Support Vector Machines in Basketball Player Development

Ethan Youso

Abstract—**This paper examines the integration of Support Vector Machines (SVMs) into basketball player development, highlighting their potential to transform traditional training methodologies. With their robust capabilities in the classification of complex data, SVMs provide a sophisticated approach to analyzing performance. This enables the customization of training programs tailored to the specific needs of athletes, moving beyond general training regimens. Utilizing data from diverse sources, including player performance metrics and physical attributes, SVMs facilitate a more targeted approach to athlete development. The study emphasizes the significant implications of SVMs in sports analytics, detailing how they can optimize training strategies and improve overall athlete performance. This paper not only shows the current applications of SVMs in basketball performance but also sets the stage for future explorations into their broader impacts on sports training.**

CONTENTS

LIST OF FIGURES

I. INTRODUCTION

In modern sports, data analytics has become key to competitive success. In basketball, with its fast pace and sophisticated strategies, data-driven methods have transformed player development, game planning, and analysis. The search for precise improvement strategies has highlighted Support Vector Machines (SVMs) as a powerful tool for advancing these efforts.

SVMs are celebrated for their accuracy in classification and regression. They are adept at categorizing data in high-dimensional spaces, making them ideal for analyzing basketball performance metrics. Currently, player development regimens are largely generalized, designed to heighten standard basketball skills that will be used in games [10]. While these skills are important, training may be inefficient, focusing on areas for improvement that are not as impactful for certain players. By applying SVMs to player data, the goal is to identify specific areas for athlete improvement, merging the fields of sports science and machine learning. This method promises to refine training strategies and underscore the value of machine learning in sports, aiming to elevate player performance and pave the way for future advancements in sports analytics.

II. LITERATURE REVIEW

This literature review focuses on the convergence of SVMs, sports analytics, and basketball training. It evaluates the existing research to briefly explain the theory behind SVMs, highlight how SVMs have been applied in enhancing sports analytics, identifies research gaps, and discusses the potential of SVMs in refining basketball training programs. By analyzing scholarly articles, technical manuals, and practical case studies, this section aims to present a comprehensive overview of the role of SVMs in sports analytics, emphasizing their impact on advancing athlete performance and guiding future research directions in this field.

In 1995, Corinna Cortes and Vladimir Vapnik of Bell Labs introduced the Support Vector Network (SVN), which was later known as the Support Vector Machine (SVM) [4]. SVMs are supervised learning machines, meaning they need to be trained on sample data before they can be used [4]. The primary application of SVMs is to handle complex two-group classification problems [4]. They do this by mapping the input data into higher dimensions, allowing for separation of the points via hyperplane [4]. The SVMs find the optimal hyperplane by maximizing the distance, or margin, between the hyperplane and the closest points in either class, called the support vectors [4].

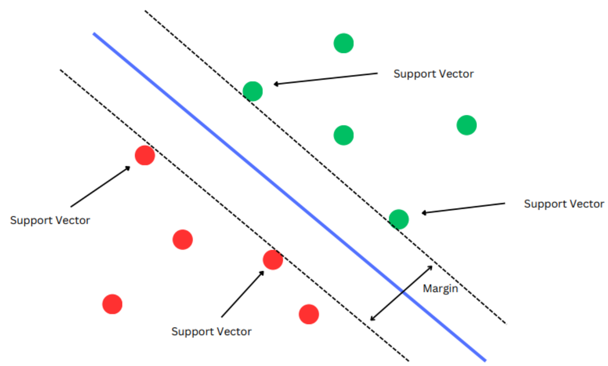

Fig. 1. The data points closest to the hyperplane are called support vectors, and the area in between them is called the margin.

Due to their ability to effectively categorize complex data, SVMs are applied to a variety of problems including facial recognition and medical diagnostics [7]. Data in sports analytics are also complex and difficult to interpret due to context, sparsity, and irregularity [15]. So, it follows that SVMs should be utilized to handle classification tasks within sports analytics.

SVMs have been used in sports analytics to tackle an array of tasks. In 2005, Sadlier and O'Connor trained an SVM to recognize a scoring event in field-based sports such as soccer, American football, and field hockey [14]. Audio and visual equipment were used to capture data such as player movement, objective positioning, crowd noise, and announcer volume [14]. Based on changes in these data, the SVM was able to recognize when a scoring event took place in real-time [14]. Chang, Sun, and Ali applied an SVM to table tennis in 2023 to recognize forehand, backhand, and serving strokes [3]. The SVM was combined with a Convolutional Neural Network (CNN) and an Internet of Things (IoT) system of cameras and sensors to create a comprehensive monitoring system [3]. The IoT system provided data, while the SVM and CNN each made predictions [3]. The final output was a result of weighted voting between the SVM and CNN [3]. In both examples, SVM's aptitude for classification was leveraged for use in sports analytics.

Other methods for classification include CNNs and Bayesian Networks [15]. Like SVMs, CNNs must be trained on a sample dataset [3]. CNNs differ because they perform pattern recognition and deep learning [3]. In doing so, they form hierarchies that are used for classification [3]. Bayesian Networks classify based on probabilities [15].

Basketball analytics is changing the game, transforming how strategies are developed and decisions are made on and off the court. The advent of advanced metrics and data analysis tools has allowed teams to dissect player performance and game dynamics with unprecedented precision. This analytical approach enables coaches to individualize training, adjust tactics, and optimize lineups based on objective data rather than intuition alone. As a result, basketball is evolving into a more strategic sport, where evidence-based decisions are shaping the development of players and the outcomes of games. In 2023, Matt Dawson described the role of analytics in determining the best shot opportunities to take [6]. Using statistics on shooting percentages from different places on the floor, along with shot values, the average points per possession was calculated for different types of shots [6]. It was found that the shots that yielded the most points per attempt were free-throws, layups, and threes [6]. The least efficient shots were two-point attempts from between 10 feet and the three-point arc [6]. As a result, modern basketball teams seek to shoot on the best opportunities while avoiding mid-range shots. The increasing relevance of analytics is not just changing the way basketball is played; it's fostering a new era of competition that blends athletic talent with scientific insight.

In 2016, Pinig, Lan, and Kuo used an SVM in a Hybrid Support Vector Machine Decision Tree (HSVMDT) to analyze basketball games from the National Basketball Association (NBA) to generate rules for decision makers [12]. As part of the process, they generated features using an algorithm called Correlation-Based Feature algorithm (CBF) [12]. This algorithm determines how much influence each feature has over the results and selects the most important [12]. Then, they trained the SVM to classify the important features [12]. Finally, rules for decision making in games were generated by the C4.5 decision tree, which weighs options and selects the most optimal solution [12]. As a result, data-driven approaches to basketball strategy were provided for coaches.

Luke Lefebure used an SVM in 2014 to predict the position of individual basketball players based on 19 different features [9]. The SVM was trained on these features using data from the 2013-2014 NBA season [9]. Then, it was asked to predict the positions of 114 players [9]. The highest accuracy score received by the SVM was just under 65% [9]. This result highlights the ambiguity in basketball positions and gives insight into the effectiveness of SVMs with difficult tasks.

The results from these studies show the ability of SVMs to use basketball data for classification tasks. Basketball data can often be complex and irregular, providing a challenge for SVMs. By meaningfully classifying the data, SVMs can be applied to basketball-related tasks on a large scale, giving us access to more information than ever before. Additionally, the importance of feature selection is illustrated in these examples. Training the SVM on too many features will result in a lower accuracy score. Conversely, selecting too few features can make the classifications less meaningful.

Implementing SVMs in basketball analytics involves a structured process, starting with the meticulous collection of player performance data, such as shooting percentages, defensive metrics, and physical attributes. Ideally, the data consists of mainly support vector candidates, ensuring each point affects the SVM [11]. Preprocessing this data is crucial, involving normalization and handling of missing values to ensure the model accurately interprets the diverse range of basketball statistics [11]. Model tuning, a critical step, requires selecting the appropriate kernel function and adjusting parameters like the penalty term (C) and gamma (γ), to optimize the balance between model complexity and generalization ability [11]. This process allows for the development of SVMs that are as accurate and efficient as possible.

Implementing Support Vector Machines (SVMs) in sports analytics, especially in basketball, extensively leverages programming languages and libraries designed for machine learning tasks. Python, renowned for its simplicity and robust ecosystem, emerges as the primary choice for developers and analysts. Within Python's ecosystem, the scikit-learn library (sklearn) is particularly invaluable for SVM implementation due to its comprehensive suite of tools for machine learning, including functions for data preprocessing, model training, and validation [5]. Sklearn simplifies the process of selecting kernel functions, adjusting hyperparameters, and evaluating model performance, making it an indispensable tool for analysts looking to harness the predictive power of SVMs in enhancing player performance and strategic decision-making in basketball [5].

Despite the growing application of SVMs in sports analytics, the literature reveals a notable gap in their specific use for basketball player development. Most existing studies focus on immediate game outcomes and player performance metrics, with less emphasis on long-term development strategies and potential. This oversight presents a significant opportunity for further research, particularly in understanding how SVMs can be leveraged to predict and enhance individual player growth over time. By exploring the predictive capabilities of SVMs in identifying key developmental indicators and optimizing training programs, future studies could provide deeper insights into personalized athlete development plans. This under-explored area not only opens avenues for enhancing player performance but also sets the stage for our study to contribute valuable knowledge to the intersection of machine learning and athlete development strategies in basketball.

This literature review has explored the intersection of SVMs, sports analytics, and basketball training, emphasizing SVMs' role in classification tasks and their application in various fields, including sports. Introduced by Cortes and Vapnik, SVMs have advanced from facial recognition to sports event detection and player performance analysis, proving essential in data-driven sports strategies. Despite their widespread use, a significant research gap exists in applying SVMs for basketball player development, underscoring an opportunity for detailed exploration. This gap highlights the potential of SVMs to transform basketball training strategies and improve athlete performance, setting a foundation for future studies, including this research, to delve deeper into SVMs' contributions to sports analytics and player development.

III. Theoretical Framework

In this section, we will explain the theoretical framework of SVMs in detail, exploring its fundamental concepts and mathematical formulations. SVMs are primarily used for classification and regression tasks, due to their ability to effectively separate data. They accomplish these by defining the optimal hyperplane with the greatest margin. Support vectors define the width of the margin, and they are the most influential points in datasets.

SVMs operate under the principle that data can be transformed and best understood in higher-dimensional spaces [4]. For linearly separable datasets, SVMs find a straight line (in two dimensions) or a plane (in three dimensions) that separates the classes. However, real-world data is often more complex, consisting of non-linear relationships. SVMs solve this problem using the kernel trick, a method allowing the algorithm to operate in a high-dimensional space without explicitly performing the transformation [4]. By applying different kernel functions, such as polynomial or radial basis function (RBF), SVMs can classify data that is not linearly separable by finding a hyperplane in an expanded feature space, thereby accommodating the complex patterns observed in sports analytics and other fields [7].

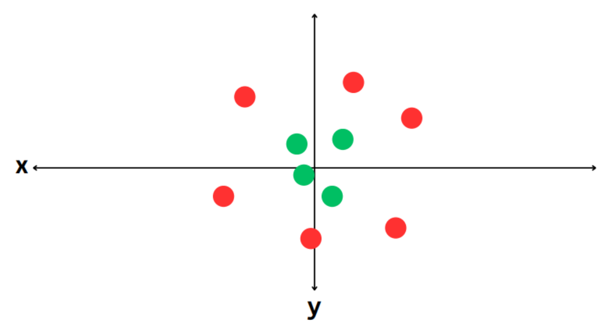

Fig. 2. A set of data points in a two dimensional space. In this dimension, it is impossible to draw a hyperplane between the red and green points.

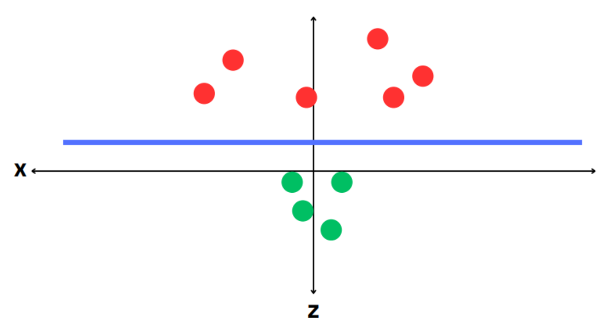

Fig. 3. By transforming the points into a third dimension, the z direction, it is now possible to draw a hyperplane between the two sets of data. This transformation is done through the kernel trick.

The objective of a linear SVM is to maximize the margin between the support vectors of the two classes [4]. The margin is defined by the distance between the parallel hyperplanes that are as far apart as possible while still separating the data [4]. This is achieved by minimizing the norm (length) of the weight vector w, which is perpendicular to the hyperplane [4]. The objective function can be represented as [4]:

$$min\frac{1}{2}||w||^2$$

The separation of classes with the hyperplane is subject to certain constraints, ensuring that each data point x_i is classified correctly. This is enforced by the following constraints for each data point, where y_i is the class label (either 1 or -1), w is the weight vector, b is the bias term, and x_i is a feature vector [4]:

$$y_i(w \cdot x_i + b) \geq 1, for\ all\ i$$

These constraints ensure that data points from one class will fall on one side of the hyperplane and be labeled with $y_i = 1$, while data points from the other class will fall on the opposite side and be labeled with $y_i = -1$ [4]. The decision function for classifying new data points is then given by the sign of $w \cdot x + b$ [4]. The solution to this optimization problem provides the parameters of the hyperplane (w and b) that maximizes the margin between the classes. The linear SVM model is particularly effective when the data is linearly separable [7]. For non-linearly separable data, SVM can be extended using the kernel trick to project the data into a higher-dimensional space where it becomes linearly separable [7].

The essence of the kernel trick lies in its ability to compute the inner products of data points in the high-dimensional feature space without directly performing the transformation. If we have a transformation t that maps our original data points x into a higher-dimensional space, the linear SVM would require the computation of the dot product $t(xi) \cdot t(xj)$ for the data points x_i and x_j [7]. Directly computing this in higher-dimensional space could be impractical or computationally infeasible.

Kernel functions, $K(x_i, x_j) = t(x_i) \cdot t(x_j)$, simplify this process by computing the inner products in the original feature space, effectively bypassing the explicit computation in the high-dimensional space [7]. Common kernel functions include:

- Polynomial Kernel: $K(x_i, x_j) = (1 + x_i \cdot x_j)d$, where d is the degree of the polynomial [16]. This kernel computes interactions between features up to the d-th degree.
- Radial Basis Function (RBF) Kernel: $K(x_i, x_j) = exp(-\gamma||x_i - x_j||^2)$, where γ is a parameter that determines the spread of the kernel [17]. It creates complex regions by measuring the distance between points in the input space.

The kernel trick relies on the fact that certain nonlinear transformations of the input space correspond to linear separations in the high-dimensional feature space. By using a kernel function, the SVM effectively treats the data as if it has been transformed, allowing the identification of an optimal separating hyperplane in the high-dimensional space. The choice of kernel and its parameters can significantly affect the model's ability to capture the underlying patterns in the data, making kernel selection and parameter tuning critical aspects of model training.

IV. Methodology

Implementing SVMs in basketball player development involves a series of steps from data collection to model validation, often utilizing programming languages like Python due to their extensive ecosystem of data science libraries. One such library, scikit-learn (sklearn), provides robust tools for SVM implementation and other machine learning tasks [5]. This section outlines the tools and methods used to generate an SVM for use in player development.

The first step involves gathering comprehensive data relevant to basketball player development. This might include traditional statistics like points per game, assists, and rebounds, as well as more advanced metrics such as player efficiency rating (PER) and win shares [15]. Additionally, physiological data (e.g., speed, agility scores) and even video data from games and practices can be collected to analyze player movements and actions on the court [9]. The mode of collecting this data may vary depending on type and complexity.

Before feeding the data into an SVM model, preprocessing is crucial to ensure the data is clean and formatted correctly. This includes handling missing values, normalizing or standardizing numerical data to bring everything to a similar scale, and encoding categorical variables [5]. Python, with libraries like pandas and NumPy, provides powerful tools for data manipulation and preprocessing. Additionally, sklearn includes a scaler for scaling data to the correct specifications of the SVM [5].

With the pre-processed data, the next step is to train the SVM model. This involves choosing a kernel type (e.g., linear, polynomial, RBF) based on the data's characteristics and the problem's complexity [5]. The scikit-learn library in Python offers a straightforward way to train SVM models through its Support Vector Classification (SVC) class for classification tasks or Support Vector Regression (SVR) for regression tasks [5]. Hyperparameters such as the regularization parameter C, the kernel coefficient γ , and the degree of the polynomial kernel (if used) need to be selected, often through cross-validation to find the combination that yields the best model performance [5].

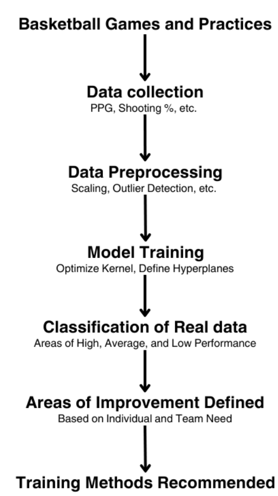

Fig. 4. The steps in the process of using SVMs for basketball player development. Data is collected from basketball games and used to train the SVM. The SVM can then classify the performance of future players and define improvement areas for training.

V. Challenges and Considerations

Collecting high-quality, comprehensive data on player performance for SVM analysis presents several challenges that can affect the efficacy of the analysis. Firstly, the granularity and consistency of data collection across different levels of play (e.g., college basketball vs. professional leagues) can vary significantly, leading to incomplete or biased datasets [7]. Moreover, capturing the full spectrum of player performance requires not just traditional statistics but also advanced metrics derived from player tracking technologies, which might not be available for all games or teams [1]. Privacy concerns and data sharing restrictions can further limit access to detailed player data. Additionally, ensuring data accuracy and dealing with missing or erroneous data entries can be labor-intensive, requiring sophisticated data cleaning and preprocessing techniques. These challenges necessitate rigorous data management practices and can introduce complexity into the modeling process, potentially impacting the performance and generalizability of SVM models in basketball analytics.

Using athletes' data for analysis necessitates ethical attention to consent and privacy. Athletes should consent to how their data is used and understand its purposes. Protecting their data from unauthorized access is paramount, ensuring sensitive information remains confidential. Ethical practices require transparency about data use, access control, and prioritizing athletes' well-being, safeguarding their rights and maintaining trust in sports analytics.

VI. Future Trends

The sports analytics market is experiencing significant growth, driven by advancements in technologies that enhance player performance and strategic planning. According to a report by Grand View Research, the sports analytics market is poised to expand with a substantial annual growth rate, underscoring the increasing reliance on analytical tools to optimize performance and strategy in sports [13]. The market size, which was dominated by software segments providing crucial insights through advanced analytics, is expected to grow significantly from 2023 to 2030, reflecting broader adoption across various sports disciplines [13].

Further supporting this trend, Mordor Intelligence forecasts a robust growth trajectory for the sports analytics market, with a projected increase from $2.87 billion in 2024 to $13.93 billion by 2029 [8]. This surge is attributed to the rising adoption of big data analytics, artificial intelligence, and machine learning technologies within the sports sector [8]. The report highlights how sports organizations are increasingly leveraging these technologies to gain a competitive edge, enhance player safety, and improve fan engagement, suggesting a deepening integration of data analytics into sports management and operations [8].

Together, these reports from Grand View Research and Mordor Intelligence illustrate a dynamic and rapidly evolving landscape where sports analytics is becoming indispensable, driven by technological innovations and an increasing emphasis on data-driven decision-making in the sports industry.

The growing global fascination with sports has intensified competition among teams and athletes, compelling them to adopt advanced analytics for a competitive edge [2]. SVMs are increasingly utilized in this high-stakes environment due to their ability to uncover complex patterns in performance data that are beyond human detection. Over the next six months to a year, this reliance on SVMs is expected to grow as teams continue to seek new ways to secure a competitive advantage in an increasingly crowded field.

The sports industry's use of technologies such as virtual reality, IoT wearables, and motion tracking is well-established, but the integration of SVMs with these technologies is a game-changer [10]. This combination enhances the precision of insights into player performance, allowing for more targeted improvements. As SVMs prove their value in complementing existing technologies, their adoption is poised to expand, driven by teams eager to maximize the benefits from their technological investments.

The effectiveness of big data analytics in sectors like education and industry has not gone unnoticed by sports organizations [10]. Motivated by the successes in these fields, the next six months to a year will likely witness a surge in the application of big data techniques, including SVMs, within sports. This trend is aimed at refining training programs and enhancing player development strategies through proven data-driven approaches.

As video technology continues to advance, the quality and detail of data it captures improve significantly, making it a crucial tool for sports analytics [2]. SVMs are exceptionally adept at analyzing this rich video data to extract actionable insights, which can dramatically improve player assessments and strategic game planning. The ongoing advancements in video analytics technology are expected to further boost the use of SVMs in the near future.

Among the various machine learning techniques available, SVMs are particularly noted for their superior ability to predict player success. Edwin M. Torralba's 2020 study of different machine learning techniques for predicting basketball player performance showed that SVMs yielded the most accurate results, outperforming models such as Random Forest and Logistic Regression [10]. Their capability to manage large, complex datasets and deliver accurate predictions makes them invaluable for sports analytics. As awareness of these benefits grows among sports teams, the adoption of SVMs is anticipated to surge, particularly over the next year.

The exponential growth in big data usage within the sports sector is a reflection of its proven impact on enhancing team and player performance [10]. This trend is not only fueled by the increasing availability of data but also by the strategic need for data-driven decisions. As the use of big data continues to grow, so too will the deployment of sophisticated tools like SVMs, which are essential for mining this data for competitive insights, thereby accelerating their adoption in sports analytics.

Within the next six months to a year, SVMs are expected to see enhanced and broader application in player development. As sports increasingly utilize big data, SVMs will provide detailed insights into player capabilities and health, guiding personalized training and injury prevention. Enhanced video and biometric technologies will enable SVMs to process richer data, offering real-time analytics for strategic decisions. Collaborations across tech and sports sectors will refine SVMs' use, focusing on ethical integration and maximizing performance outcomes in competitive sports environments. As teams and players search for a competitive edge, SVMs will be a large part of the machine learning strategy in the pursuit of winning.

VII. Discussion

The exploration of SVMs in basketball player development underscores the significant potential of machine learning in sports analytics. The introduction and application of SVMs across fields demonstrate their ability to manage complex classification challenges, crucial in sports data's intricate nature. Theoretical discussions reveal SVMs' capability to operate in high-dimensional spaces, making them ideal for sports analytics' nonlinear data. Implementing SVMs involves detailed steps from data collection to model tuning, with Python and sklearn facilitating this process.

Despite SVMs' broad applicability, a notable research gap exists in their use for specific basketball player development. This presents a significant opportunity for future research to leverage SVMs for predicting and enhancing player growth. Addressing this gap can deepen our understanding of machine learning's role in revolutionizing player development and performance analysis in basketball.

In summary, SVMs hold great promise for improving basketball player development through refined training strategies and enhanced performance analysis. As machine learning's application in basketball evolves, it is poised to offer new insights and opportunities, driving innovation in player development practices.

VIII. Conclusion

This paper explores SVM's role in basketball player development, showcasing a shift towards data-driven training strategies. Originating from Cortes and Vapnik's work, SVMs have evolved to address complex classification tasks across various domains, including sports analytics. This paper highlights SVMs' potential to customize training to individual athletes' needs by analyzing performance data, a step beyond traditional generalized training approaches.

Utilizing Python and the sklearn library, the methodology outlined here underscores the practical application of SVMs in sports analytics, from preprocessing to model validation. Despite the progress, a gap in using SVMs for long-term player development suggests a significant area for future research.

In the next 6 months to one year, the usage of SVMs in player development is poised to increase as teams try to gain a competitive advantage. This is evident because the market for sports analytics has been steadily rising in recent years. Attributing to this rise is intensified competition, integration of technology into athletics, usage of big data in other fields, improved video capture technology, SVM's prowess in predicting player success, and rapid growth of big data in sports.

In conclusion, SVMs offer a promising avenue for advancing basketball player analytics, fostering personalized training and improved decision-making. As the field grows, the potential for SVMs to revolutionize sports analytics and athlete development remains vast, with data-driven insights paving the way for future innovations.

References

[1] AIPedia. Ai in basketball: How artificial intelligence is changing the game. Website, 2024. Available at: https://ai-pedia.org/ai-in-basketball-how-artificial-intelligence-is/ (Accessed: Date).

[2] Patrick Carrington and Eliezer Bernart. Computer science and sports: The digital evolution of physical competition. *XRDS*, 25(4):8–9, jul 2019.

[3] Kang Chang, Peng Sun, and Muhammad Usman Ali. A cloud-assisted smart monitoring system for sports activities using svm and cnn. *Soft Computing*, 28(1):339–362, 2024.

[4] Corinna Cortes and Vladimir Vapnik. Support-vector networks. *Machine Learning*, 20(3):273–297, 1995.

[5] datagy. Support vector machines (svm) in python with sklearn. https://datagy.io/python-support-vector-machines/, 2022. Accessed on: March 10, 2024.

[6] Matt Dawson. The iron cage of efficiency: analytics, basketball and the logic of modernity. *Sport in Society*, 26(11):1785–1801, 2023.

[7] Theodoros Evgeniou and Massimiliano Pontil. Support vector machines: Theory and applications. volume 2049, pages 249–257, 09 2001.

[8] Mordor Intelligence. Sports analytics market - size, forecast & trends. https://www.mordorintelligence.com/industry-reports/sports-analytics-market, 2024. Accessed: April 25, 2024.

[9] Luke Lefebure. Understanding player positions in the nba. December 2014.

[10] Edwin Mendoza Torralba. Sports ed 3.5: Establishing the value of data-driven sports development programs for universities through machine learning models. In *Proceedings of the 2020 8th International Conference on Information Technology: IoT and Smart City*, ICIT '20, page 51–57, New York, NY, USA, 2021. Association for Computing Machinery.

[11] Jakub Nalepa and Michal Kawulok. Selecting training sets for support vector machines: a review. *Artificial Intelligence Review*, 52:857–900, 2019.

[12] P.F. Pai, L.H. ChangLiao, and K.P. Lin. Analyzing basketball games by a support vector machines with decision tree model. *Neural Computing and Applications*, 28:4159–4167, 2017.

[13] Grand View Research. Sports analytics market size, share & trends report, 2030. https://www.grandviewresearch.com/industry-analysis/sports-analytics-market, 2024. Accessed: April 25, 2024.

[14] David A. Sadlier and Noel E. O'Connor. Event detection in field sports video using audio–visual features and a support vector machine. *IEEE Transactions on Circuits and Systems for Video Technology*, 15(10), 2005.

[15] Vangelis Sarlis and Christos Tjortjis. Sports analytics — evaluation of basketball players and team performance. *Information Systems*, 93:101562, 2020.

[16] Josh Starmer. Support vector machines part 2: The polynomial kernel (part 2 of 3). https://www.youtube.com/watch?v=Toet3EiSFcM, 2019. YouTube video.

[17] Josh Starmer. Support vector machines part 3: The radial (rbf) kernel (part 3 of 3). https://www.youtube.com/watch?v=Qc5IyLW_hns, 2019. YouTube video.

Appendix

To complete this paper, I called on knowledge and skills I have learned both in class and in my own experiences. At St. John's University, I have not only learned how to study computer science, but also how to write and think more critically. This well-rounded education is important in tying together interdisciplinary works. Outside of class, I have learned to communicate more effectively, as well as gain some technical ability necessary to complete this paper. My success in this course has been the culmination of all that I have learned during my time at St. John's University.

Courses such as computer theory, software engineering, data structures, and algorithms have informed my approach to the field of computer science, defining the way I think about technology. In these courses, I learned not only the high-level details about how computers work, but also many of the low-level intricacies that accomplish specific tasks. I learned to understand algorithms and the theory behind them, which was needed to grasp the way SVMs work. I also learned to implement these algorithms, necessary for creating my demonstration of SVMs in action.

Through individual efforts, I learned to code in Python, the language used to implement my SVM. I gained this skill by working on personal projects, a practice recommended to me by peers and professors. I also learned a lot about basketball, playing collegiately for five years. This experience inspired the topic of my paper and assisted me in identifying the specific ways in which SVMs could be used for basketball player development.

The experience of taking this course and writing this paper has not only utilized my prior knowledge; it has reinforced all that I have learned. By exploring SVMs in detail, I have gained a better understanding of how to look at algorithms and techniques, evaluating them for effectiveness. I obtained a better grasp of technical writing, refining my techniques throughout the semester. My research abilities improved as I searched for, verified, and read sources needed to build my background knowledge of the subject. I also learned how to stay up to date with the latest trends in the industry. Overall, this project has not only taught me a lot, it has bolstered all my prior learning.