Application of the DBSCAN method in analyzing aerobic and anaerobic thresholds in athletes – A new approach to data segmentation in sports training

Dariusz Kaczmarek, Michał Hamela and Marcin Mokrzycki

Politechnika Opolska, Prószkowska 76, Opole, 45-758, Poland

ARTICLE INFO

Keywords:
DBSCAN
Aerobic Threshold
Anaerobic Threshold
Data Clustering
Athlete Performance
Density-Based Clustering

ABSTRACT

This article explores the application of the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) method in analyzing aerobic and anaerobic thresholds in athletes. Identifying these physiological thresholds is essential for optimizing training programs and improving athletic performance. Traditional approaches often rely on predetermined threshold values, which may not accurately reflect the diverse physiological profiles of athletes. DBSCAN, a clustering algorithm that groups data points based on density, offers a data-driven approach to segmenting threshold data without prior assumptions. By leveraging this method, we can better identify unique patterns in oxygen and lactate levels, providing more personalized and adaptive training insights. This approach holds promise for enhancing training efficacy and tailoring programs to individual athletes' needs, thereby advancing the field of sports science.

1. Introduction

Lactate analysis has long been central to sports science, providing insights into an athlete's metabolic responses under varying exercise intensities (1; 2). For over two centuries, researchers have explored lactate's role in both anaerobic and aerobic glucose metabolism, generating ongoing discussions around its measurement and interpretation. Concepts such as the lactate threshold, lactate turn point, onset of blood lactate accumulation (OBLA), maximal lactate steady state (MLSS), anaerobic threshold, ventilatory threshold, and individual anaerobic threshold have introduced valuable, yet sometimes confusing, metrics for performance assessment (3). These thresholds underpin a tri-phasic model of energy delivery and lactate production, distinguishing aerobic (AeT) and anaerobic thresholds (AnT), which are critical for assessing an athlete's endurance and overall performance (4).

The aerobic and anaerobic thresholds are key markers in evaluating an athlete's capacity and performance level. They offer insights into physiological capabilities, highlighting an athlete's ability to manage and clear lactate, a byproduct of intense exercise that can contribute to fatigue. Higher AeT and AnT values indicate a more efficient physiological system, often correlating with greater endurance. Athletes with elevated thresholds can sustain high-intensity exercise longer without significant fatigue, a crucial factor in endurance sports like long-distance running, cycling, or triathlons (1; 2; 5; 6; 7).

AeT and AnT are connected to different energy systems, and understanding these thresholds helps athletes target the appropriate energy systems for various types of sports. Training within AeT and AnT zones aligns exercise intensity with the athlete's physiological capacity, leading to more efficient and targeted training outcomes (1). Athletes and coaches use these thresholds to fine-tune training intensities and prevent overtraining, which can lead to burnout and potential injuries if unmanaged.

Moreover, knowledge of AeT and AnT can guide tactical decisions in team sports. Coaches may use this information to make strategic substitutions or adjust tactics based on the athlete's current energy levels (8; 9). Recognizing the signs of overtraining, as indicated by AeT and AnT data, enables immediate intervention, such as reducing training intensity, incorporating rest days, or modifying the training program to allow recovery (10).

In recent years, machine learning (ML) techniques have become instrumental in predictive analysis across multiple domains, including sports science (11). Among these techniques, the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm has shown promise for identifying patterns in complex, multidimensional datasets. In the context of sports performance, DBSCAN can be effectively used to cluster physiological data, such as heart rate, oxygen consumption, and blood lactate levels, allowing for the identification of distinct performance zones corresponding to the aerobic threshold (AeT) and anaerobic threshold (AnT) (12; 13; 14). By grouping similar data points and distinguishing outliers, DBSCAN provides a robust approach for analyzing the variability and transitions between these thresholds.

This study aims to assess the potential of DBSCAN in accurately identifying AeT and AnT by clustering physiological data and comparing the resulting clusters with thresholds determined by conventional methods. Utilizing DBSCAN's capacity to reveal underlying patterns in physiological responses, we seek to enhance our understanding of these thresholds, thereby supporting a more individualized approach to athlete performance and endurance training.

2. Literature review

The determination of parameters for endurance training, applicable to both professional and amateur athletes, relies on various established systems. A critical component of this process involves defining heart rate zones. These zones can be derived through traditional methods, such as exercise intensity levels recommended by the American College of Sports Medicine (15), or by using metrics like maximum heart rate, heart rate reserve, or oxygen uptake reserve (16; 17; 18). Such methodologies have proven invaluable for athletes and their coaches in developing training plans. However, they are not without limitations. For instance, estimating maximum heart rate often depends on age-based formulas, which have significant drawbacks. The standard deviation of these methods ranges from ±10 to ±12 bpm, frequently overestimating maximum heart rate in younger individuals while underestimating it in older populations (17).

Despite their popularity, there is substantial evidence (5; 6; 7) suggesting that using percentages of VO2max or HRmax to define exercise intensities is insufficient. Factors such as individual variability, age-related changes, fitness levels, and methodological imprecision contribute to these shortcomings. Research highlights that a more precise approach involves determining training intensities based on metabolic variables (19). As exercise intensity increases, the body transitions through distinct energy utilization phases, marked by two key metabolic thresholds: aerobic threshold (AeT) and anaerobic threshold (AnT) (1; 2; 12; 13; 20; 21).

These thresholds can be identified during progressive exercise tests by monitoring heart rate (for runners) or power output (for cyclists), while measuring blood lactate concentration or analyzing ventilation and gas exchange indices (VO2 and VCO2) (20; 21; 22). Visually, the AeT corresponds to the point on the lactate curve where it deviates from the baseline, while the AnT represents the onset of accelerated lactate accumulation. Anoula and Rusko (23) define these thresholds as approximately 2 mmol/L and 4 mmol/L of lactate concentration, respectively, but emphasize the need to account for individual variability.

The D-max method is one of the most popular techniques for determining AnT. This method involves connecting a straight line between the first and last measurement points on a graded exercise test and identifying the point on the lactate curve farthest from this line (17; 22; 24). An alternative approach is respiratory gas exchange analysis, which allows for automated threshold detection. This not only accelerates the analysis process but also improves the accuracy of threshold identification (25). Among the various methods, the ventilatory equivalent method is regarded as one of the most reliable (26). It calculates thresholds based on the ventilatory equivalent for oxygen (VE/VO2) and carbon dioxide (VE/VCO2), identifying key points such as Ventilatory Threshold 1 (VT1) and Ventilatory Threshold 2 (VT2). These thresholds correspond to transitions between aerobic and anaerobic metabolism (23; 25; 27).

Despite these advancements, the determination of AeT and AnT thresholds is not without challenges. There is a lack of consensus among researchers regarding precise definitions and protocols. Traditional laboratory methods, such as frequent blood sampling during intense exercise to measure lactate concentration, are invasive and impractical. Furthermore, interpreting the results often requires expertise, limiting accessibility for broader use.

Recent studies suggest that heart rate variability (HRV) might offer a viable alternative for determining cardiorespiratory fitness thresholds. HRV-based metrics, which are non-invasive and easier to measure, have shown promise in identifying thresholds automatically through machine learning techniques (28). However, a comprehensive review assessing how closely HRV-derived thresholds align with established concepts is still lacking (29; 30). Further research is essential to validate these methods and integrate them into practical applications for athletes and coaches.

3. Objective of the work

The aim of this study is to conduct a comprehensive analysis of data concerning the aerobic and anaerobic thresholds of athletes using the DBSCAN clustering method. The key aspects of the study include:

3.1. Understanding and identifying patterns

- Investigating how various factors, such as the type of sport, training level, age, and gender, influence athletes' aerobic and anaerobic thresholds.

- Analyzing the data will allow for the identification of specific patterns that may indicate different training strategies or potential areas for improving performance.

3.2. Application of the DBSCAN Algorithm

- Using the density-based spatial clustering algorithm DBSCAN (Density-Based Spatial Clustering of Applications with Noise) to cluster the data. DBSCAN is particularly useful in situations where the data is heterogeneous and contains noise, which is typical for sports data.

- Careful configuration of the algorithm's parameters, such as the neighborhood radius (epsilon) and the minimum number of points (minPts) in a cluster, to achieve optimal clustering results.

3.3. Analysis of results

- Conduct a detailed analysis of the clustering results to determine the characteristics of the different groups of athletes, as well as the differences and similarities in their aerobic and anaerobic thresholds.

- Visualization of clusters using appropriate graphical techniques, such as scatter plots, 3D plots, and other data visualization methods, to facilitate the interpretation of the results.

3.4. Training recommendations

- Developing personalized training programs based on the results of the clustering. These recommendations will take into account the individual needs of athletes in the context of their performance and training goals.
- Investigating how appropriate adjustments to training programs based on identified groups can enhance training effectiveness and contribute to better sports performance.

3.5. Practical application of results

- The study aims not only to theoretically develop a clustering method but also to provide practical tools for coaches and athletes that can be used in daily training and competition preparations.
- The application of the research findings in sports practice can contribute to a better planning of training cycles and increase the efficiency of preparatory processes.

3.6. Conclusions and future research directions

- Summarizing the main findings and conclusions resulting from the analysis of data clustering, and indicating possible directions for further research in this area.
- Proposing future research steps that could expand the understanding of phenomena related to sports performance and their applications in practice.

4. Methodology

- **Data Collection:** The analysis will be based on the results of the fitness tests carried out on a group of athletes. In the absence of access to data, it may be possible to use public data or conduct original tests.
- **Statistical Analysis:** Applying statistical analysis tools for preliminary data processing, including normalization, outlier removal, and exploratory data analysis.
- **Use of Computational Tools:** Implementing the DBSCAN algorithm in Python, utilizing libraries such as scikit-learn and pandas for data analysis and visualization.

5. Expected outcomes

- Enabling a better understanding of the dynamics of athletes' performance based on their results in aerobic and anaerobic tests.
- Developing practical tools and strategies for coaches that can lead to improved outcomes in sports performance.
- Creating a foundation for further research into the application of data analysis methods in sports.

This work aims at not only theoretical advancement but also practical application of modern data analysis methods in the field of sports, which may contribute to innovations in training approaches and athlete preparation.

6. Dataset description

Below is a description of a dataset that contains the results of graded exercise tests conducted on a group of 161 amateur athletes.

6.1. General information

- **Number of records:** 161
- **Number of variables:** 29
- **Participants:** Men (1) and women (0).
- **Age range:** 16–62 years (*Mean:* 36.1, *Std:* 10.84).
- **Disciplines:** Running, triathlon, kickboxing, skiing, handball, MMA, football, basketball, cross-fit, hokey, wrestling, ice skating, martial arts.

6.2. Key variables

1. **Demographics:**
   - *sex:* Gender of the participant (1 - male, 0 - female).
   - *age:* Age of the participant (in years).
   - *height* and *weight:* Physical attributes (cm and kg).
2. **Performance metrics:**
   - *AeT* (Aerobic Threshold) and *AnT* (Anaerobic Threshold): Key thresholds determined during the test.
   - *vo2max:* Maximal oxygen uptake (ml/min/kg), an indicator of aerobic capacity.
   - *hrmax:* Maximum heart rate achieved during the test (bpm).
   - *r:* Recovery time (minutes).
3. **Heart rate and lactate data:**
   - *hr_6*, *hr_8*, *hr_10*, etc.: Heart rates recorded at various treadmill speeds (6–22 km/h).
   - *la_8*, *la_10*, *la_12*, etc.: Lactic acid concentrations at the respective speeds of the treadmill.
4. **Heart rate zones:**
   - *z2* to *z5*: Heart rate zones for different intensity levels:
     - Zone 2: Aerobic endurance.
     - Zone 3: Aerobic power (mixed zone).
     - Zone 4: Aerobic-anaerobic threshold.
     - Zone 5: Anaerobic endurance.
5. **Additional measurements:**
   - *vo2_at*: VO2 at the aerobic threshold.
   - *ve*: Ventilatory equivalent.
   - *rf*: Respiratory factor.
   - *vo2max_l_m*: Absolute VO2 max (liters/min).

6.3. Data collection context

The dataset was collected during a controlled graded to failure test on a treadmill, with continuous monitoring of respiratory, cardiovascular and metabolic parameters. Heart rates and lactate concentrations were recorded at various stages to define individual training zones.

7. Algorithms and methods used

The Jupyter Notebook employs various algorithms and techniques for data analysis, preprocessing, and clustering. These are described below:

7.1. Data preprocessing

- **Exploratory Data Analysis (EDA):** The dataset is analyzed using descriptive statistics (`describe()`), pair plots (`sns.pairplot()`), and box plots for identifying outliers.

- **Handling Missing Values:** Missing values in the dataset are filled using strategies such as:

  - Mean imputation for continuous variables like *weight* and *height*.
  - Median imputation for variables like *age* and *vo2max*.

- **Feature Scaling:** The dataset is normalized using `StandardScaler` to standardize features before clustering.

7.2. Clustering algorithms

- **DBSCAN (Density-Based Spatial Clustering of Applications with Noise):**

  - This algorithm is used to group data points into clusters based on density.
  - Key parameters include:
    * `eps`: Maximum distance between two samples for them to be considered as in the same neighborhood.
    * `min_samples`: Minimum number of points required to form a dense region.
  - The `NearestNeighbors` algorithm is used to estimate the optimal `eps` parameter by analyzing the k-distance plot.

7.3. Dimensionality reduction

- **Principal Component Analysis (PCA):**

  - PCA is applied to reduce the dimensionality of the dataset while retaining most of the variance.
  - It helps visualize the data in lower-dimensional space, making clustering results more interpretable.

7.4. Validation metrics

- **Silhouette Score:**

  - This metric is used to evaluate the quality of clustering by measuring how similar each data point is to its own cluster compared to other clusters.
  - A higher silhouette score indicates better-defined clusters.

7.5. Visualization techniques

- `Seaborn` and `Matplotlib` are extensively used for visualizing data distributions, relationships, and clustering results.

- K-distance plots are employed to determine the optimal `eps` parameter for DBSCAN.

8. Visualizations and Results

8.1. Pairplot analysis

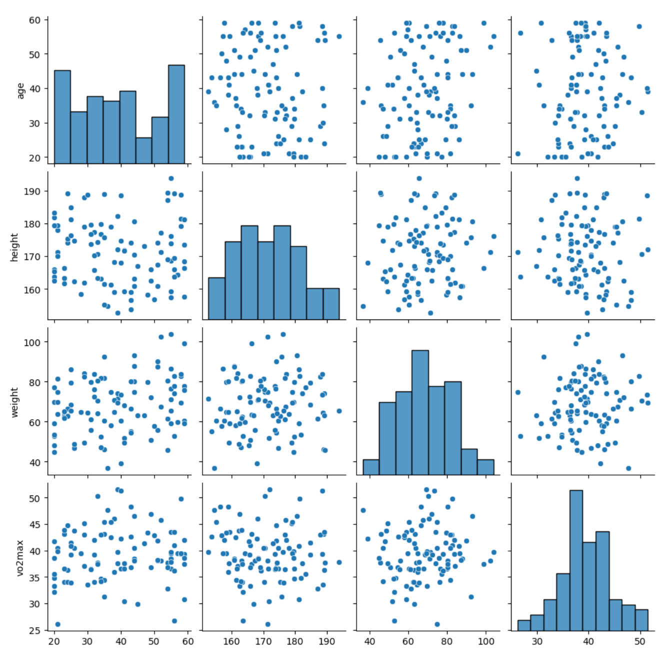

Figure 1: Pairplot showing the relationships between age, height, weight, and VO2max.

The pairplot (Figure 1) serves as a foundational tool for visual exploration of the dataset. It visualizes the pairwise relationships among key variables: **age**, **height**, **weight**, and **VO2max**, providing insights into both individual variable distributions and their interdependencies.

8.1.1. Distribution Insights

The diagonal subplots display the histograms of each variable. These plots reveal critical information about the data distribution:

- **Age:** The histogram of age shows a relatively normal distribution with a slight skew toward younger individuals, indicating the sample may be biased toward younger or middle-aged participants.
- **Height and Weight:** Both height and weight exhibit expected distributions for an athletic population, with a noticeable clustering in ranges typical for endurance athletes.
- **VO2max:** The VO2max histogram highlights a peak around certain fitness levels, likely corresponding to recreationally trained individuals. The tail of the distribution suggests a smaller subgroup of elite athletes with exceptionally high VO2max.

8.1.2. Scatterplot Relationships

The off-diagonal scatterplots offer pairwise comparisons, revealing potential trends and clusters. For instance:

- **Height vs. Weight:** A strong positive trend is observed, consistent with general anthropometric relationships.
- **Weight vs. VO2max:** The scatterplot suggests a subtle inverse relationship, where lower body weights may correspond to higher VO2max values, reflecting the advantage of a lower body mass in endurance sports.
- **Age vs. VO2max:** A weak negative trend is noticeable, aligning with the known physiological decline in VO2max with age.

Interestingly, the data also exhibit clustering patterns that could suggest subgroupings based on fitness levels, training status, or physiological traits. These patterns motivate further clustering analysis to delineate the structure within the data.

8.2. DBSCAN clustering results

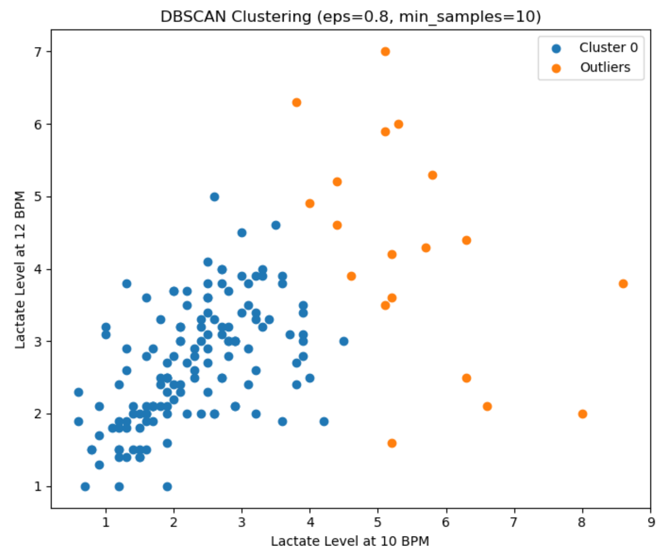

Figure 2: DBSCAN clustering results for lactate levels at configuration: *eps*=0.8, *min_samples*=10

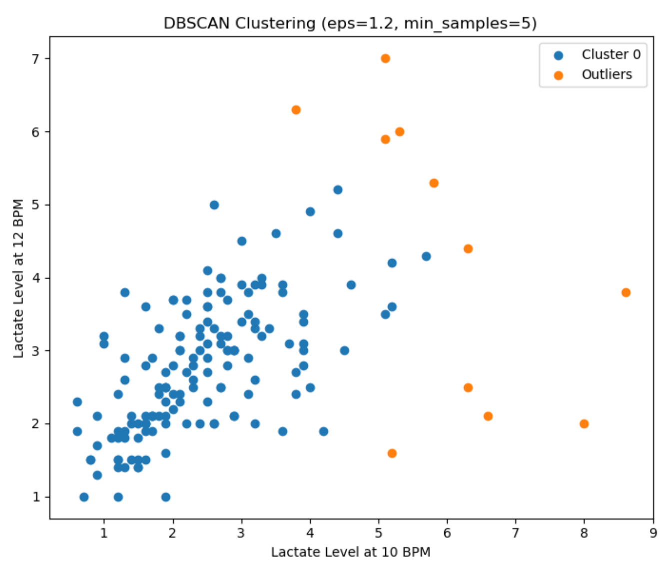

Figure 3: DBSCAN clustering results for lactate levels at configuration: *eps*=1.2, *min_samples*=5.

The DBSCAN algorithm was applied to analyze lactate levels across different heart rates, revealing the natural structure within the data. Two parameter configurations were tested to assess the impact of algorithm sensitivity:

- **Configuration 1:** *eps*=0.8, *min_samples*=10.
- **Configuration 2:** *eps*=1.2, *min_samples*=5.

8.2.1. Results from Configuration 1

With stricter parameters (*eps*=0.8, *min_samples*=10), the algorithm identified a limited number of clusters with more outliers. This approach emphasizes well-separated data groups:

- **Cluster Characteristics:** These clusters likely represent individuals with distinct lactate response profiles, such as those who exhibit a sharp lactate rise at lower heart rates versus those with a more gradual response.
- **Outliers:** The high number of outliers indicates that many data points do not conform to the stringent clustering criteria, potentially highlighting atypical physiological responses or measurement noise.

8.2.2. Results from Configuration 2

Relaxing the parameters (*eps*=1.2, *min_samples*=5) resulted in more inclusive clustering:

- **Cluster Characteristics:** The clusters formed under this configuration capture broader patterns and reduce the number of outliers. While these clusters are less precise, they are useful for identifying general trends across the population.
- **Insights:** This configuration may be particularly beneficial for analyzing heterogeneous datasets, such as mixed populations of elite athletes and recreational participants.

8.3. VO2max distribution in clusters

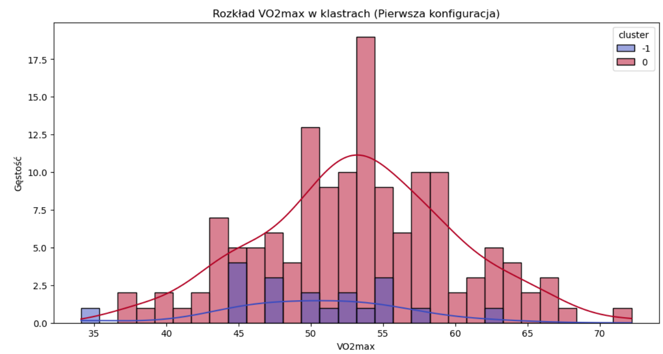

Figure 4: VO2max distribution across clusters for the first configuration. (*eps*=0.8, *min_samples*=10)

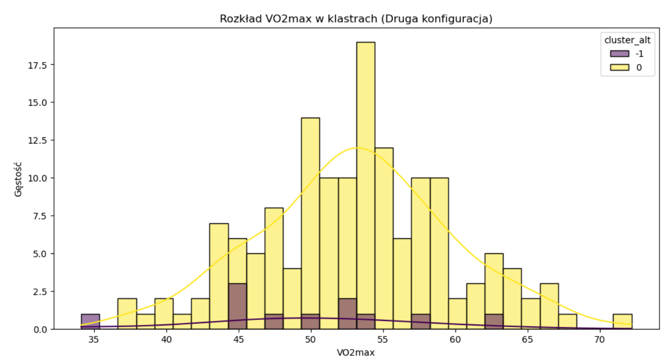

Figure 5: VO2max distribution across clusters for the second configuration. (*eps*=1.2, *min_samples*=5)

Figures 4 and 5 focus on the distribution of VO2max values within the clusters identified by DBSCAN. This analysis is crucial for understanding how physiological traits vary across the dataset:

- **Cluster Comparisons:** Clusters with higher VO2max values are associated with athletes possessing superior aerobic capacity. These clusters may correspond to individuals who regularly engage in endurance training or exhibit a genetic predisposition for high aerobic performance.
- **Variability in VO2max:** The density plots within clusters highlight the degree of intra-cluster variability. Clusters with narrow VO2max ranges suggest homogeneity in aerobic capacity, while broader ranges may indicate diverse training backgrounds or varying fitness levels.
- **Outlier Behavior:** Outliers from DBSCAN clustering often exhibit extreme VO2max values, which could correspond to either highly trained elite athletes or individuals with abnormal physiological profiles.

This visualization underscores the utility of clustering for segmenting athletes based on fitness levels, providing actionable insights for individualized training prescriptions.

8.4. Heatmap visualization of DBSCAN clustering

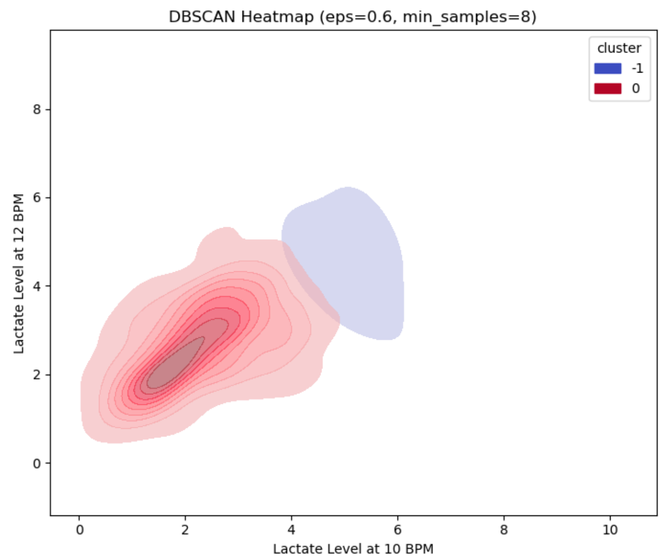

Figure 6: Heatmap visualization of DBSCAN clustering results for lactate levels (*eps*=0.6, *min_samples*=8).

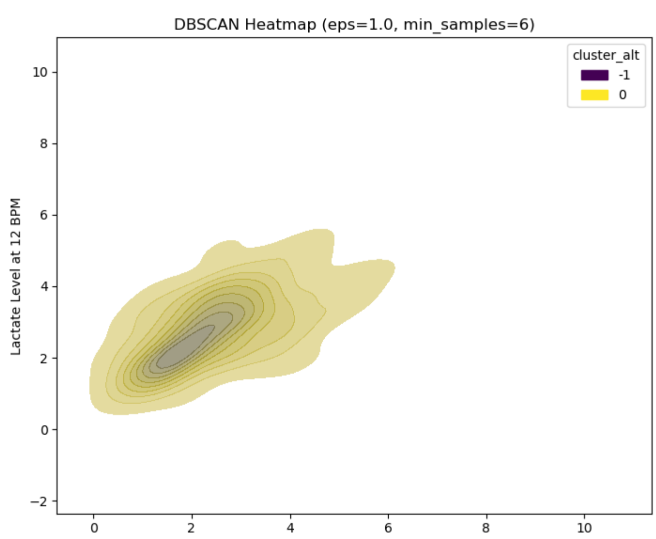

Figure 7: Heatmap visualization of DBSCAN clustering results for lactate levels (*eps*=1.0, *min_samples*=6).

Heatmaps were generated to complement the scatterplot results and provide a detailed visualization of data density across clusters (Figures 6 and 7). The heatmaps highlight regions of high-density clustering and sparse areas, offering additional clarity to the results of DBSCAN:

- **Configuration 1 (eps=0.6, min_samples=8):** The heatmap reveals compact, well-defined clusters with distinct boundaries. Darker regions represent areas of high-density data points, corresponding to physiological thresholds, such as lactate turn points. These areas are particularly relevant for defining training zones.
- **Configuration 2 (eps=1.0, min_samples=6):** A more relaxed configuration captures broader clusters, resulting in larger contiguous high-density areas. While the boundaries between clusters become less distinct, this visualization highlights global trends in the data.

8.4.1. *Physiological Interpretation*

The heatmaps provide valuable physiological context to the DBSCAN results:

- **High-Density Regions:** These regions may correspond to key physiological states, such as the aerobic-anaerobic transition zone, where lactate begins to accumulate exponentially.
- **Sparse Regions:** Low-density areas often indicate outliers or transitional states that do not fit neatly within defined physiological thresholds. These points may represent individuals with atypical responses or inconsistent data.

9. Conclusion

The analysis highlights the effectiveness of DBSCAN clustering in identifying patterns and outliers within datasets involving physiological measurements. While the clustering parameters significantly influence results, the visualizations provide meaningful insights into relationships among variables, particularly VO2max and lactate levels.

Future analyses could explore additional clustering methods, such as hierarchical or k-means clustering, to compare results. Parameter optimization through grid search or cross-validation may also improve clustering accuracy. Moreover, integrating additional variables, such as training intensity or duration, could further enhance understanding of athlete performance and recovery patterns.

References

[1] Ghosh AK. Anaerobic threshold: its concept and role in endurance sport. *The Malaysian Journal of Medical Sciences: MJMS*. 2004; 11:24–36. PMID: 22977357.

[2] Faude O, Kindermann W, Meyer T. Lactate threshold concepts: how valid are they? *Sports Medicine*. 2009; 39:469–490. PMID: 19453206.

[3] Krishnan A, Guru CS, Sivaraman A, Alwar T, Sharma D, Angrish P. Newer Perspectives in Lactate Threshold Estimation for Endurance Sports—A Mini-Review. *Central European Journal of Sport Sciences and Medicine*. 2021; 35:99–116. https://doi.org/10.18276/cej.2021.3-09.

[4] Binder RK, Wonisch M, Corra U, Cohen-Solal A, Vanhees L, Saner H, et al. Methodological approach to the first and second lactate threshold in incremental cardiopulmonary exercise testing. *European Journal of Cardiovascular Prevention and Rehabilitation*. 2008; 15:726–734. https://doi.org/10.1097/HJR.0b013e328304fed4. PMID: 19050438.

[5] Neufeld EV, Wadowski J, Boland DM, Dolezal BA, Cooper CB. Heart Rate Acquisition and Threshold-Based Training Increases Oxygen Uptake at Metabolic Threshold in Triathletes: A Pilot Study. *International Journal of Exercise Science*. 2019; 12:144–154. PMID: 30761193.

[6] Meyer T, Gabriel HHW, Kindermann W. Is determination of exercise intensities as percentages of OV_{O2max} or HR_{max} adequate? *Medicine and Science in Sports and Exercise*. 1999; 31:1342–1345. https://doi.org/10.1097/00005768-199909000-00017. PMID: 10487378.

[7] Lounana J, Campion F, Noakes TD, Medelli J. Relationship between Medicine and Science in Sports and Exercise. 2007; 39:350–357. https://doi.org/10.1249/01.mss.0000246996.63976.5f. PMID: 17277600.

[8] Piero DWD, Valverde-Esteve T, Castań JCR, Pablos-Abella C, Díaz-Pintado JVSA. Effects of work-interval duration and sport specificity on blood lactate concentration, heart rate and perceptual responses during high intensity interval training. *PLOS ONE*. 2018; 13(7):e0200690. https://doi.org/10.1371/journal.pone.0200690.

[9] Hwang JH, Moon NR, Heine O, Yang WH. The ability of energy recovery in professional soccer players is increased by individualized low-intensity exercise. *PLOS ONE*. 2022; 17(6):e0270484. https://doi.org/10.1371/journal.pone.0270484. PMID: 35771850.

[10] Yu Y, Li D, Lu Y, Jing M. Relationship between methods of monitoring training load and physiological indicators changes during 4 weeks cross-country skiing altitude training. *PLOS ONE*. 2023; 18(12):e0295960. https://doi.org/10.1371/journal.pone.0295960. PMID: 38100499.

[11] Krishnan A, Sivaraman A, Alwar T, Sharma D, Upadhyay V, Kumar A. Relevance of lactate threshold in endurance sports: a review. *European Journal of Pharmaceutical and Medical Research*. 2020; 7:513–524.

[12] Etxegarai U, Portillo E, Irazusta J, Arriandiaga A, Cabanes I. Estimation of lactate threshold with machine learning techniques in recreational runners. *Applied Soft Computing*. 2018; 63:181–196. https://doi.org/10.1016/j.asoc.2017.11.036.

[13] Huang S, Casaburi R, Liao M, Liu K, Chen YJ, Fu T, et al. Noninvasive prediction of Blood Lactate through a machine learning-based approach. *Scientific Reports*. 2019; https://doi.org/10.1038/s41598-019-38698-1. PMID: 30778104.

[14] Govers R. Predicting Heart Rates Of Sport Activities Using Machine Learning;. Available from: http://essay.utwente.nl/85685/1/Govers_BA_EEMCS.pdf.

[15] Medicine ACOS. ACSM's guidelines for exercise testing and prescription. 9th ed. Wolters Kluwer/Lippincott Williams Wilkins Health; 2014.

[16] Traninger H, Haidinger M, Zemljic-Harpf AH, Harpf HH. Personalized determination of target training heart rates for all ages, including patients with heart disease. The FASEB Journal. 2020; 34:1–1. https://doi.org/10.1096/fasebj.2020.34.s1.03824

[17] Marx A, Porcari J, Doberstein S, Arney B, Bramwell S, Foster C. The Accuracy of Heart Rate-Based Zone Training using Predicted versus Measured Maximal Heart Rate. Int J Res Ex Phys. 2018; 14:21–28.

[18] Hofmann P, VON Duvillard SP, Seibert FJ, Pokan R, Wonisch M, Lemura LM, et al. HRmax target heart rate is dependent on heart rate performance curve deflection. Medicine Science in Sports Exercise. 2001; 33:1726–1731. https://doi.org/10.1097/00005768-200110000-00017 PMID: 11581558

[19] van Loon, L.J.C., Greenhaff, P.L., Constantin-Teodosiu, D., Saris, W.H.M., Wagenmakers, A.J.M. The effects of increasing exercise intensity on muscle fuel utilisation in humans. *The Journal of Physiology*. 2001; 536:295–304. https://doi.org/10.1111/j.1469-7793.2001.00295.x PMID: 11579177.

[20] Dumke, C.L., Brock, D.W., Helms, B.H., Haff, G.G. Heart rate at lactate threshold and cycling time trials. *The Journal of Strength Conditioning Research*. 2006; 20:601. https://doi.org/10.1519/R-17525.1 PMID: 16977709.

[21] Dolezal, B.A., Storer, T.W., Neufeld, E.V., Smooke, S., Tseng, C.H., Cooper, C.B. A Systematic Method to Detect the Metabolic Threshold from Gas Exchange during Incremental Exercise. *Journal of Sports Science Medicine*. 2017; 16:396–406. PMID: 28912658.

[22] Nascimento, E.M.F., Antunes, D., do Nascimento Salvador, P.C., Borszcz, F.K., de Lucas, R.D. Applicability of Dmax Method on Heart Rate Variability to Estimate the Lactate Thresholds in Male Runners; 2019. Available from: https://www.hindawi.com/journals/jsm/2019/2075371/.

[23] Aunola, S., Rusko, H. Aerobic and Anaerobic Thresholds Determined from Venous Lactate or from Ventilation and Gas Exchange in Relation to Muscle Fiber Composition. *International Journal of Sports Medicine*. 1986; 07:161–166. https://doi.org/10.1055/s-2008-1025755 PMID: 3733312.

[24] Chalmers, S., Esterman, A., Eston, R., Norton, K. Standardization of the Dmax Method for Calculating the Second Lactate Threshold. *International Journal of Sports Physiology and Performance*. 2015; 10:921–926. https://doi.org/10.1123/ijspp.2014-0537 PMID: 25710184.

[25] Santos, E.L., Giannella-Neto, A. Comparison of computerized methods for detecting the ventilatory thresholds. *European Journal of Applied Physiology*. 2004; 93:315–324. https://doi.org/10.1007/s00421-004-1166-6 PMID: 15349782.

[26] Okano, A.H., Altimari, L.R., Moraes, A.C., Teixeira, O., Ravagnani, F.C.P., Coelho, C.F., et al. Comparison between individual anaerobic threshold and ventilatory threshold determined in cyclists. *Medicine Science in Sports Exercise*. 2003; 35:S118. https://doi.org/10.1097/00005768-200305001-00642.

[27] Anselmi, F., Cavigli, L., Pagliaro, A., Valente, S., Valentini, F., Cameli, M., et al. The importance of ventilatory thresholds to define aerobic exercise intensity in cardiac patients and healthy subjects. *Scandinavian Journal of Medicine Science in Sports*. 2021; 31:1796–1808. https://doi.org/10.1111/sms.14007 PMID: 34170582.

[28] Kaufmann, S., Gronwald, T., Herold, F., Hoos, O. Heart Rate Variability-Derived Thresholds for Exercise Intensity Prescription in Endurance Sports: A Systematic Review of Interrelations and Agreement with Different Ventilatory and Blood Lactate Thresholds. *Sports Medicine—Open*. 2023; 9. https://doi.org/10.1186/s40798-023-00607-2 PMID: 37462761.

[29] Mongin, D., Chabert, C., Extremera, M.G., et al. Decrease of heart rate variability during exercise: An index of cardiorespiratory fitness. *PLOS ONE*. 2022; 17(9). https://doi.org/10.1371/journal.pone.0273981 PMID: 36054204.

[30] Rogers, B., Berk, S., Gronwald, T. An Index of Non-Linear HRV as a Proxy of the Aerobic Threshold Based on Blood Lactate Concentration in Elite Triathletes. *Sports*. 2022; 10(2):25. https://doi.org/10.3390/sports10020025 PMID: 35202064.