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Evaluation of Match Outcomes in Elite European Basketball: A Machine Learning Approach to Fenerbahçe Beko's Euroleague Campaigns

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Abstract

Basketball is a popular sport. It features high competition and tactical depth. Coaches' strategies play a decisive role in team success. Field statistics also determine these results. This study aims to analyze the performance of Fenerbahçe Beko in the Euroleague. It uses machine learning algorithms for this analysis. The research examines an eight-year dataset between the 2017-2018 and 2024-2025 seasons. Artificial Neural Networks (ANN), deep learning (DL-ANN), and Dagging-ANN algorithms are used in the analysis. The Filtered Attribute algorithm identifies the 15 most critical variables affecting match results. Results show that the DL-ANN model achieves the highest success with an 89.40% accuracy rate. 'Opponent defensive rebounds', 'halftime results', and '3-Point %' stand out as the effective variables for classification. Consequently, these findings demonstrate that data mining methods provide a specialized, data-driven decision support mechanism in professional sports management, offering elite basketball teams and stakeholders actionable insights to optimize tactical planning and game preparation in high-stakes organizations like the Euroleague.

Keywords: euroleague, classification, machine learning, artificial neural network

Elit Avrupa Basketbolunda Maç Sonuçlarının Değerlendirilmesi: Fenerbahçe Beko'nun Euroleague Sezonlarına Bir Makine Öğrenmesi Yaklaşımı

Öz

Basketbol, dünya genelinde yüksek rekabetin ve taktiksel derinliğin ön planda olduğu popüler bir spor dalıdır. Takımların başarısında koçların stratejileri ve sahadaki istatistiksel veriler belirleyici rol oynamaktadır. Bu çalışma, Fenerbahçe Beko'nun Euroleague'deki performansını makine öğrenmesi algoritmalarıyla analiz etmeyi amaçlamaktadır. Araştırma kapsamında 2017-2018 ve 2024-2025 sezonları arasındaki sekiz yıllık veri seti incelenmektedir. Analizlerde Yapay Sinir Ağları (ANN), derin öğrenme (DL-ANN) ve Dagging-ANN algoritmaları kullanılmaktadır. Filtre tabanlı öznitelik seçim algoritması ile maç sonuçlarına etki eden en kritik 15 değişken belirlenmektedir. Elde edilen sonuçlar, DL-ANN modelinin %89,40 doğruluk oranıyla en yüksek başarıyı sergilediğini göstermektedir. Rakip savunma ribaundu, devre sonucu ve üç sayı yüzdesi maç sonucu sınıflandırmasının en güçlü belirleyicileri olarak öne çıkmaktadır. Sonuç olarak bu bulgular, veri madenciliği yöntemlerinin profesyonel spor yönetiminde uzmanlaşmış ve veri odaklı bir karar destek mekanizması sunduğunu göstermekte; elit basketbol takımlarına ve paydaşlarına, Euroleague gibi rekabetin yüksek olduğu organizasyonlarda taktiksel planlamayı ve maç hazırlıklarını optimize etmek için uygulanabilir öngörüler sağlamaktadır.

Anahtar Kelimeler: euroleague, sınıflandırma, makine öğrenmesi, yapay sinir ağları

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Introduction

Modern professional basketball has evolved into a highly dynamic and tactically complex discipline within the contemporary sports industry, characterized by continuous athletic advancements and strategic innovations. As game play grows increasingly sophisticated, understanding the determinants of team success requires rigorous quantitative scrutiny rather than subjective evaluation. This game is more than just a sport today. It is a massive passion for millions of people worldwide. Fans love this game with great devotion. High energy in arenas draws the audience in. Uncertainty until the final second sets basketball apart. The economic dimension of the game grows daily. Professional players earn very high salaries now. Advertising deals and broadcasting rights transform the industry. This popularity brings intense competition. On-court struggle becomes tougher every day. The National Basketball Association (NBA) sits at the top of world basketball. The NBA is the primary showcase and the largest economic market. European basketball has built its own strong identity in recent years. Euroleague is the highest quality organization after the NBA. It offers great tactical depth. The NBA focuses on athleticism and showmanship. Euroleague provides a disciplined and tactic-oriented game. Interaction between these two giants shapes global basketball development. NBA stars experience the toughness of Euroleague. Top players in Euroleague continue their careers in the NBA.

European basketball stands as a top sports arena. Euroleague is at the heart of this world. Its tactical depth and tough competition grab attention. Coaches' smart moves and team stability drive success here. The organization also represents a massive economic system. Global broadcasts and modern tech offer a unique experience to everyone. Athletes use this stage to show their skills to the whole world. This trophy is the ultimate development ground for players and clubs in Europe. Turkey holds a powerful position in this organization over the last decade. Fenerbahçe Beko made history as the first Turkish champion in 2017. The club represents Turkey well with steady results and Final Four trips. It serves as a main engine for Turkish basketball alongside Anadolu Efes. These two giants push the country's brand value to the top. Anadolu Efes also boosts this status with two back-to-back titles.

Data production in modern basketball never stops. Top organizations like the Euroleague collect thousands of data points every second. The extensive match history of Fenerbahçe Beko has generated a massive dataset that frequently pushes the boundaries of traditional analytical frameworks. As modern research increasingly requires more sophisticated tools to navigate such complexity, machine learning has emerged as a premier solution for extracting meaningful insights. Specifically, deep learning offers a distinct advantage by uncovering latent patterns within the data, which, when integrated with ensemble learning approaches, yields significantly more robust and precise results. Machine learning, ensemble learning, and deep learning perform different tasks on basketball data. Classification models predict match outcomes with high accuracy. Prediction models show team performance through numbers. Clustering analysis groups seasons or opponents with similar styles. Feature selection is a vital step here. Removing useless data makes algorithms faster and more successful. Finding the right variables helps discover the most effective variables for classification on the path to victory.

While classifying match outcomes in elite basketball organizations is a well-established area of research, dealing with high-dimensional sports data often introduces informational noise that challenges tactical interpretation. In this regard, feature selection mechanisms play a pivotal role in contemporary sports analytics. Rather than processing raw statistical data indiscriminately, feature selection filters out redundant variables, thereby crystallizing the most critical game variables that directly govern match outcomes. The integration of feature selection within machine learning frameworks does not merely enhance algorithmic efficiency and classify accuracy; it provides coaches, technical staffs, and sports executives with an actionable, highly focused decision-support mechanism. By filtering out non essential metrics, this approach allows decision-makers to formulate data driven, opponent specific strategies in high-stakes environments like the Euroleague.

Contributes to the existing literature by explicitly demonstrating how feature selection can bridge the gap between complex machine learning algorithms and practical court-side tactics.

Literature reviews show many studies on basketball and team performance. Similar research exists in football (Alanazi & Khan, 2026; Filiz, 2023; Fernandes et al., 2024; Hägglund et al., 2013). Volleyball (Eom & Schutz, 1992; López-Serrano et al., 2022; Palao et al., 2004) and handball (Henze et al., 2026; Lago-Peñas et al., 2013; Wagner et al., 2016) also feature similar studies. Dirks (2000) investigates the link between trust, leadership, and team performance in the NCAA. Results from the NCAA sample show that trust in leadership is both a product and a determinant of performance. Heuzé et al. (2006) look at the connections between cohesion, collective efficacy, and performance. Staff members working with players below normal levels see a specific trend. Performance drops often lead to a decline in internal cohesion and collective efficacy. This highlights the human element in professional sports team dynamics. Csatalja et al. (2009) identify critical performance indicators that distinguish winning and losing in basketball. Winners in close games show significantly fewer three-point attempts. These teams also exhibit higher shooting percentages. Successful free throws, free throw percentages, and defensive rebounds contribute to higher scores. These factors directly determine success. Sabin and Marcel (2015) use sociometric surveys to examine relationships in a youth basketball team. They aim to improve communication, socialization, and cohesion. Their results show that better communication helps build a stronger group. In the existing literature, data-driven approaches to predicting basketball match outcomes have extensively utilized diverse machine learning frameworks. Rather than evaluating these methodological efforts in isolation, recent studies collectively underscore the necessity of synthesizing game-related statistics with tactical performance indicators. For instance, while traditional models primarily focus on isolated box-score metrics, contemporary research increasingly highlights the conditional impact of contextual variables and coaching strategies on overall team efficiency. By shifting the focus from descriptive analysis to advanced predictive modeling, current sports analytics literature demonstrates that integrating ensemble techniques offers a more granular understanding of victory determinants in elite basketball organizations like the Euroleague. Examining the specific indicators that drive success, Leicht et al. (2017) demonstrated that Olympic women's basketball outcomes are largely dictated by a synergy of shooting efficiency, defensive rebounding, steals, and turnovers, whereas a lack of precision in these areas remains the strongest predictor of defeat. Methodologically, Terner and Franks, (2021) advanced the field by exploring quantitative ways to characterize team strategy, emphasizing that the future of player evaluation lies in robust causal inference rather than simple observation. The significance of offensive structures was further reinforced by Chen et al. (2023), who found that specific offensive roles are pivotal to overall team success. Contextual factors also play a critical role; for instance, Sansone et al. (2024) observed that Euroleague performance is significantly affected by scheduling and travel, where long-distance trips correlate with diminished three-point accuracy and increased foul counts. Finally, advancing into modern computational techniques, Li (2025) introduced a hybrid LSTM-CNN framework capable of classifying complex defensive strategies, providing a sophisticated analytical tool that allows coaches to break down and evaluate defensive movements with unprecedented clarity.

The intersection of basketball analytics and machine learning has fostered a diverse range of predictive modeling and strategy evaluation studies. For instance, Jain and Kaur, (2017) pioneered a Hybrid Fuzzy-SVM model designed to assist coaches in performance enhancement, yielding promising results for game analysis. Building on the use of advanced metrics, Sarlis and Tjortjis (2020) conducted a comparative investigation between NBA and Euroleague datasets, demonstrating how performance analysis can effectively guide roster construction and career trajectory forecasts. Methodological diversity is further highlighted by Horvat et al. (2020), who tested various classification algorithms through cross-validation and training-test sets, concluding that the nearest neighbor approach outperformed decision tree models in predictive accuracy. Similarly, Alonso and Babac (2022) focused on comparing algorithmic precision for match forecasting, while Lampis et al. (2023) explored logistic regression, random forest, and gradient boosting across various European leagues, finding only marginal performance gaps between these techniques. Recent comparative studies by Plakias et al. (2024) have pinpointed effective shooting percentages and assist-to-turnover ratios as critical league-specific discriminators. Furthermore, Ou-Yang et al., (2025) identified free throw accuracy and rebounding as primary success drivers in the Chinese Basketball League, a finding echoed by a growing body of literature that continues to leverage machine learning to decode Euroleague dynamics (Ballı & Özdemir, 2021; Foteinakis et al., 2025; Giasemidis, 2020).

Focusing on the modern Euroleague era, this study examines Fenerbahçe Beko's performance through an extensive dataset spanning the 2017-2018 to 2024-2025 seasons. To classify match outcomes, the research utilizes various Artificial Neural Network (ANN) architectures, including standard ANN, deep learning hybrid models (DL-ANN), and the Dagging-ANN algorithm, providing a robust basis for identifying the most effective models for basketball analytics. A central component of the work involves isolating the key variables that drive match results via the Filtered Attribute Feature Selection algorithm. By bridging these variables with specific coaching styles and on-court metrics, the study demonstrates on a scientific level how distinct tactical approaches translate into victories. What distinguishes this research is its emphasis on tactical evolution; rather than merely forecasting wins and losses, it leverages machine learning to decode how different coaching methodologies reshape the game. Ultimately, by aligning high-dimensional data features with coaching philosophies over an eight-year period, this study offers a unique framework that integrates the technical nuances of professional basketball with advanced computational intelligence.

Materials and Methods

Data Set

The study focuses on how Fenerbahçe Beko performs in the Euroleague. The analysis starts with the 2017-2018 season, following their last trophy win. Data collection covers an eight-year stretch, including the 2024-2025 season. All information comes from the Mackolik website (Mackolik web page). The dataset tracks every technical detail of the modern game. The research looks at the eras of five different head coaches. These names include Z. Obradovic, I. Kokoskov, A. Djordjevic, D. Itoudis, and S. Jasikevicius. Each coach has its own statistical records in the data. This long timeframe helps show how coaching shifts change things on the court. The dataset includes 35 different variables. 34 of these are independent variables. The last one is the 'match result', which is the focus of the study. Table 1 lists the definitions and types for everything. To prepare this raw dataset for robust algorithmic execution, a meticulous data preprocessing workflow was conducted. First, the data was audited for structural integrity, confirming that there were no missing or null values across the seasonal records. Categorical attributes, including the coaching eras and the binary target variable (match result: win/loss), were formally encoded into appropriate nominal formats suitable for machine learning frameworks. During the data cleaning phase, points scored and conceded are removed. The variables are included exclusively for descriptive analysis to reflect the general performance profiles of the coaches. To ensure model integrity and prevent data leakage, these variables were completely excluded from all machine learning and classification processes. These numbers relate too directly to winning or losing. This choice makes the models focus purely on game performance stats. These stats serve as the effective variables for classification.

Table 1. Variables Used in The Study and Their Definitions

Variable Name	Variable Definition	Variable Type
Season	1: 2017/2018, 2: 2018/2019, 3: 2019/2020, 4: 2020/2021, 5: 2021/2022, 6: 2022/2023, 7: 2023/2024, 8: 2024/2025	Independent Variables
Match Type	1: Regular Season, 2: Play-off, 3: Final-four	
Venue	1: Home, 2: Away, 3: Neutral ground	
1P Result	0: Lose, 1: Draw, 2: Win	
2P Result	0: Lose, 1: Draw, 2: Win	
3P Result	0: Lose, 1: Draw, 2: Win	
4P Result	0: Lose, 1: Draw, 2: Win	
Halftime Result	0: Lose, 1: Draw, 2: Win	
2-Point %	-	
3-Point %	-	
Free Throw %	-	
Offensive Rebounds	-	
Defensive Rebounds	-	
Total Rebounds	-	
Assists	-	
Turnovers	-	
Steals	-	
Blocks	-	
Fouls	-	
Opponent 2-Point %	-	
Opponent 3-Point %	-	
Opponent Free Throw %	-	
Opponent Offensive Rebounds	-	
Opponent Defensive Rebounds	-	
Opponent Total Rebounds	-	
Opponent Assists	-	
Opponent Turnovers	-	
Opponent Steals	-	
Opponent Blocks	-	
Opponent Fouls	-	
Number of Players Played	-	
Number of Players Scored	-	
Opponent Players Played	-	
Opponent Players Scored	-	
Match Outcome	0: Lose, 1: Win	Dependent Variable

Algorithms

The main goal of the study is to classify Fenerbahçe Beko's match results with the highest possible accuracy. Instead of traditional methods, the analysis focuses on machine learning, ensemble learning, and deep learning. At the center of this process is the Artificial Neural Network (ANN) as the primary classifier. Additionally, an DL-ANN architecture and the Dagging ensemble learning approach are included. These algorithms are chosen specifically for their ability to untangle the complex; non-linear relationships found in basketball data. To find out which data points matter during classification, the Filtered Attribute Feature Selection algorithm is used. This selection process cleans out useless data that could lower the quality of the analysis. It also brings the parameters directly related to coaching strategies to the surface. For the training and testing phases, the k-fold cross-validation method is applied. This is vital to keep the models from simply memorizing the data (overfitting). Since the entire dataset is used in both phases, no information is lost. To ensure the statistical robustness of the claasify models and to mitigate the risk of overfitting, a 10-fold cross-validation protocol was systematically implemented during the algorithmic execution phase. Within this validation framework, the entire Euroleague match dataset is randomly and proportionally partitioned into ten mutually exclusive, equal-sized subsets (folds). The classification models are iteratively trained ten times; in each iteration, nine folds are utilized for model fitting and parameter tuning, while the remaining single fold is reserved exclusively as an independent testing set for performance evaluation. This iterative process ensures that every match record is utilized exactly once for testing and nine times for training, thereby producing an unbiased, highly generalized estimation of the models' classification accuracy, precision, and recall rates on unseen sports analytics data. The Weka software handles the data mining tasks, including classification, prediction, and feature selection. These analytical frameworks enhance model interpretability by accurately classifying the critical performance indicators that directly influence team victory.

Artificial Neural Network Classifier

Artificial Neural Networks (ANN) take their inspiration from how the human brain works. This model is built from a network of connected artificial cells. The system generally consists of three main parts: the input, hidden, and output layers. Every data connection has a specific weight assigned to it. During the training process, these weights are constantly updated. This helps push the error rate down to the lowest possible level. The biggest advantage of this algorithm is its ability to deliver high success even with messy, complex data. It successfully solves multi-dimensional relationships that traditional methods just can't handle. While it performs great on its own for classification, it also works well in hybrid structures with other algorithms to produce even better results. These models are perfect for identifying the classification within large datasets (Han et al., 2012).

Deep Learning Algorithm

Deep learning represents a deep architecture of neural networks. It has very complex structures. This approach teaches hidden patterns automatically. It works from the lowest to the highest levels. The hybrid structure processes data through deep layers. It finishes the task with an ANN classifier. This algorithm minimizes error rates in large datasets. An increase in the structural depth of neural networks enhances the model's capacity to represent high-level abstractions, thereby potentially improving classification performance by capturing intricate non-linear relationships within the sports dataset. Deep learning discovers invisible links between features on its own (LeCun et al., 2015).

Dagging Ensemble Learning Algorithm

Dagging ensemble learning algorithm works by splitting the dataset into smaller parts. It creates many subsets through random sampling. A different classifier trains on each subset. This study uses the Artificial Neural Network (ANN) as the base classifier. These networks train different data pieces. They reach a common decision through a voting process at the end. This algorithm succeeds in minimizing errors and noise. The ensemble structure catches details that a single model might miss. Dagging provides significant success in modern data mining processes (Ting & Witten, 1997).

Filtered Attribute Feature Selection Algorithm

Feature selection directly impacts success in data mining. It represents a critical point. The Filtered Attribute algorithm identifies variables in the study. It selects the factors affecting match results. The algorithm calculates the impact of each statistic mathematically. It removes unnecessary data from the system completely. It filters out low impact variables. This algorithm reduces the processing load significantly. It highlights key indicators related to coaching strategies. Reducing the number of features lowers the risk of overfitting. Working with less data increases quality. Classification success rises this way (Witten et al., 2005; Weka web page).

Classification Performance Criteria

The study measures algorithm success through specific criteria. Four main metrics evaluate how accurately models classify Fenerbahçe Beko results. The analysis uses Accuracy (Acc), Precision, Kappa Statistic, and Root Mean Square Error (Rmse). These criteria show how well the models separate wins from losses. Acc represents the total correct classification rate. Precision shows the percentage of correctly predicted wins. The Kappa Statistic measures success beyond random chance. Values close to 1 indicate high performance for these three metrics. Rmse measures the deviation between predicted and actual classes. A value close to 0 shows minimized error. The formulas for these criteria are given below:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Kappa = \frac{P_0 - P_e}{1 - P_e} \tag{3}$$

$$Rmse = \sqrt{\frac{\sum_{i=1}^{n}(P_i - A_i)^2}{n}} \tag{4}$$

Application

The application section classifies Fenerbahçe Beko’s Euroleague results as wins or losses. It also examines the tactical approaches of the coaches. The process consists of three complementary steps.

The first step uses all variables in the dataset. ANN, DL-ANN, and Dagging-ANN algorithms train on this full data. Each model's success is evaluated using Acc, Precision, Kappa, and Rmse.

The second step uses the Filtered Attribute Feature Selection algorithm. This identifies the critical variables for correct classification. Specific match statistics are extracted for each coach. This stage finds links between effective features and coaching systems.

The final step runs the algorithms again using only the selected variables. Performance metrics measure the success of the models once more. The results from the first and third steps are compared in detail. Table 2 shows the flowchart and Table 3 shows parameters used in algorithms of the study.

Table 2. Flowchart of the Study

Steps	Algorithms	Main Objective
Step 1: General Classification	ANN, DL-ANN, Dagging-ANN	Determining initial success rates with the full dataset.
Step 2: Feature Selection	Filtered Attribute, Coach-Based Analysis	Identifying the attributes and coaching tactics that have the effective features on the match outcome.
Step 3: Performance Benchmarking	ANN, DL-ANN, Dagging-ANN	To investigate the effect of feature selection on classification success.

Table 3. Parameters Used in Algorithms

Parameter	ANN Classifier	DL- ANN	Dagging-ANN
Batch Size	100	100	100
Debug	False	False	False
Do Not Check Capabilities	False	False	False
Num Decimal Places	2	2	2
Num Functions	2	-	-
Num Threads	1	-	-
Pool Size	1	-	-
Ridge	0.01	-	-
Seed	1	1	1
Tolerance	1.0E-6	-	-
Use CGD	False	-	-
Number of Epochs	-	10	-
Data Queue Size	-	0	-
Resume	-	False	-
Preserve Filesystem cache	-	False	-
Number of GPUs	-	1	-
Model Parameter Averaging Frequency	-	10	-
Num Folds	-	-	10
Verbose	-	-	False

Findings

The study focuses on the match results of Fenerbahçe Beko. It aims to determine performance progress over the last eight years. A three-stage application structure is used for this purpose. All analyses are performed using the Weka software.

The first stage evaluates classification performance with all variables. No feature selection is applied at this point. ANN, DL-ANN, and Dagging-ANN algorithms process the full data. Table 4 details the numerical values for the classification performance of these algorithms.

Table 4. Classification Success Rates Obtained Using All Variables

	ANN Classifier	DL- ANN	Dagging-ANN
Acc	88.70%	89.40%	86.30%
Precision	0.8870	0.8970	0.8640
Kappa statistic	0.7662	0.7837	0.7100
Rmse	0.2803	0.2718	0.3132

Table 4 shows the performance values of the three algorithms using all variables. The DL-ANN model reaches the highest success rate with an Acc value of 89.40%. Precision (0.8970) and Kappa statistic (0.7837) values support this result. The ANN Classifier follows it with 88.70%. The Dagging-ANN algorithm shows a correct classification rate of 86.30%. Looking at the Rmse values, the DL-ANN model has the lowest error rate at 0.2718.

The second stage of the application uses the Filtered Attribute algorithm. This identifies the most important variables for classification. These effective features and their importance ratings appear in Table 5 and Figure 1.

Table 5. Effective Variables and Their Importance Ratings with Feature Selection

Effective features	Importance Ratings
Opponent Defensive Rebounds	0.1659
Halftime Result	0.1535
3-Point %	0.1347
Assists	0.1054
4P Result	0.1051
Opponent Assists	0.0722
2P Result	0.0720
Opponent Total Rebounds	0.0718
2-Point %	0.0696
Defensive Rebounds	0.0640
Opponent 2-Point %	0.0590
3P Result	0.0555
Opponent Steals	0.0515
Opponent 3-Point %	0.0501
Turnovers	0.0389

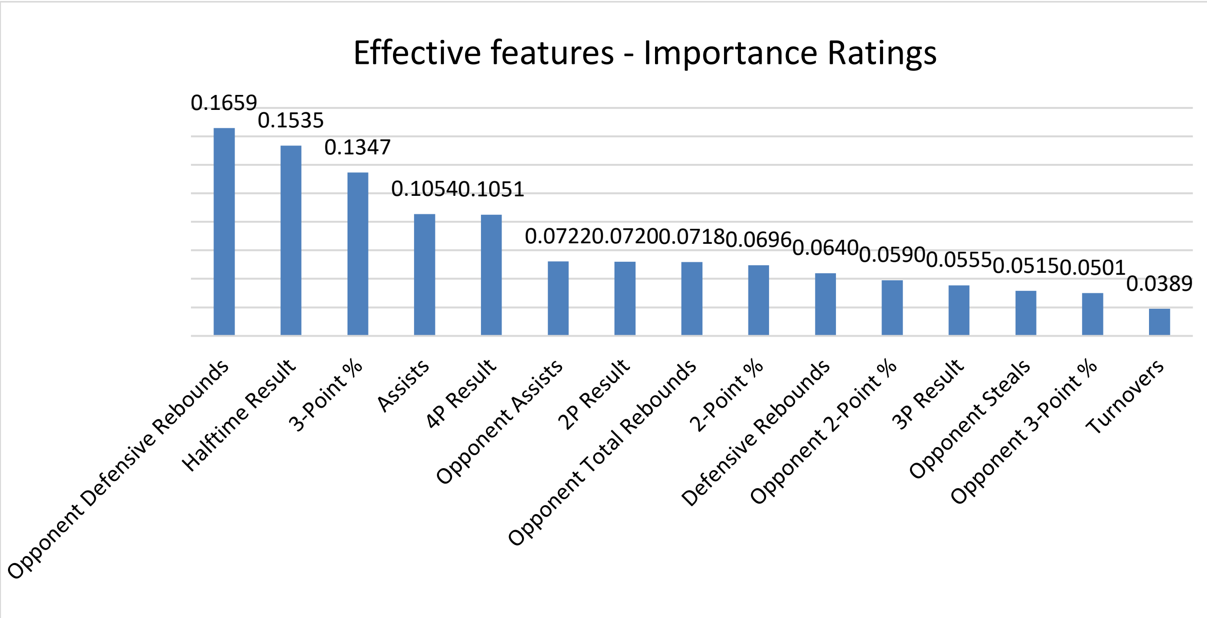

Figure 1. Representation of Effective Variables and Their Importance Ratings

Table 5 shows that Opponent Defensive Rebounds are the most effective variable. It has an importance degree of 0.1659. Halftime Result follows it with a value of 0.1535. The 3-Point % ranks third at 0.1347. Assists (0.1054) and 4P Result (0.1051) also stay among the top five variables. Opponent Assists (0.0722) and 2P Result (0.0720) show very similar importance levels. Basic statistics like 2-Point % (0.0696) and Defensive Rebounds (0.0640) directly impact decisions. Turnovers rank last with a score of 0.0389. These 15 features form the key variable set. The third step is to optimize performance.

The second part of the stage extracts statistical profiles of the coaches. It covers eight seasons at Fenerbahçe Beko. The analysis includes Obradovic, Kokoskov, Djordjevic, Itoudis, and Jasikevicius. Data highlights their game philosophies and tactical choices. It shows their effectiveness in different periods of the games. Table 6 presents the average values for each coach during their terms.

Table 6. General Statistics Table according to the Coaches

	Z.Obradovic	I.Kokoskov	A.Djorjevic	D.Itoudis	S.Jasikevicius
Games Played	100	37	28	52	67
1P Result	1.30	0.89	1.04	1.04	0.85
2P Result	1.15	1.19	0.96	1.02	1.21
3P Result	0.96	1.22	1.11	1.02	1.15
4P Result	1.20	0.97	0.93	1.08	1.01
Halftime Result	1.24	1.00	0.93	0.90	1.07
2-Point %	0.56	0.57	0.57	0.55	0.54
3-Point %	0.42	0.40	0.32	0.37	0.39
Free Throw %	0.79	0.83	0.73	0.74	0.80
Offensive Rebounds	7.45	6.16	7.96	9.19	8.91
Defensive Rebounds	19.85	20.32	20.79	20.33	21.72
Total Rebounds	27.30	26.49	28.75	29.52	30.90
Assists	18.36	18.14	17.89	17.56	17.78
Turnovers	11.41	13.65	12.43	11.02	11.67
Steals	6.51	6.51	7.79	6.15	6.16
Blocks	2.42	1.95	2.07	1.90	2.36
Fouls	20.76	18.86	18.64	20.71	21.43
Opponent 2-Point %	0.54	0.54	0.54	0.55	0.54
Opponent 3-Point %	0.36	0.38	0.34	0.36	0.35
Opponent Free Throw %	0.75	0.78	0.83	0.78	0.78
Opponent Offensive Rebounds	8.43	9.08	8.71	9.48	7.93
Opponent Defensive Rebounds	19.13	19.76	21.18	21.71	21.01
Opponent Total Rebounds	27.60	28.84	29.32	31.19	28.99
Opponent Assists	16.96	19.11	16.54	17.00	16.66
Opponent Turnovers	11.69	12.70	13.25	11.60	10.79
Opponent Steals	6.05	7.00	7.57	6.25	5.93
Opponent Blocks	2.08	2.27	2.50	2.31	1.69
Opponent Fouls	20.66	18.65	19.29	20.46	20.18
Number of Players Played	10.48	10.62	10.57	10.60	11.04
Number of Players Scored	9.09	8.76	8.93	8.71	9.46
Opponent Players Played	10.70	10.68	10.25	10.79	10.63
Opponent Players Scored	9.03	9.08	8.89	9.31	9.10
Points Against	76.81	79.54	74.86	81.19	80.57
Points Scored	81.14	77.84	73.25	82.29	84.49

Table 6 shows how each coach reflects their philosophy in the numbers. Jasikevicius leads in many areas like 84.49 Points Scored and 30.90 Total Rebounds. His 0.67 Match Outcome shows high offensive efficiency and success. Obradovic leads in 1P Result (1.30), Assists (18.36), and 3-Point % (0.42). These technical markers reflect his playmaker and disciplined style. Djordjevic creates a more resilient team with 74.86 Points Against and 7.79 Steals. Kokoskov stands out with 0.83 Free Throw % and 1.22 3P Result. Itoudis reaches the highest value in post aggression with 9.19 Offensive Rebounds. Jasikevicius and Obradovic share the lead in win-oriented stats. Other coaches specialize in specific areas like defense or period performances.

Relationships exist between selected features and team statistics. These links focus on specific variable groups. The results follow the second step of the study. Figure 2, Figure 3, and Figure 4 show these connections.

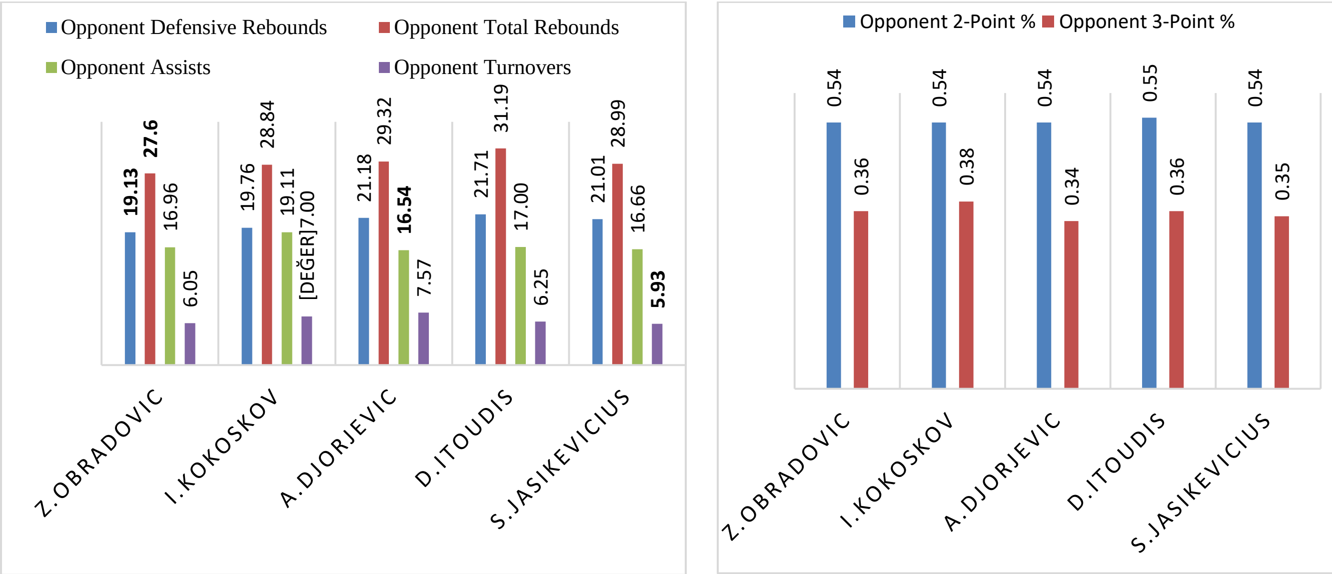

Figure 2. Statistics of Defensive Efficiency, A Key Attribute That Limits Opponent Performance, according to Coaching Periods

According to Figure 2, looking at Opponent Defensive Rebounds (0.1659) identified as the most important variable for classification Jasikevicius restricted opponents to only 21.01 defensive rebounds per game. He also stood out by limiting Opponent Assists (0.0722) to 16.66, creating pressure both in the paint and on passing lanes. Obradovic allowed the fewest Opponent Defensive Rebounds (19.13) and Opponent Total Rebounds (27.6), while Djordjevic kept Opponent Assists at the lowest level (16.54). However, Jasikevicius reached the highest match outcome success (0.67) by balancing these decisive opponent statistics. While Opponent 2-Point % remained similar for all coaches (0.54-0.55), Opponent 3-Point % was lowest for Djordjevic (0.34) and Jasikevicius (0.35).

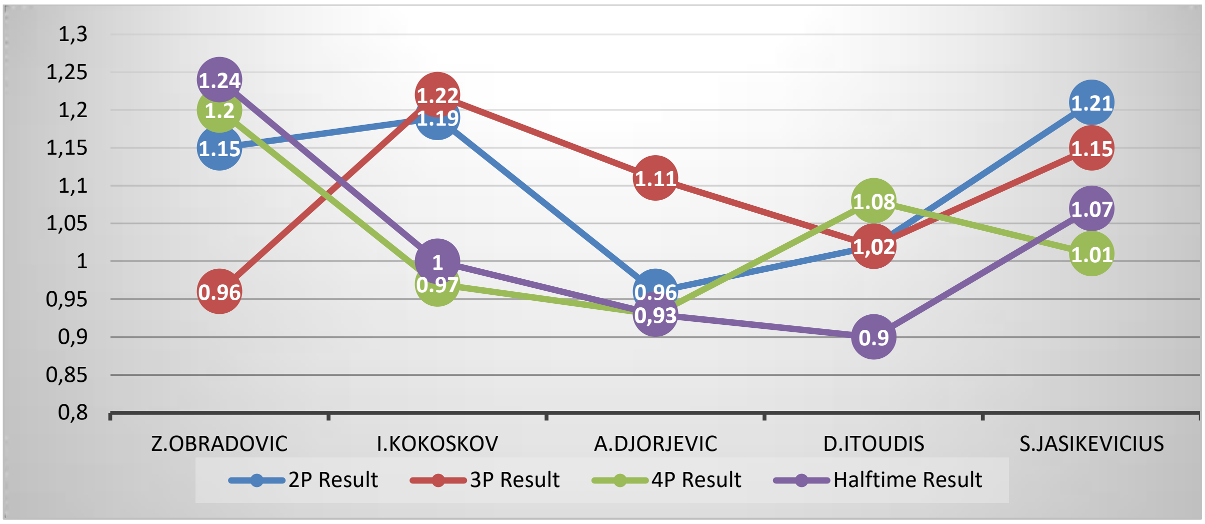

Figure 3. Statistics of Period Efficiency and Cycle Result Attributes according to Coaching Periods

According to Figure 3, data such as Halftime Result (0.1535) is the second most effective variable identified by the feature selection algorithm and the highly significant 4P Result (0.1051) reveal the strategic superiority of Obradovic and Jasikevicius. Obradovic achieved a very high average of 1.24 in Halftime Result, showing that he takes early control of the game in the algorithm's most critical variables. Specifically, his 1.20 average in 4P Result, which directly impacts the match outcome, documents his disciplined end-game management. Jasikevicius, on the other hand, reached the highest values among all coaches in 2P Result (1.21) and 3P Result (1.15) efficiencies, reflecting his success in turning the tide of the game in his favor through tactical effectiveness before and after the halftime break.

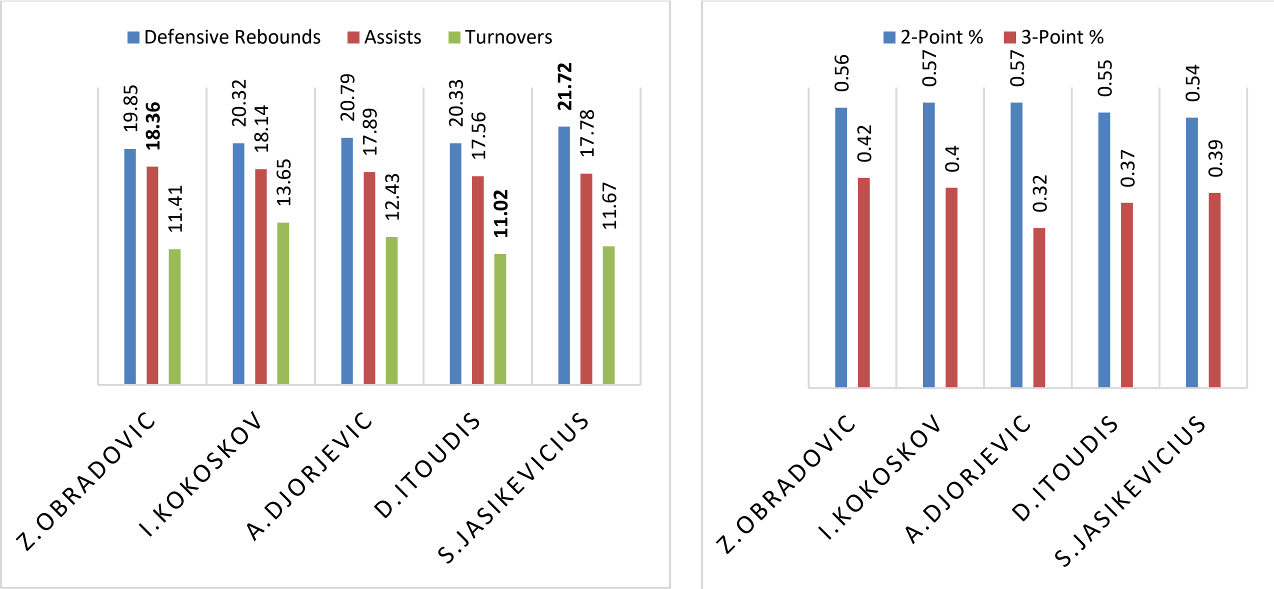

Figure 4. Statistics of Key Attributes of Offensive Efficiency according to Coaching Periods

Figure 4 analyzes the offensive philosophies of the coaches and the court reflections of the offensive features identified by the algorithm as most effective for winning. Variables with high importance in classification, such as 3-Point % (0.1347), Assists (0.1054), and 2-Point % (0.0696), reveal the fundamental successes and differences in the coaches' offensive efficiency. Obradovic ranks at the top among all coaches in 3-Point % (0.42) the third most critical variable in the classification and achieves the highest level in this area with an average of 18.36 Assists per game, demonstrating his strategy of outside shooting and selfless play. Jasikevicius maintained a high efficiency level in these core features with a 0.39 3-Point % and 17.78 Assists, displaying a balanced offensive structure on the path to success. On the other hand, while Kokoskov was efficient with a 0.57 2-Point %, he lagged behind Obradovic in variables such as Assists and Turnovers; Djordjevic fell behind all coaches with a 0.32 3-Point % one of the most important classification variables failing to meet expectations in classification success. Although Itoudis offered an aggressive structure with 9.19 Offensive Rebounds in the paint, he could not reach the success achieved by the championship-winning coaches in 3-Point % (0.37) and Assist production (17.56).

In the third step of the study, the classification performances of the algorithms were determined using the 15 most effective variables identified by the Filtered Attribute feature selection algorithm. The main objective at this stage is to obtain more optimized and generalizable results using variables that directly affect the match outcome (Opponent Defensive Rebounds, Halftime Result, 3-Point %, etc.). Table 7 presents the Acc, Precision, Kappa statistic, and Rmse values for the ANN, DL-ANN, and Dagging-ANN algorithms based on these selected effective features.

Table 7. Classification Success Rates Obtained Using Effective Variables

	ANN Classifier	DL- ANN	Dagging-ANN
Acc	85.20%	87.30%	87.30%
Precision	0.8520	0.8740	0.8730
Kappa statistic	0.6915	0.7384	0.7349
Rmse	0.3324	0.2987	0.3051

Table 7 presents the classification performance values of the three algorithms in the third stage, where only the effective variables were used. Both the DL-ANN and Dagging-ANN algorithms reached the highest success rate with an Acc value of 87.30%. The Precision (0.8740) and Kappa statistic

(0.7384) values support the performance of the DL-ANN algorithm, which yielded slightly better results than Dagging-ANN in criteria other than Accuracy. However, compared to the results obtained with all variables, the Dagging-ANN algorithm achieved more successful classification results with the selected effective features than the other algorithms. The ANN Classifier followed these results with 85.20%. Looking at the Rmse values representing the error margins of the models, it is understood that the DL-ANN model has the lowest error rate at 0.2987.

Discussion

The analysis process, conducted in line with the study's objective and the designed application steps, has been completed. The results and classification outputs are presented in the Results section, where the findings are discussed within the framework of modern basketball's tactical requirements and coaching approaches.

Fenerbahçe Beko's Euroleague journey over the last eight years clearly reveals the impact of coaching changes on on-court statistics and winning success. One of the most striking findings of the study is that Euroleague champions Obradovic and Jasikevicius exhibit similarities in the most critical attributes affecting classification through machine learning algorithms. Obradovic reflects a disciplined mentality that takes control of the game in the first half, as evidenced by his high average in Halftime Result (1.24), which is one of the most vital variables in the classification. Furthermore, Obradovic's status as the leader among all coaches in high-impact categories specifically Assists (18.36) and 3-Point % (0.42) validates a fundamental game concept centered on collective ball movement and perimeter accuracy. In contrast, while Jasikevicius maintained a comparable Match Outcome (0.67), his success appears to stem from a more symmetrical integration of offensive and defensive strategies. Jasikevicius notably excels in neutralizing 'Opponent Defensive Rebounds' (21.01) identified as the most critical variable in the classification while leveraging tactical adjustments (2P Result: 1.21) to shift the momentum of a game. This emphasis on defensive discipline and the containment of opponent metrics represents a cornerstone of success in the modern Euroleague. These findings align with broader academic literature, reinforcing the significance of these specific performance indicators (Csatalja et al., 2009; Leicht et al., 2017; Ou-Yang et al., 2025; Plakias et al., 2024).

When assessing algorithmic performance, the importance of feature selection in optimizing classification success becomes strikingly evident. Effective variables such as 'Opponent Defensive Rebounds', 'Halftime Result', and '3-Point %', isolated by the Filtered Attribute algorithm, and offer a direct explanation for the performance trajectories of different coaches. From a tactical analytics perspective, the high importance rating assigned to 'Opponent Defensive Rebounds' and 'Halftime Result' within the developed classification models underscores a critical operational paradigm in contemporary Euroleague basketball. The statistical supremacy of opponent defensive rebounding ratings suggests that limiting the opponent's transition opportunities and controlling the defensive glass directly dictates the tempo-shifting boundaries of elite matches. This finding aligns with the broader sports science literature which posits that defensive efficiency and possession control are premier drivers of victory in high stakes tournaments (Bustamante-Sánchez & Jiménez-Saiz, 2024; Leicht et al., 2017; Tsagris et al., 2024; Zhang et al., 2020;). Additionally, the potential impact of spectator-free during the COVID-19 pandemic should be considered. Literature shows that the absence of crowds significantly reduced the traditional home-court advantage and altered psychological pressure on players and referees (Alonso et al. 2022; De Angelis & Reade, 2023; Mochales Cuesta et al., 2024; Paulauskas et al., 2022). In this study, this pandemic may have temporarily shifted classification weights, making match outcomes and variables like 'Halftime Result' more dependent on pure tactical discipline rather than emotional crowd momentum. Furthermore, the predictive weight of the 'Halftime Result' confirms that early-game strategic consistency and tactical adjustments executed during the initial quarters establish a mathematical advantage that strongly correlates with the final match outcome. Notably, the model's ability to retain an 87.30% accuracy rate with only 15 refined variables nearly matching the 89.40% achieved with the full dataset underscores the immense predictive power of these specific attributes. Ultimately, the DL-ANN algorithm's capacity to deliver the lowest Rmse and highest accuracy across both datasets confirms that hybrid neural architectures are uniquely equipped to handle the multidimensional and non-linear complexities of professional basketball data. The results show that elite coaches achieve sustainable success not only through their game knowledge but also by optimizing the critical performance indicators coded as impacting the match result in the classification. The significant overlap between the statistical profiles of championship winning coaches and the effective variables determined by machine learning algorithms confirms that data mining algorithms can be utilized as a strategic decision support mechanism in sports sciences and technical management processes.

Conclusion and Recommendation

This study successfully investigated the structural determinants of match outcomes in elite European basketball by executing advanced machine learning and ensemble classification frameworks on an extensive eight season dataset of Fenerbahçe Beko's Euroleague campaigns. By evaluating data patterns across distinct head coaching eras, the algorithmic architectures demonstrated that victory in modern high stakes basketball is governed by a systemic interaction of defensive rebounding control and early game tactical consistency rather than isolated offensive outputs. The methodological pipeline proves that advanced ensemble techniques, specifically Dagging integrated with neural networks, offer superior predictive stability and granular insights into sports performance modeling.

The primary contribution of this research lies in its analytical utility, as it bridges the gap between raw box-score statistics and actionable courtside intelligence. By shifting the interpretive focus from descriptive statistics to predictive ensemble modeling, the framework provides sports scientists and tactical managers with an objective, data-driven approach to benchmark complex performance structures. This methodological execution successfully highlights how advanced machine learning applications can transform retrospective seasonal data into highly functional evaluation profiles.

Based on these insights, several forward-looking recommendations are proposed for future research. First, subsequent studies should incorporate real-time tracking data and shot-chart metrics to better capture the spatial and fluid dynamics of offensive and defensive sets. Second, the classification framework could be extended to include longitudinal data from multiple teams across the entire Euroleague organization to comprehensively test the global generalizability of the developed models. Finally, integrating live match streams into deep learning architectures would allow for the development of dynamic, in-game predictive models, substantially optimizing immediate tactical decision-making processes on the court.

The scope of the study is limited to the Euroleague competitions played by the Fenerbahçe Beko basketball team across eight seasons, spanning from the 2017-2018 season to the 2024-2025 season. Classification performances within the study were measured exclusively using Artificial Neural Networks (ANN), deep learning-based DL-ANN, and Dagging-ANN, which is an ensemble learning approach. Furthermore, in determining the variables affecting Fenerbahçe Beko's match outcomes, 15 effective variables were identified solely by utilizing the Filtered Attribute Feature Selection algorithm.

Ethics

There are no ethical issues regarding the publication of this article.

Conflict of Interest

The author declares that he has no conflict of interest.

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