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Identification of high-performance volleyball players from anthropometric variables and psychological readiness: A machine-learning approach

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Abstract

Modern indoor volleyball has evolved into a high-level strength sport and is seen as one of the most popular open-skilled team sports. The nature of the sport as an open-based skill requires players to have a high degree of both psychological skill and physical ability to cope with the sport's externally and internally induced pace. The purposes of this study were to examine the essential basic anthropometric variables, as well as competition and practice psychological readiness, that could provide a performance edge and identify high and low-performance players based on the parameters. The anthropometric variables of height, weight, and age were assessed, while the test for performance strategies instrument was used to evaluate competition and practice psychological readiness skills of the players. The players' performances were analyzed in real-time during a volleyball tournament. The Louvain clustering algorithm was used to determine the performance class of the players with reference to the variables evaluated. A total of 45 players were ascertained as high-performance volleyball players (HVP), while 20 players were deemed as low-performance volleyball players (LVP) via the clustering analysis technique. The logistic regression classifier was used to classify the performance of the players. Nonetheless, owing to the skewed representation between the HVP and LVP during the training of the model, the Synthetic Minority Oversampling TEchnique (SMOTE) was employed to artificially increase the minority class dataset to avoid the overfitting notion upon classification. It was shown from the study that, through the machine learning pipeline developed, an excellent identification of the HVP and LVP could be attained. The findings could be invaluable to coaches and other relevant stakeholders in team preparation and the selection of high-performance players in volleyball.

Keywords

Anthropometric index, psychological readiness, indoor volleyball, high-performance players, logistic regression, SMOTE

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Introduction

Volleyball is a popular sport played in countries throughout the world at varying levels of expertise. Typically, volleyball is considered a team sport that involves frequent short bouts of high- and low-intensity jumping and strolling activity.[1] The characteristic of the sport as an open based skill requires players to possess a high level of psychological skills, as well as physical prowess, to cope with the externally and internally induced pace of the sport. The players are expected to quickly make decisions and align their skills to the changing or otherwise unpredictable competitive environment. On a 900 ft^2 court with six players on each

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side of the net, players must attenuate the opposing players from hitting the ball across to their side of the court, coordinate team movement via reading the game, and react and move rapidly while the ball is in play. Hence, the players may not have control over what happens during the game. However, to ensure success during the game and effectively execute the skills, the possession of certain performance elements become imperative.

Several studies have examined the physical and physiological characteristics of volleyball players at both elite and amateur levels.[2–5] The anthropometric profile and somatotype characterization of elite volleyball players are not only important to determine the physical condition of the athletes, but also for their potential performance in relation to their function during the game.[6] For instance, a recent study that compared the anthropometric measurement and body composition between junior basketball and volleyball players of the Serbian National League documented that the basketball and volleyball players were significantly taller and heavier than the recreational players.[2] However, there was no significant difference in the body height and body weight between the basketball and volleyball players. These findings contradict previous research, in which significant differences were reported in most of the anthropometry components examined between basketball and volleyball players. The basketball players had significantly greater values of height, weight, body surface, body fat percentage, total body fat, and fat free mass components as compared to volleyball players. Nonetheless, the volleyball players had significantly greater body density as compared to basketball players.[7]

The application of psychological strategies is crucial for athletes, as it promotes better coping skills during competition.[8,9] During competitions, athletes are expected to deliver their best performance, irrespective of the physiological and psychological factors inherent in the sport.[10] The ability of an athlete to perform under any circumstances defines the worth of the athlete on the team. Moreover, sporting competition, especially at the elite level, is undertaken in an environment that is characterized by a high level of stress and arousal due to the desire attached to winning the competition.[11] The stress involved is described as an uncomfortable mental situation or disorder, marked by subjective feelings of tension, fear, and concern.[12] This stress is generally referred to as pre-competition stress or fear in the athletics context. Furthermore, studies have shown that fear has a negative impact on sports outcomes.[13] Therefore, the use of certain psychological strategies to curtail the aforesaid stressors, as well as improve performance in sports, has significantly evolved in the contemporary sporting domain.[14] The application of such psychological strategies is crucial for the athletes, as it promotes better coping skills during competitions.[8,9]

The utilization of machine learning has gained popularity due to attention in recent years within the sporting domain, particularly in activity recognition,[15–17] match outcome predictions[18–20] and performance analysis[9,21,22] amongst others. For instance, van den Tillaar et al.[23] evaluated the classification of different handball throws, apart from the prediction of ball velocity, through the employment of different supervised machine learning models. A classification accuracy (CA) between 79% and 87% was reported to be attained via the Gradient Boosting Machine, while an excellent prediction of the ball speed was obtained through a variation of the Support Vector Machine (SVM) model. Conversely, Liu et al.[24] investigated paddle stroke classification of female kayakers using a variety of machine learning models with data captured via inertial measurement units (IMUs). From that study, it was shown that the SVM and k-Nearest Neighbor (kNN) model could attain a CA up to 98.98% in identifying different paddle strokes.

Nonetheless, it is worth mentioning that despite the wide popularity of indoor volleyball, limited studies have thus far endeavored to employ machine learning in the identification of players' performance class with respect to the anthropometric characteristics and psychological readiness of the players. Therefore, this study attempted to examine the influence of anthropometric variables coupled with the psychological readiness skill toward the identification of high-performance volleyball players via machine learning techniques.

Materials and method

Participants

The participants in this study included 24 teams that were involved in the 2020 UMT open volleyball tournament held in Terengganu, Malaysia. The teams, which consisted of male players, were assigned to a group of four (Group A–F) in a typical congested fixture tournament schedule. Each of the above-mentioned teams is considered an elite team with players having an average of at least 6 years of volleyball playing experience. Moreover, a number of the players on some of the teams have already represented their states/country in both national and international competitions. Before beginning the data collection, all the coaches, managers, and organizing committee were informed about the aim of the study and verbal consent was obtained via the Universiti Malaysia Terengganu 2020 Volleyball Technical Committee (VBALL2020-29-JLD-UMT).

Anthropometric characteristics and psychological skill readiness assessments

Before the beginning of the tournament, basic player information regarding their standing height, age, and weight, as well as years of playing experience, was recorded. The standing height was collected in cm to the nearest 0.5 cm, while the weight was obtained in kg to the nearest 0.01 kg.[25] For the psychological readiness assessment, the test for performance strategies instrument (TOPS) originally developed and validated by the preceding researchers was utilized to assess the psychological readiness of the players in the current investigation.[26] The TOPS assessed sixteen psychological coping strategies during competition and training. The coping strategies for the competition scale constituted self-talk, activation, imagery, emotion control, automaticity, relaxation, and goal setting, as well as negative thinking. The scale evaluated the psychological variables during training, except for negative thinking, which was replaced by attentional control. The players completed the TOPS inventory and the summation of the scores for each player was used. Internal consistency reliability was carried out to ascertain the consistency of the responses on the items of the instrument. A Cronbach's alpha coefficient analysis was used to assess the level of consistency among the items, ensure that the items were evaluating a single construct (unidimensional), and confirm that the players' responses were autonomous to one another.[27] An acceptable coefficient value of the items was found ranging from 0.78 to 0.89, reflecting that the responses of the players on the instrument were consistent and reliable.[28]

Notational analysis for performance evaluation

A total of eight technical and tactical performance parameters were considered for evaluating the performance of all the players on the 24 teams. The performance parameters of Ace, Block, Set, Spike, Fault, Tap, Dig, and Passing were used to analyze the players' performance in real-time. The selection of the aforesaid performance parameters was made based on their relevance to the game of volleyball, as highlighted in some of the previous studies.[29,30] A StatWatch application, a notational analysis framework built on an android application, was utilized as the device for assessing the performance of the players and teams in accordance with the protocols previously reported by the previous investigators.[31] Twelve experienced performance analysts were responsible for notating the performance of each player, such that each analyst covered one particular player at a time. The performance analysts were trained on the performance parameters selected before the beginning of the analysis. Using video from a separate match, reliability analysis was conducted. To maintain accuracy and test the observational errors on the selected performance parameters, the performance analysts were advised to notate the match separately and then their analyses were compared. The Cohen's Kappa statistical test and Cronbach's alpha analysis were used to assess the analysts' consensus and consistency with respect to the performance parameters.[32] A Kappa of .92 and a Cronbach's alpha of .96 were found, suggesting a high level of consensus and accuracy in the analysis between the performance analysts. It is important to note that players who were unable to play at least 70% of the matches were not considered for the final analysis in this study.

Statistical analysis

Clustering technique

The Louvain clustering algorithm was employed to establish the performance class of the players. The algorithm is considered as one of the modern clustering algorithms that is powerful in grouping data or a set of observations into a meaningful class(es). The algorithm is built to perform a task following two distinctive steps. In the first step, the algorithm aims for a "thin" group by maximizing the modularity in a traditional technique. In the second step, the algorithm puts together nodes of related communities and thereafter creates a distinctive community, thus creating a new network of nodes of communities.[33] These processes can be performed iteratively until a modularity criterion is reached. This also contributes to the hierarchical disintegration of the system and formation of many partitions.[34] The performance of the players, anthropometric variables, score summation of the players in the competitional strategic elements, as well as in the practice scales, were used as input variables for the clustering analysis. The clustering analysis is essentially applied to ascertain the performance group of the players in order to give room for the assignation of class membership based on all the aforementioned variables.[35,36]

Classification

In the present study, a conventional supervised machine learning model (i.e. the logistic regression) was employed. The cost function for the model was based on the "sigmoid" or "logistic" function that limits the decision boundary of the output classes between the probability score of 0 and 1. As reported in the literature, the aforesaid classifier does reasonably well in classifying binary problems.[18,37–40] The dataset was split into training and test with a stratified ratio of 70:30. Therefore, a total of 65 datasets (45 from high-performance volleyball players (HVP) and 20 from low-performance volleyball players (LVP)) were used for training, while 28 datasets (20 from HVP and 8 from LVP) were used as a test dataset. Nonetheless, owing to the skewed (class-imbalanced) nature of the dataset upon clustering as illustrated in Figure 1, the Synthetic Minority Oversampling TEchnique (SMOTE) was utilized in order to increase the training dataset to mitigate the overfitting notion that may arise from the skewed training dataset.[41,42] SMOTE, which was introduced by Chawla et al.[43] is an oversampling technique that creates synthetic minority class samples, which was considered LVP for this study. SMOTE creates the new synthetic samples by leveraging the k-nearest neighbors for each minority class sample and randomly

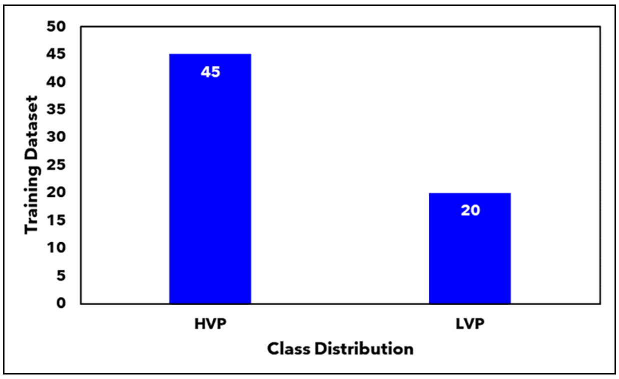

Figure 1. Class distribution attained by the Louvain clustering algorithm in demarcating the high-performance volleyball players (HVP) and low-performance volleyball players (LVP).

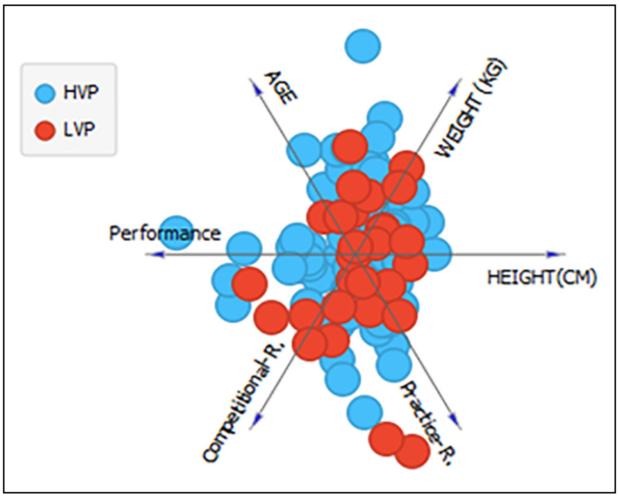

Figure 2. Class membership allotted by the Louvain clustering algorithm.

interpolating between them. The features were then transformed via standardization, as shown in equation (1), prior to being fed into the machine learning model.

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

In this equation, μ is the mean and σ is the standard deviation. The analysis was carried out via Spyder IDE (an open-source platform licensed by MIT) running on Python 3.7. The scikit-learn, as well as its associated libraries, were utilized in the present investigation.

Results

Figure 2 projects the clusters allotted by the Louvain clustering algorithm with respect to the evaluated parameters in this investigation. Two clusters were observed based on the similarities in the characteristics of the variables assessed. The figure further illustrates that the scores of the clusters within each of the variables evaluated were somewhat unique, which is important in assigning the identity to each of the clusters, either HVP or LVP.

Table 1 tabulates the descriptive as well as the inferential statistics of the variables investigated. The mean and standard deviation of each cluster, along with the corresponding p values, were projected. The clusters appeared to be different in the performance of the variables assessed, as shown by the HVP scoring higher in most of the variables including competitional readiness, practice readiness, weight, age, and volleyball performance delivery. No significant difference was observed in the height between the HVP and LVP.

Once the classes were discernable via the clustering technique, the features were transformed via the standardization technique. In the first analysis, the dataset was used as-is to train the model before testing them based on the 70:30 ratio. For this analysis, a classification accuracy of 100% was achieved for both test and training datasets. However, for the initial training dataset, a total of 45 HVP and 20 LVP were recorded. The confusion matrix of the training dataset based on original clustered data is shown in Figure 3. Hence, in order to avoid the overfitting notion that arises from the skewed dataset, the SMOTE technique was employed and artificially increased the LVP data to 45 to obtain an equal representation of HVP:LVP. The analysis was then run again considering the new training dataset and it was found that this analysis could also achieve a classification accuracy of 100% for both training and testing (the test dataset was not altered). The confusion matrix of the training dataset after employing SMOTE is depicted in Figure 4, while the test dataset is shown in Figure 5.

Discussion

The current investigation aimed at identifying HVP with reference to anthropometric variables coupled with psychological readiness. To achieve the aforesaid objective, the anthropometric characteristics of height, weight, and age were recorded, while the psychological readiness of both competitional and practice scales was determined using a previously developed questionnaire (i.e. a test of performance strategies (TOPS)). The performance ability of the players was evaluated in real-time during a congested fixture tournament that lasted two consecutive days. A machine learning analysis, namely cluster analysis, was used to group the players based on their performance levels (i.e. high or low performance). In addition, a logistic regression model was also used to classify the grouping of the players that was made earlier. Moreover, analysis of variance (ANOVA) was employed to ascertain the differences between the HVP and LVP with respect to the anthropometric characteristics, coupled with the psychological readiness and the performance delivery evaluated.

Table 1. Physical characteristics and psychological readiness variations between the two clustered groups of players.

Performance variables	HVP		LVP		Significance
	Mean	Std. dev.	Mean	Std. dev.	
Height (cm)	174.62	10.40	174.86	6.59	0.712
Weight (kg)	73.72	19.99	63.64	18.20	0.016*
Age (year)	24.62	5.85	21.14	2.62	0.003*
Competitional-readiness	31.09	3.58	24.95	2.31	0.001*
Practice-readiness	31.28	3.20	24.95	2.02	0.001*
Volleyball performance	17.98	16.47	8.29	7.50	0.007*

*$p < 0.05$.

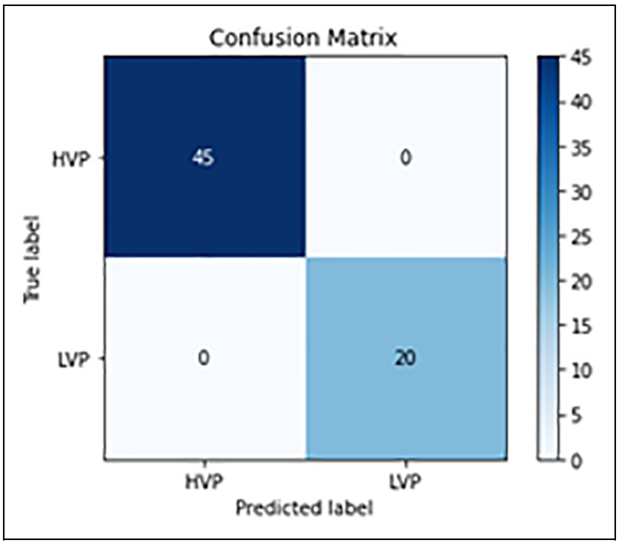

Figure 3. Confusion matrix of the training dataset before SMOTE.

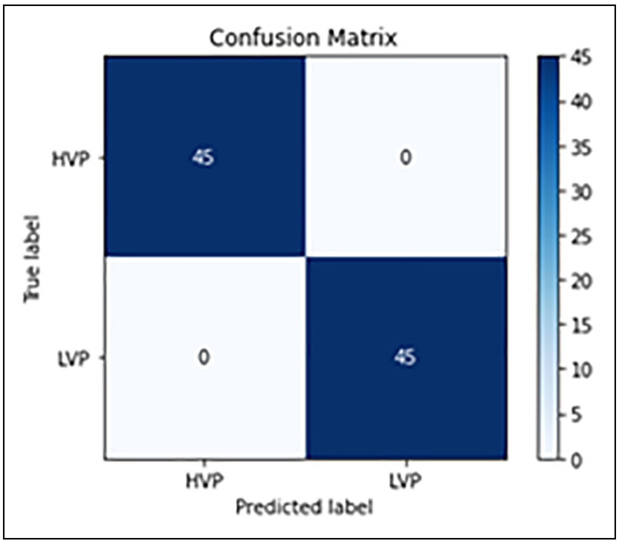

Figure 4. Confusion matrix of the training dataset after SMOTE.

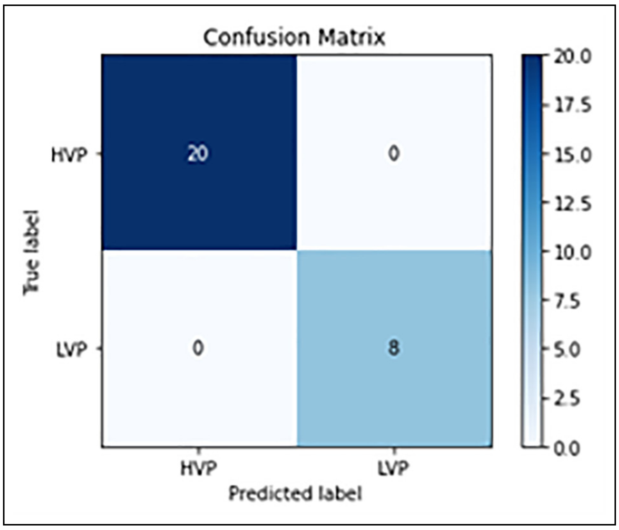

Figure 5. Confusion matrix of the test dataset.

Based on the findings of the current investigation, the HVP significantly differed from LVP in psychological strategies (i.e. competitional and practice readiness), coupled with age and weight as shown in Table 1. The demands for various forms of sports skills and training have greatly increased. The gaps between the players' physical performance and achievement are close. Thus, psychological abilities have become increasingly important, such that several coaches and team managers have stressed the significance of psychological abilities toward the attainment of athletic excellence.[11,13,14,44–46] The findings of this study are unanimous with previous investigations, which demonstrated that successful elite volleyball players possessed a better mental fitness compared to unsuccessful players.[46] The authors further inferred that the successful players have a high level of self-confidence, better concentration, and mental toughness, which shield them from being affected by emotions and hitherto demonstrate more successful delivery of performance.

The findings from the present investigation also demonstrated that there is a strong association between volleyball performance ability and physical characteristics in unification with age. Physical attributes, such as body composition, are reported to be vital in the classification, as well as differentiation of athletic performances.[8,36,47,48] The detailed information about the players' anthropometric characteristics, primarily their body weight and age, as well as their performance ability, could be used as reference values in the a team's selection and training process.[49–51] Furthermore, as volleyball players attain the peak level of performance age, these variables could guide the coach in team management.[52] Age also provides a temporal reference for estimating how long it would take to reach optimum efficiency. The machine learning approach employed in the current study serves useful in the identification of high-performance players. The efficacy of the logistic regression model in providing an excellent classification of the players is important in revealing the performance variables that could be used to ascertain the players' performance levels. Machine learning models have been reported to be effective in solving classification problems in a myriad of studies.[21,53–56] In the present study, the ability of the classification model in demonstrating an excellent classification of the players reflects the importance of the selected variables.

Conclusion

Based on the findings of the current investigation, successful performance in elite men indoor volleyball tournaments could be influenced by the players' body structure and age. In addition, HVP were essentially better in psychological readiness, both during practice and competition, while LVP were found to be associated with low psychological readiness. Moreover, a logistic-based classification model was found to be effective in the identification of the performance classes of the players, which is important in mapping out the high-performance players from a combination of anthropometric characteristics and psychological readiness variables. The findings herein could be beneficial to coaches and other relevant stakeholders to make an informed decision when preparing teams and selecting players in this sport.

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