speeds and distances covered. It extends to more complex metrics like player load, acceleration patterns. In a study by Wu & Bornn which gives insight on how LeBron James and Stephen Curry accelerate towards the basket for a drive we will take the shooting chart of each player into account and derive a player profile.

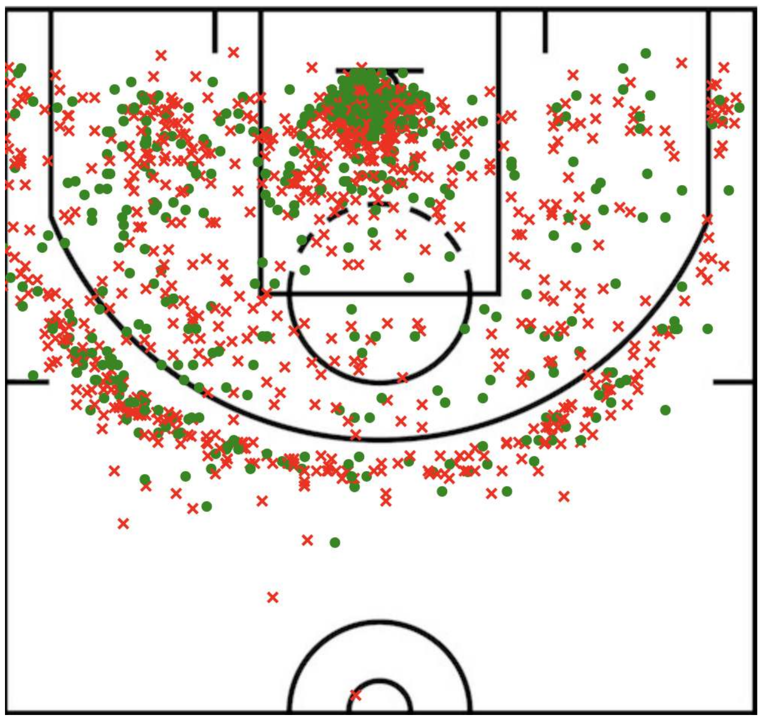
LeBron James



Lebron James season 15/16 on- and off-ball acceleration pattern towards the basket [34]

LeBron James, widely recognized for his adept driving skills towards the basket while maintaining ball control, has consistently ranked among the league's elite in this domain since his debut. His physical strength, and ball-handling proficiency enables him to navigate through, deflect, and absorb contact from defenders, thereby facilitating successful scoring endeavors near the rim.

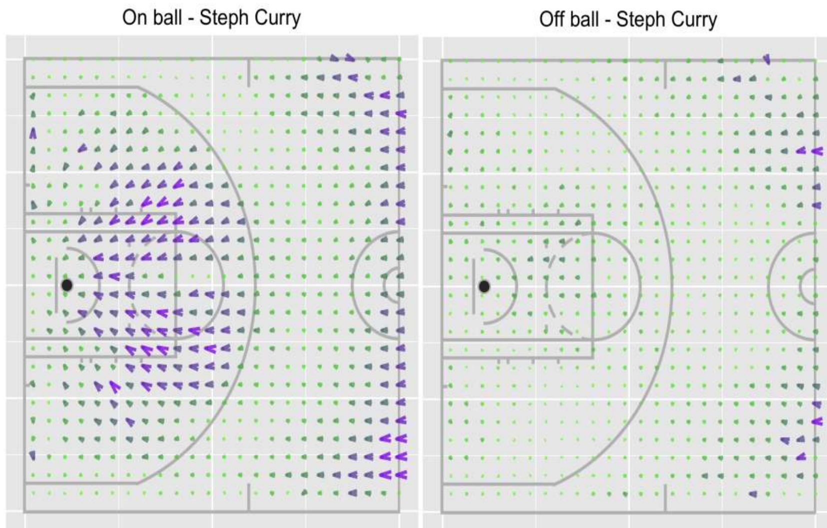
LeBron James exemplifies a unique blend of skills that manifest distinctly in both on-ball and off-ball scenarios on the basketball court. In off-ball situations, particularly when transitioning from defense to offense, LeBron leverages his exceptional athleticism and strategic positioning, primarily on the wings, to exploit high-percentage fastbreak opportunities. His ability to sprint forward during transitions, especially when facilitated by skilled passers, underscores his significant impact in off-ball contexts.



Lebron James season 15/16 shooting chart [37]

Conversely, in on-ball scenarios, LeBron's prowess is markedly evident in his driving capabilities towards the basket. His combination of height, muscular strength, and dribbling skills not only enables him to adeptly navigate through defenders but also to absorb and deflect contact, thereby enhancing his ability to score successfully in proximity to the rim as seen in the graphic above. This duality in LeBron's playing style, characterized by strategic off-ball movements and dominant on-ball drives, underscores his multifaceted impact on the game's dynamics and outcomes.

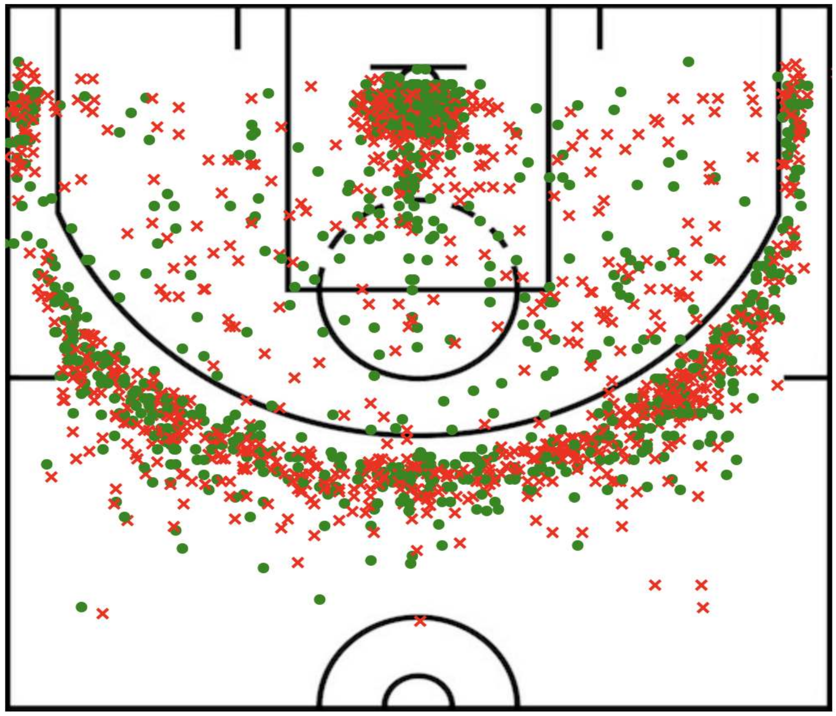
Stephen Curry



Stephen Curry season 15/16 on- and off-ball acceleration pattern towards the basket [34]

Stephen Curry, renowned for his shooting and dribbling skills, demonstrates a distinct approach in both on-ball and off-ball scenarios, which starkly contrasts with players like LeBron James. When considering on-ball situations, Curry exhibits a remarkable ability to successfully accelerate towards the hoop from a wide array of angles while maintaining control of the ball. His game doesn't stem from an overtly athletic nature, akin to LeBron, but rather from his extraordinary shot-making and dribbling capabilities. The on-ball plot reveals the extensive action he generates towards the rim with ball possession, even when compared to top-performing peers like LeBron.

In off-ball contexts, Curry's approach diverges significantly. His acceleration values are notably smaller, attributed to his role as the primary ball-handler for his team, making him more likely to lead fastbreak opportunities with ball possession as opposed to running on the wing without the ball. Famously recognized for effortlessly sinking 3-point shots well beyond the 3-point line, Curry doesn't necessitate substantial acceleration to find himself in a scoring position once he crosses the half-court line.



Stephen Curry season 15/16 shooting chart [38]

Stephen Curry, with his signature playing style, exemplifies a unique blend of on-ball and off-ball strategies that diverge notably from other NBA stars. His on-ball prowess is characterized by a wide-ranging ability to accelerate towards the hoop, leveraging his exceptional dribbling and shot-making skills, even without relying on sheer athleticism. Conversely, his off-ball play, marked by relatively smaller acceleration and a propensity to lead fastbreaks as the primary ball-handler, highlights his capability to position himself for scoring, especially with his famed 3-point shooting, without needing to significantly accelerate post half-court crossing. Curry's multifaceted skill set, thus, underscores a distinctive impact on the game, navigating through various on-ball and off-ball dynamics to optimize scoring opportunities.

Challenges and Limitations

While AI has the potential to revolutionize professional basketball, there are several challenges and limitations associated with its implementation. In this section, we will explore some of the key challenges and limitations of implementing AI in professional basketball.

Model Interpretability

Another challenge in implementing AI in professional basketball is model interpretability. Model interpretability refers to the ability to understand and explain the model's predictions. Many machine learning models, especially deep learning models, are complex and difficult to interpret.

For example, a neural network trained on game videos may be able to track player movements accurately, but it may be difficult to understand how the model makes its predictions. This can make it challenging to trust the model's predictions and use them to make informed decisions.

Human Expertise

Another limitation of implementing AI in professional basketball is the potential impact on human expertise. While AI can enhance player performance, optimize game strategies, and prevent injuries, it cannot replace human expertise.

For example, a machine learning model may be able to predict player performance based on historical statistics, but it cannot account for factors such as player motivation, team dynamics, and game context. A reinforcement learning model may be able to optimize game strategies based on game simulations, but it cannot account for factors such as player emotions, opponent strategies, and game pressure.

Conclusion

It is evident that Artificial Intelligence (AI) stands as a pivotal force with the capacity to reshape the landscape of professional basketball. From enhancing player performance to optimizing game strategies, etc. the application of machine learning and deep learning techniques has opened avenues for more nuanced and data-driven decisions in the sport.

However, the journey towards fully integrating AI into professional basketball is not devoid of challenges, with hurdles such as ensuring, navigating through model interpretability and integrating human expertise emerging as critical focal points.

While AI brings forth a wealth of opportunities, it is not an absolute solution and must be approached with a balanced perspective. The successful implementation of AI in the sport necessitates a harmonious blend of technical acumen, domain-specific knowledge, and human insight. Thus, while AI serves as a potent tool capable of revolutionizing various facets of basketball, it must be employed in a manner that complements, rather than supplants, human expertise, ensuring that the integrity and spirit of the sport remain intact and celebrated.

References

[1] Mondello, M., & Kamke, C. (2014). The Introduction and Application of Sports Analytics in Professional Sport Organizations.

[2] Fry, M. J., & Ohlmann, J. W. (2012). Introduction to the Special Issue on Analytics in Sports, Part I: General Sports Applications.

[3] Lucey, P., Bialkowski, A., Monfort, M., Carr, P., & Matthews, I. (2014). Quality vs Quantity: Improved Shot Prediction in Soccer using Strategic Features from Spatiotemporal Data. MIT Sloan Sports Analytics Conference.

[4] Goldsberry, K. (2012). CourtVision: New Visual and Spatial Analytics for the NBA. MIT Sloan Sports Analytics Conference.

[5] Cervone, D., D'Amour, A., Bornn, L., & Goldsberry, K. (2014). POINTWISE: Predicting Points and Valuing Decisions in Real Time with NBA Optical Tracking Data. MIT Sloan Sports Analytics Conference.

[6] B. T. Naik, M. F. Hashmi, Z. W. Geem, and N. D. Bokde, “Deepplayertrack: player and referee tracking with jersey color recognition in soccer,” IEEE Access, vol. 10, pp. 32 494–32 509, 2022.

[7] Maheswaran, R., Chang, Y., Henehan, A., & Danesis, S. (2012). Deconstructing the Rebound with Optical Tracking Data. MIT Sloan Sports Analytics Conference.

[6] Oliver, D. (2004). Basketball on Paper: Rules and Tools for Performance Analysis.

[7] Franks, A., Miller, A., Bornn, L., & Goldsberry, K. (2015). Characterizing the spatial structure of defensive skill in professional basketball. Annals of Applied Statistics.

[8] Thomas, G., Gade, R., Moeslund, T. B., Carr, P. W., & Hilton, A. (2017). Computer vision for sports: Current applications and research topics. Computer Vision and Image Understanding. https://doi.org/10.1016/j.cviu.2017.04.011

[9] [Wearable Technology and Analytics as a Complementary Toolkit to Optimize

Workload and to Reduce Injury Burden]

[10] Wambsganß, Thiemo & Molyndris, Nikolaos & Söllner, Matthias. (2020). Unlocking Transfer Learning in Argumentation Mining: A Domain-Independent Modelling Approach.

[11] C. Zhang, M. Wang, and L. Zhou, “Recognition method of basketball players’ throwing action based on image segmentation,” International Journal of Biometrics, vol. 15, no. 2, pp. 121–133, 2023.

[13] G. Kumar and P. K. Bhatia, "A Detailed Review of Feature Extraction in Image Processing Systems," 2014 Fourth International Conference on Advanced Computing & Communication Technologies, Rohtak, India, 2014, pp. 5-12, doi: 10.1109/ACCT.2014.74.

[14] Alamar, Benjamin, and Dean Oliver, Sports Analytics: A Guide for Coaches, Managers, and Other Decision Makers (New York, NY, 2013; online edn, Columbia Scholarship Online, 19 Nov. 2015), https://doi.org/10.7312/columbia/9780231162920.001.0001.

[15] NBA Court spatial dimensions, https://official.nba.com/rule-no-1-court-dimensions-equipment/

[16] Wen PC, Cheng WC, Wang YS, Chu HK, Tang NC, Liao HM. Court Reconstruction for Camera Calibration in Broadcast Basketball Videos. IEEE Trans Vis Comput Graph. 2016 May;22(5):1517-1526. doi: 10.1109/TVCG.2015.2440236. PMID: 28113142.

[17] L. Sha, J. Hobbs, P. Felsen, X. Wei, P. Lucey and S. Ganguly, "End-to-End Camera Calibration for Broadcast Videos," 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Seattle, WA, USA, 2020, pp. 13624-13633, doi: 10.1109/CVPR42600.2020.01364.

[18] J. Chen and J. J. Little, "Sports Camera Calibration via Synthetic Data," 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Long Beach, CA, USA, 2019, pp. 2497-2504, doi: 10.1109/CVPRW.2019.00305.

[19] A. Cioppa, A. Deliege, F. Magera, S. Giancola, O. Barnich, B. Ghanem, and M. Van Droogenbroeck, “Camera calibration and player localization in soccernet-v2 and investigation of their representations for action spotting,” in Proceedings of the IEEE/CVF Conference on CVPR, 2021, pp. 4537–4546.

[20] X. Nie, S. Chen, and R. Hamid, “A robust and efficient framework for sports-field registration,” in Winter Conference on Applications of Computer Vision, WACV. IEEE, 2021, pp. 1935–1943. [Online]. Available: https://doi.org/10.1109/WACV48630.2021.00198

[21] Y.-J. Chu, J.-W. Su, K.-W. Hsiao, C.-Y. Lien, S.-H. Fan, M.-C. Hu, R.-R. Lee, C.-Y. Yao, and H.-K. Chu, “Sports field registration via keypoints-aware label condition,” in Conference on Computer Vision and Pattern Recognition Workshops, CVPRW. IEEE/CVF, 2022, pp. 3523–3530. [Online]. Available: https://doi.org/10.1109/CVPRW56347.2022.00396

[22] LeCun, Y., Bengio, Y., & Hinton, G. (2015). "Deep learning." Nature, 521(7553), 436-444.

[23] Phung, & Rhee,. (2019). A High-Accuracy Model Average Ensemble of Convolutional Neural Networks for Classification of Cloud Image Patches on Small Datasets. Applied Sciences. 9. 4500. 10.3390/app9214500.

[24] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). "Imagenet classification with deep convolutional neural networks." Advances in neural information processing systems, 25.

[25] P. R. Kamble, A. G. Keskar, and K. M. Bhurchandi, “Ball tracking in sports: a survey,” Artificial Intelligence Review, vol. 52, no. 3, pp. 1655–1705, 2019.

[26] A. L. Maas, A. Y. Hannun, A. Y. Ng, et al., “Rectifier nonlinearities improve neural network acoustic models,” in Proc. icml, vol. 30, p. 3, Atlanta, Georgia, USA, 2013.

[27] J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 779-788, doi: 10.1109/CVPR.2016.91.

[28] A. Bewley, Z. Ge, L. Ott, F. Ramos and B. Upcroft, "Simple online and realtime tracking," 2016 IEEE International Conference on Image Processing (ICIP), Phoenix, AZ, USA, 2016, pp. 3464-3468, doi: 10.1109/ICIP.2016.7533003.

[29] Acuna, D. (2017, December). Towards real-time detection and tracking of basketball players using deep neural networks. In Proceedings of the 31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA (pp. 4-9).

[30] B. T. Naik and M. F. Hashmi, “Yolov3-sort: detection and tracking player/ball in soccer sport,” Journal

[31] Parico, Addie Ira & Ahamed, Tofael. (2021). Real Time Pear Fruit Detection and Counting Using YOLOv4 Models and Deep SORT. Sensors. 21. 4803. 10.3390/s21144803.

[32] B. T. Naik, M. F. Hashmi, Z. W. Geem, and N. D. Bokde, “Deepplayertrack: player and referee tracking with jersey color recognition in soccer,” IEEE Access, vol. 10, pp. 32 494–32 509, 2022.

[33] Y. Zheng and H. Zhang, “Video analysis in sports by lightweight object detection network under the background of sports industry development,” Computational Intelligence and Neuroscience, vol. 2022, 2022.

[34] Wu, S., & Bornn, L. (2018). Modeling Offensive Player Movement in Professional Basketball. The American Statistician. https://doi.org/10.1080/00031305.2017.1395365

[35] Y. Yoon et al., "Analyzing Basketball Movements and Pass Relationships Using Realtime Object Tracking Techniques Based on Deep Learning," in IEEE Access, vol. 7, pp. 56564-56576, 2019, doi: 10.1109/ACCESS.2019.2913953.

[36] Shah, Rajiv & Romijnders, Rob. (2016). Applying Deep Learning to Basketball Trajectories.

[37] https://www.basketball-reference.com/players/c/curryst01/shooting/2016

[38] https://www.basketball-reference.com/players/j/jamesle01/shooting/2016