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Data Mining Analysis of Overall Team Information Based on Internet of Things

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ABSTRACT In professional basketball games, big data has been largely used in analyzing the reasons for winning or losing games and further to design relevant stratagem according to the analytic results to attain victory. Nonetheless, the High School Basketball League (HBL) in Taiwan never used big data or relevant research to analyze game results. The study aims to conduct big data analyses to discuss the key winning factors and trends for HBL. Using Excel and multiple linear regression to understand the importance level and trend of each variable to the winning rate. Additionally, combining with the Support Vector Machine (SVM) prediction to confirm whether the big data analytic result is applicable for implementing in realistic games. After implementing the analysis of multiple linear regression, based on the yearly trends, the significant influence factors are 2P%, 3P%, FTM, TRB, OREB, STL, and TOV. Consequently, the prediction has reached 85% after inputting these data into SVM.

INDEX TERMS Internet of Things, data mining, e-sports, spectator sport.

I. INTRODUCTION

Basketball is a popular sport around the world; because it is a team sport, the techniques instructed by coaches and the overall team member performance will influence the win rate in a game. Literature [1] has suggested that the personal decision-making of the coach and the attitudes of being positive or negative toward the game of overall team members have an impact on the game performance. Therefore, apart from examining the performance of Point Differential (PD), it is necessary to review whether the strategies suggested by the coaches are appropriate. On the other, literature [2] also pointed out that many fans only focus on personal records; yet, basketball relies heavily on teamwork, excellent personal records do not mean to possess higher win rates. Hence, literature [3] mentions that basketball teams usually cooperated with one single coach in the past; with the trend of American basketball education, which emphasizes on teamwork, many countries today tend to hire coaching teams to improve the training of individual players and to decide tactics based on the coaching team's opinions during a game, which could avoid lowering down win rates by misjudged strategies. Nonetheless, many Taiwanese basketball teams belong to schools or organizations that only have limited budgets for training, it is difficult for them to hire coaching teams to develop personal training and team decision-making. The methodology offered by this research enables basketball teams to examine game strategies from previous records and to consider if they should adjust and improve the skills of a player. The approach in this study can enhance the self-improvement of a team and further to increase the win rate.

Literature [4] uses cameras to video game processes for analyzing each player's capabilities and team tactics, as well as reviewing multimedia materials to determine fouls and judgements. Thus, video analysis has gradually become a surveillance system in games for developing game control and post-game analyses. Moreover, literature [5] suggests the technique of Wild-Open Warning for assisting basketball coaches and players to comprehend the tactics of their opponents; the system can also track the movements of players. Literature [6] proposes a strategic simulation system for players and coaches to simulate the offensive and defensive reactions of the opponents. Literature [7] mainly utilizes virtual reality to train players and offensive and defensive stratagems under diverse court environments. Literature [8] presents a method to predict the best players in professional basketball matches. Literature [9] implements a virtual-reality system

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for players to practice in different conditions, such as three-on-three games, which makes players conduct virtual practices similarly to playing games. The approach demonstrated in this article emphasizes various analytic items in a game to investigate coaching strategies and define whether a player is offensive or defensive. Through the algorithm in this research to boost the training styles of a team and its strategic applications.

The study proposes an algorithm to analyze the overall team effectiveness based on data mining that takes High School Basketball League (HBL) as the research subject. Because of high schools usually only one coach in a team, which the overall stratagems and training rely heavily on the coach. To increase the average win rate of the team, the study analyzed the team performance of Points (PTS) and Point Allowed (PA) in all of the matches during the past year for further discussion. The calculations of the algorithms in the study are 1. to calculate the team Efficiency (EFF) of the year for understanding the current match style and trends of a team; 2. using multiple linear regression to analyze team stratagems; combing with the gaming curves to examine whether the stratagems were positive while comprehending the PTS conditions in each analytic item to adjust the skills of the players; 3. conducting the Support Vector Machine (SVM) algorithm to judge the predictions of various analytic items toward win rates. The approach offered by this article empowers coaches and players to understand if it is necessary to amend a strategy effectively; on the other hand, it helps a team to know the win rates. The experiment has proved that the methodology is feasible and assists coaches and player to know their overall trends better via analytic curves.

II. RELATED WORKS

In the literature [10], it particularly introduces the analysis by taking videos via cameras, which can conduct slow-motion analysis for important moments such as goals and free throws. Additionally, the system can help referees to judge if there is a foul and remark the evidence for reference; literature [11] presents an electronic referee system for remarking fouls in videos, which an approach to implement image processing through machine learning and the analysis can be processed during the intermission to avoid post-game conflicts. For literature [12], it filters if fans bring dangerous objects into the court and analyzes diverse types of violent behaviors to avoid such kind of conditions in the public during outdoor activities. The surveillance system will examine if an object the fan carries is dangerous and continues judging if a violent behavior might happen. This system suggested by the literature is capable of analyzing crowd behaviors for the police to control violent issues rapidly. Literature [13] analyzes videos through Discrete Fourier Transform by judging human movements for behavioral analysis.

The electronic referee system suggested by literature [14] is to do slow motion and zoom lens for behavioral analysis, which could additionally discuss the technical terms and meanings of the commentators. Furthermore, the system enables users to find videos with fouls and understand the tactics through the explanation. Literature [15] uses the scenes in the court to locate camera positions and support cameras to track the trajectories of a player quickly for videoing by different angles. Literature [16] implements gamification to recognize the strategies and temples of a player. The example of the research was using the system in training football players that helps them to realize the strategic applications of the team for promoting the familiarity toward a stratagem. Literature [17] mainly talks about the calculation of personal PTS from videos. Firstly, it sorts the teams by jerseys and recognizes the numbers on it; later, the system will track the jersey numbers to track and analyze behaviors for recording personal PTS. The system is capable of reducing the personnel costs of scoring staff while calculating the total PTS of each player rapidly. Literature [18] recommends a method to judge whether the gestures of a referee and the foul video of a player is reasonable; apart from validating the foul, it determines if the judgement is reasonable.

Literature [19] mainly focuses on lowering down the numbers of camera sets, to learn foul and PTS conditions via the words of commentators and relevant information instead. Lastly, literature [20] offers a video system that could capture video clips of PTS and important moments directly, which enables coaches and players to learn the stratagems of opponents. The study is beneficial for coaches and players to absorb information about tactics and skills in a short time. Therefore, this article presents an analysis by multiple linear regression to investigate team stratagems and uses the SVM algorithm to calculate gaming records and predict win rates. The method in this research is valuable for coaches and players to learn their overall team performance and PA conditions based on their past games, which supports them to review if they need to adjust the strategy to promote win rates.

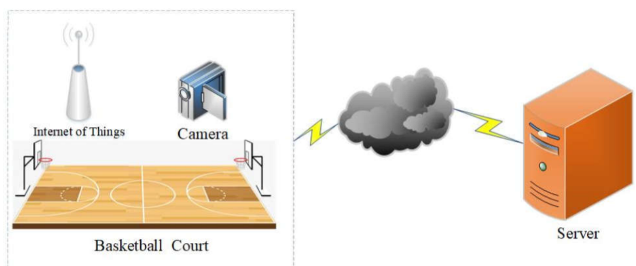

FIGURE 1. System illustration.

III. SYSTEM MODEL

The system model is shown as Figure 1, which is to set a touch backboard in the basketball court; to record the PTS result of each scoring on the board and send the scores to the server. Moreover, the completed process will be videoed, the data will also be sent to the server for records. With the gaming data, the algorithms will calculate the curves of win rate, multiple linear regression, and match predictions.

Under the analysis of game results, because many teams belong to the same coach and the coach usually has a certain strategic operation, it becomes possible to understand whether a strategy is successful from win rates and PTS conditions. On the other hand, according to game records and predictions, it helps to acquire gaming styles and the required techniques for winning; coaches could decide to adjust strategies and the tactics of players from the analysis, which will raise win rates and skills.

A. RESEARCH DATA

The research takes the participant teams in HBL as research targets and collects the match data from the HBL website at Yahoo Sports between 2016 and 2018. There were a total of 42 male basketball teams and 17 female basketball teams; from 2016 to 2018, there are total 1,185 matches including qualifiers, preliminaries, second rounds, semifinals, and finals. The offensive and defensive records In each game are total 21 items: EFF, PTS, PA, PD, 2-point Field Goals Made (2PM), 2-point Field Goals Attempted (2PA), 2-point Field Goals Percentage (2P%), 3-point Field Goals Made (3PM), 3-point Field Goals Attempted (3PA), 3-point Field Goals Percentage (3P%), Free Throws Made (FTM), Free Throws Attempted (FTA), Free Throws Percentage (FT%), Offensive Rebounds (OREB), Defensive Rebounds (DREB), Total Rebounds (TRB), Assists (AST), Steals (STL), Blocks (BLK), Team Fouls (TF), and Turnovers (TOV). After organizing the data into the computer, the study utilizes software such as SPSS17.0, Excel, and Weka to analyze the data into curve calculations, multiple linear regression, and SVM data mining.

IV. THE PROPOSED SCHEME

A. DATA CALCULATIONS FOR GAME CURVES

Firstly, the research calculates the EFF for the further analyses of PTS, PA, PD, 2PM, 2PA, 2P%, 3PM, 3PA, 3P%, FTM, FTA, FT%, OREB, DREB, TRB, AST, STL, BLK, TF, and TOV. Afterward, to draw the yearly curves for understanding the gaming trends. The study will divide the gaming data according to the values of each year for attaining three final values for 2016, 2017 and 2018. Next, to draw the trend curves by Excel as shown in Figure 2, which enables coaches to see the current gaming trends and plan relevant gaming strategies according to the trend changes.

B. MULTIPLE LINEAR REGRESSION

Multiple linear regression could be applied to discuss the relationship of a dependent variable with multiple variables; through analyzing the relationships between independent variables (x) and the dependent variable (y) to develop a correlation model that provides researchers to investigate into the interested dependent variable (y). The formula of the multiple linear regression is $y = a + b_1x_1 + b_2x_2 + \ldots + b_f x_f$ (there are F numbers of dependent variables in total); $b_1, b_2, \ldots, b_f$ are the regression coefficients that represent the prediction

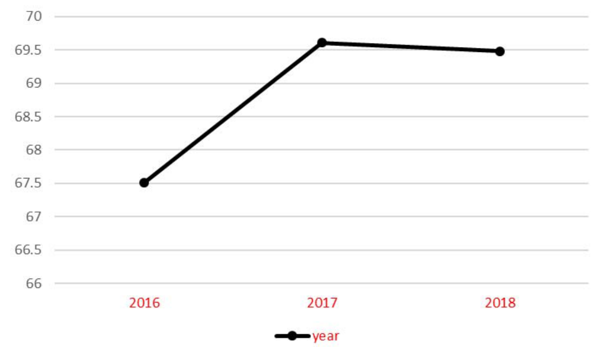

FIGURE 2. Trend predictions based on the yearly gaming data.

abilities of F numbers of variables, $x_1, x_2, \ldots, x_f$ toward y. The original prototype model is set as:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_f x_f + \varepsilon \tag{1}$$

Among the formula, β_0 is the intercept of the regression model, $\beta_1, \beta_2, \ldots, \beta_f$ are the unknown regression coefficients that required to estimate, and ε is the error term. The prediction model is then modified as below:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \ldots + \hat{\beta}_f x_f \tag{2}$$

The null hypothesis is $H_0 : \beta_1 = \beta_2 = \ldots = \beta_F = 0$ while the alternative hypothesis is $H_a : \beta_1, \beta_2, \ldots, \beta_F$ and not all of the values in H_a are 0. When at least one of the β values is not 0, the alternative hypothesis is accepted and the regression model prediction becomes valid.

The research aims to find out the influential factors toward win rates among various analytic items in HBL. Take the positive value of PD as the dependent variable example, PD equals the total PTS of a team minus the PA in the same match; a positive PD means the team wins the game and a negative value means lose. Because winning in a game is always the target of a team and this study aims to explore the influential factors; hence, the data collected in this research will only focus on winning teams and discuss the positive values of PD as the dependent variable while setting the rest of the analytic items, 2PM, 2PA, 2P%, 3PM, 3PA, 3P%, FTM, FTA, FT%, OREB, DREB, TRB, AST, STL, BLK, TF, and TOV as independent variables to discuss the impact of each item on the winning match. Afterward, to draw curves to find out the influence based on the gaming records toward positive PD, which could reveal the impact trend for winning in each year.

C. SUPPORT VECTOR MACHINE

Literature [21] has pointed out that the winning and losing results of basketball games could be predicted via SVM and the accuracy is above 85%. Linear SVM is applied by remarking each training data as "+1" or "−1" beforehand, the formula is shown as:

$$(x_1, y_1), \ldots, (x_i, y_i), \quad x_i \in R^d, \; y_i \in \{-1, 1\} \tag{3}$$

The data is remarked as "+1" or "−1" for better sorting the types and divide the shortest distances of the remarked "+1" and "−1". When Linear SVM is sorting the data, it will look for the maximal divided surface while the data should fulfill below two limited formulas:

$$x_i \cdot w + b \geqslant +1 \quad \text{for } y_i = +1 \tag{4}$$

$$x_i \cdot w + b \leqslant -1 \quad \text{for } y_i = -1 \tag{5}$$

The formulas (4) and (5) could be merged into below inequality:

$$y_i (x_i \cdot w + b) - 1 \geqslant 0 \quad \forall_i \tag{6}$$

Under the condition of formula (6), the research set the game results as the dependent variables, which is divided into two types, winning and losing.

This article utilizes SVM to discover the influential factors and predictions of win rates. Taking, 2PM, 2PA, 2P%, 3PM, 3PA, 3P%, FTM, FTA, FT%, OREB, DREB, TRB, AST, STL, BLK, TF, and TOV as the variables for data mining and to discuss the win rate predictions regarding these changes. Afterward, according to the predictions of 2016, 2017, and 2018 to draw curves for understanding the required skill trends in each winning games.

V. PERFORMANCE

A. DATA CALCULATION FOR MATCH CURVES

The EFF is a formula defined by National Basketball Association (NBA) to measure the performance of a team, the formula is EFF = (PTS + TRB + AST + STL + BLK) – (total goals attempted – total goals made) – (FTA – FTM) – TOV. The study firstly calculates the EFF and draws the trend curves after averaging the data. As shown in Figure 3, the EFF in 2016 is 63.8 and the value has increased to 70.6 in 2017; the result means the EFF of HBL is increasing and the performance of HBL teams is getting better as well. The following discussion will have a detailed analysis of other variables to recognize the growth of EFF.

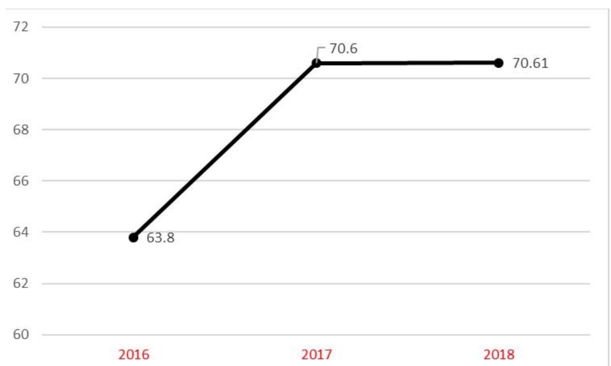

FIGURE 3. The trend of yearly EF.

This part discusses the differences between PTS, PA, and PD, as demonstrated in Figure 4, which helps to identify the offensive or defensive style of a team. Further, to analyze the variable trends of 2PM, 2PA, 2P%, 3PM, 3PA, 3P%, FTM, FTA, and FT%; the analytic results are shown in Figure 5, 6, and 7, for comparing the offensive ratios. Finally, Figure 7 and 8 show the variable trends of OREB, DREB, TRB, AST, STL, BLK, TF, and TOV to discuss the causes of EFF growth.

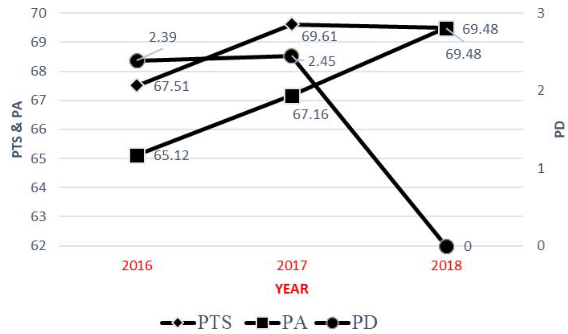

FIGURE 4. The trend of yearly PD.

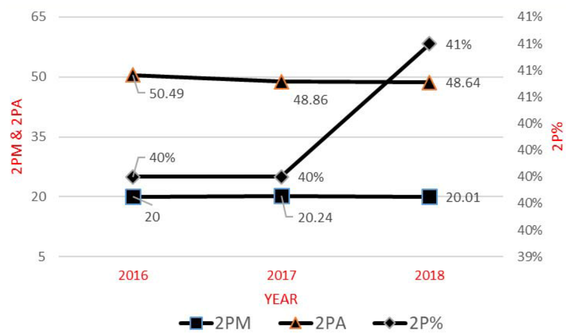

FIGURE 5. The trend of yearly 2-point field goals.

Figure 4 shows that PTS has been raised since 2017; yet, the difference is not significant. On the other hand, the yearly increase of PA also proved that the ability to make goals is improved among the teams. When comparing PD, the difference between PTS and PA narrows; this tells that there are more teams choose to do offensive style in games, which, in a way, increases PA.

Figure 5, based on the yearly statistical data of 2-point field goals, tells that there is a decreasing phenomenon. However, from the trend of 2P%, the numbers of 2PM have remained the same. The 2P% in 2018 has increased, which also proves that the offensive abilities of the teams are enhancing.

Based on Figure 6 of the data of 3-point field goals, the numbers of 3PA is growing; however, there is no significant difference in the data of 3PM, which is also obvious in the statistics of 3P%. The highest 3P% data is shown in 2017, which was only 26% and the data in 2016 and 2018 are both around 25%, this suggests these teams have to improve their abilities to make goals.

The data of free throws is shown in Figure 7; there is a decrease of FTA. Furthermore, from Figure 8 that tells about the trend of FT, there is also a decrease of FT, which explains the reason why about declining FTA. Nevertheless,

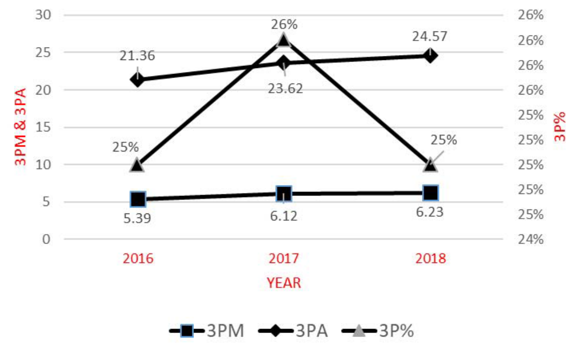

FIGURE 6. The trend of yearly 3-point field goals.

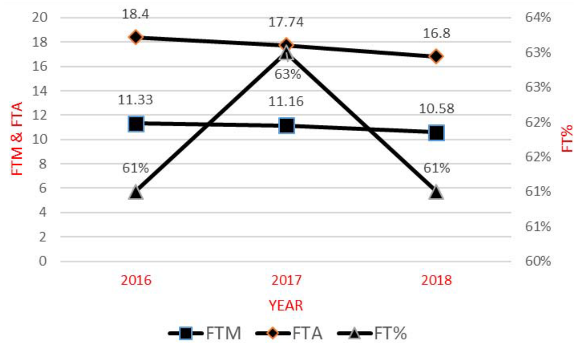

FIGURE 7. The trend of yearly free throws.

FT% is not enhancing, which means FTM is not improving. According to the data of FT%, only in the year of 2017 that reaches the highest FT% of 63% while the data is 61% in both 2016 and 2018; this shows that all of these teams require a boost in FT%.

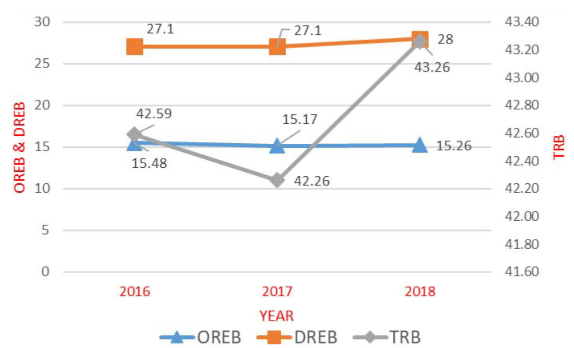

FIGURE 8. The trend of yearly rebounds.

Figure 8 is the statistical data of rebounds. The highest TRB data is in 2018, which has an average of 43.26 rebounds per game; in both 2016 and 2017, the average rebounds are around 42. For a detailed analysis, it shows that there is a decline in OREB but the difference is not significant. The data of DREB remains similar in both 2016 and 2017; only 2018 has a higher record of 28 DREB. This result echoes with the data of 3-point field goals shown in Figure 5; there is an increase in 3PA but does not have a growth in 3P%, which means the number of missing goals is also raising. On the other hand, the number of TRB in 2017 is slightly lower, it is probably related to the better performance of 3-point field goals and FT% that shows in Figure 6 and Figure 7.

Figure 9 presents that there is a yearly rise of AST, which means the offensive abilities of the teams are improving, as well as their teamwork. Regarding the data of STL; however, although the result is not obvious, there are some highs and lows; this tells that these teams have improved in their basic skills, made the opponents more difficult to steal the ball and decreased the number of STL. The record of BLK also has a declining trend, this means the skills of the team and the players are progressing. The decrease of BLK is also noticeable from the data of TF and TOV, which are both having a yearly drop; this also proves that the progress of team and player skills has caused less TF and TOV.

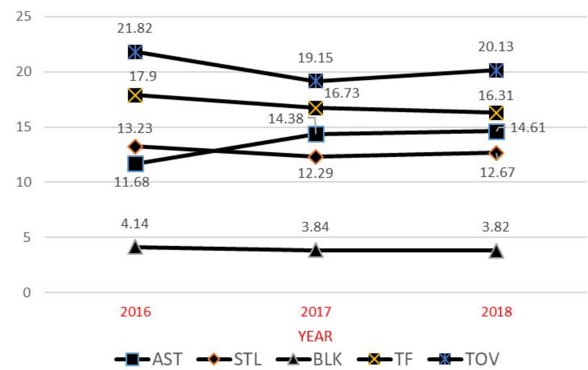

FIGURE 9. The trend of yearly records.

According to the experimental results, the increase of EFF is due to various factors, for example, the development of PTS, rebounds, and AST and the decrease of 2PA, FTA, and TOV. The result has proved that the basic abilities of the teams are improving; thus, advancing the data.

B. EXPERIMENTAL ANALYSIS OF MULTIPLE LINEAR REGRESSION

This part discusses the correlation of each analytic item toward winning a game by conducting multiple linear regression, which helps to recognize the gaming style of each team. Take the positive values of PTS and PA as dependent variables and set other gaming data as independent variables, this study analyzes the correlations of independent variables and the positive values of PTS and PA; After implementing the analysis of multiple linear regression, based on the yearly trends, the significant influence factors are 2P%, 3P%, FTM, TRB, OREB, STL, and TOV. The formula that influences the winning rate showed in this research gives readers a better understanding of the correlation between those indicators. further, preparing the curve figure of each data for demonstrating the influence.

$$\begin{aligned}\text{Formula} = {} & 0.27 \times 2PM + 0.34 \times 3PM + 0.55 \times TRB \\ & + 0.48 \times STL - 0.43 \times TOV \text{ - } 0.43 \times 2PA\end{aligned}$$

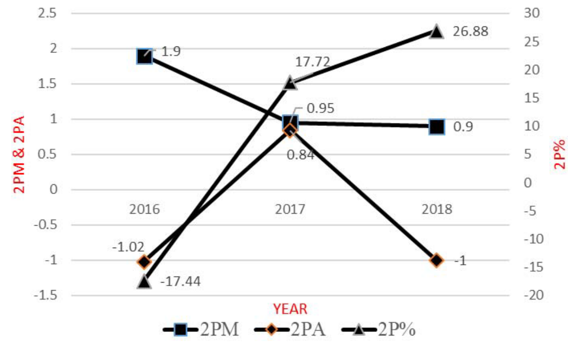

FIGURE 10. The multiple linear regression of 2-point field goals.

$$- 0.49 \times 3PA + 0.08 \times FT\% + 0.5 \times BLK + 0.04 \times AST + 0.12 \times 2P\% \quad (7)$$

From Figure 10, it is obvious that the influence of 2-point field goal is becoming more significant; the gap of yearly differences are also bigger, this says that a lower 2P% might lower down the winning rate. Yet, the impact of 2PM seems to be less significant recently because the data has become stable since 2017. Hence, there exists a certain influence in 2PM; nonetheless, that data of 2P% still dominates winning rates. Players should not make 2-point field goals without concerns; if a team aims to increase 2PM by more 2PA, it might lose the game.

The result in Figure 11 shows that the influence of 3-point field goals toward winning has increased from −12.01 to 17.69 between 2016 and 2018; this reveals that 3-point field goals are becoming more important and it might have an impact on winning. Conversely, 3PM has a lower influence on winning, the data has decreased from 2.19 to 1.19 from 2016 to 2018. 3PA on winning is always a negative influence, which means if a team wants to increase 3PA without improving its 3P%, the team might not be able to win the game.

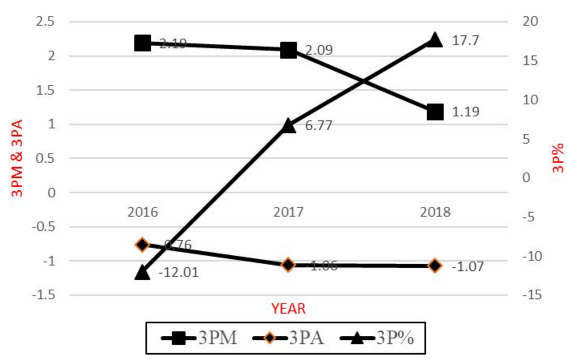

FIGURE 11. The multiple linear regression of 3-point field goals.

According to Figure 12, in the data of free throws, only FTM presents a positive influence on winning while both FTA and FT% have a negative impact during the three years to 2018. Consequently, if a team has a higher FT%, it might still lose the game if it does not maintain a higher FTA that leads to a lower FTM. As a result, among the analytic items of free throws, FTM occupies the most important role.

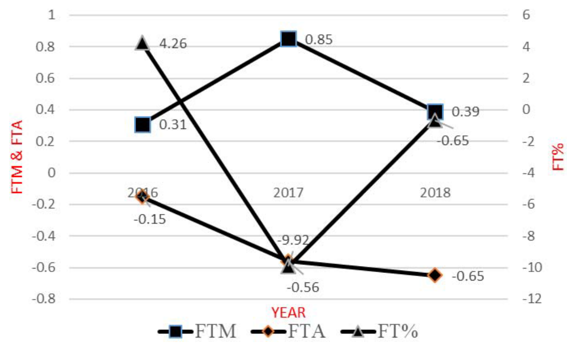

FIGURE 12. The multiple linear regression of free throws.

Figure 13 tells that the influence TRB is becoming more major; however, when looking into the details, it is found that the key influence toward winning is usually due to OREB. Because the impact of DREB is getting minor, in the future, basketball team should focus more on the main effect of OREB to achieve winning.

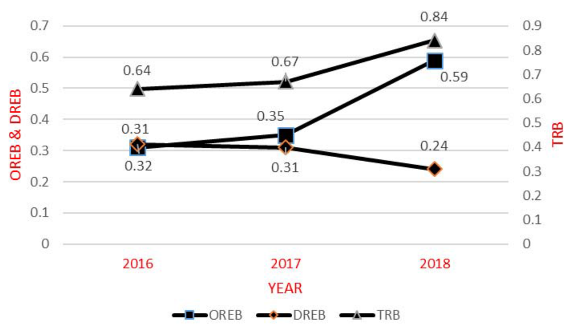

FIGURE 13. The multiple linear regression of rebounds.

From Figure 14, it tells that the impact of AST is becoming weaker, the data of it has dropped from 0.21 to 0.15 between 2016 and 2018. Yet, the influence of STL is increasing from 1.44 to 1.82 between 2016 and 2018. This is because STL reaches more possibilities to do fast break and make goals, which improves the importance of STL and develops an impact on winning. The trend of BLK varies, the value reaches the highest to 0.6 in 2018 while the values in the other two years are 0.27 and 0.17. TF has a negative influence on the game; nonetheless, the influence is becoming weaker. For instance, the influence is only −0.02 in 2018 and 0.2 in the other two years. TOV also has a negative impact, the value from −0.74 to −1.34 from 2016 to 2018, which means the negative influences are becoming major. Therefore, the more TOV a team has, the more chances it will lose the game. In sum, the most significant influence factor is STL, the value is 1.82, the following are BLK (0.60), AST (0.15), and the others are negative influences, TF and TOV, with the values of −0.02 and −1.34.

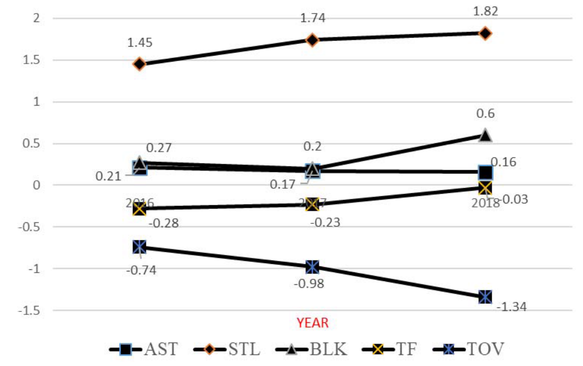

FIGURE 14. The multiple linear regression of other analytic items.

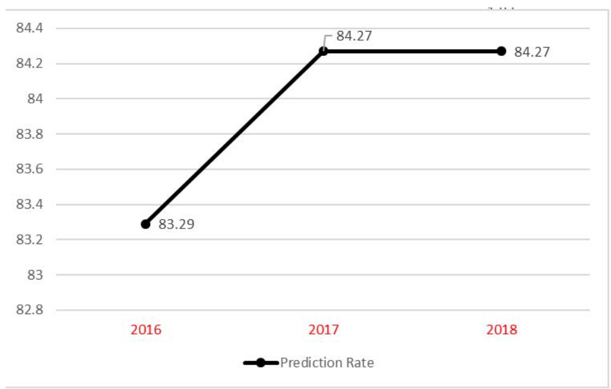

FIGURE 15. The SVM prediction of winning.

According to the above results, to win a game, the most important factors are 2P%, 3P%, FTM, OREB, STL, and TOV; among which, TOV has a negative impact. The data shows that if a team expects to win a match, it should consider improving in these sectors for boosting the possibilities of winning.

C. SVM ANALYSIS

This study uses 2PM, 2PA, 2P%, 3PM, 3PA, 3P%, FTM, FTA, FT%, OREB, DREB, TRB, AST, STL, BLK, TF, and TOV as the variables for predicting game results. By conducting Sequential Minimal Optimization (SMO) in Weka and utilizing SVM to analyze the prediction rate of the games; The 2016 and 2017 data in the SVM model were training data and the rest in 2018 was testing data. Based on the results, the training data's prediction rate is 83.29% in 2016, and 84.27% in 2017, the testing data's prediction rate is 84.27% in 2018. The data and graph are shown in Table 1 and Figure 15.

From Table 1 and Figure 15, the trend of the prediction rate in each analytic item is increasing, this proves that the teams in HBL are maturing. On the other hand, the prediction accuracy of NBA by SVM in literature [21] was 85%, which is similar to the result in this study; the data has demonstrated that these analytic items are valid for using SVM in predicting winning for HBL.

TABLE 1. SVM predictions.

Data	Year	Correctly Classified Instances	Incorrectly Classified Instances	Prediction Accuracy (%)
Training Data	2016	304	61	83.29
	2017	300	56	84.27
testing data	2018	300	56	84.27

VI. CONCLUSION

According to the yearly trends from gaming data, it is concluded that the teams pay more attention to offensive skills and have increasing trends in 2P% and 3PA. Nevertheless, the data of 3P% remains because the number of 3PM did not gain. There is a decreasing trend in FTA but FT% is not. Meanwhile, there is a rise in TRB while DREB is improving and OREB is slightly dropping. The trend of AST is growing and there are decreasing trends in both TF and TOV. Overall, the basic abilities of each team are improving and transferring to offensive gaming styles.

After implementing the analysis of multiple linear regression, based on the yearly trends, the significant influence factors are 2P%, 3P%, FTM, TRB, OREB, STL, and TOV. If a team wants to win a game, it is recommended to concentrate on these sectors. Through daily practices to enhance their basic abilities related to these items. Furthermore, from the winning predictions of SVM in each analytic item, the prediction accuracy of SVM has reached 85%, which is extremely significant. This result provides a solid suggestion for team coaches to pay extra focus on these parts for increasing winning rates.

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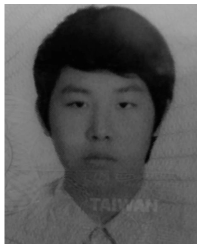

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