OPEN ACCESS
Computing Open
Vol. 2 (2024) 2450005 (14 pages)

DOI: 10.1142/S2972370124500053

Application of Support Vector Machine in the Evaluation of Table Tennis Motion Profiles

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Received 7 October 2023
Accepted 3 May 2024
Published 31 May 2024

Racket sports such as table tennis involve a wide range of three-dimensional complex spatial movements of the human body and the racket. Novice players might benefit from the evaluation of the motion profile of the racket to facilitate better adoption of more expert movement. Computer-based evaluation of such novice vs. expert play behavior characteristics includes reducing the required multiple human interactions and easy applicability for subsequent automation to accurately differentiate the motion profile of a novice player from that of an expert. This study has, for the first time, applied the widely used support vector machine (SVM) classification technique for the development of a table tennis player movement evaluation model. The model was trained using an existing dataset of displacements and velocities from various important anatomical landmarks across the body and points on the racket. These were obtained and evaluated for table tennis forehand strokes for two subgroups of expert and novice ability levels, respectively. Different combinations of variables were selected for model input from the same dataset with the outcomes being noted for each. The resulting SVM classification model exhibited good/noteworthy performance (> 90% accuracy) in distinguishing racket motion between expert and novice players.

Keywords: Support vector machine; table tennis; performance; evaluation; cross-validation.

1. Introduction

Support vector machine, also known as SVM, can be defined as a supervised algorithm for learning used in the analysis of datasets and output measures for input

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object classification.[1] SVM involves the construction of a hyperplane in a high-dimensional space, achieved by maximizing the margin between classes for sample classification.[1–3] Other popular classification methods include Fisher discriminant analysis, logistic regression, *k*-nearest-neighbor classifier, etc.; however, the performance of SVM, particularly in high-dimensional spaces, is better when compared to other classifiers and it has therefore received considerable attention in supervised machine learning applications.[2,3,20] Contemporary researchers have all implemented SVM in sports-based applications for the enhancement of sports performance analysis.[2–4]

1.1. *SVM classifier models*

SVM classifier models are increasingly gaining popularity in the evaluation of sports performance,[5–7] simulating sporting experience and predicting the outcome of both indoor and outdoor games.[7,8] The study by Acikkar *et al.*[6] explored SVM-based prediction in understanding the aerobic fitness of athletes and confirmed the efficacy of the prediction method. Chen *et al.*[9] developed the Wi-Fi-based Table Tennis (WiTT), which is based on SVM and discrete wavelet decomposition technique, to facilitate Wi-Fi-based recognition of table tennis action recognition, keystrokes, gestures and human behavior. As per the studies conducted by Powers,[5] Acikkar *et al.*,[6] Chen *et al.*[9] and Anik *et al.*,[10] classifications of physical activities using SVM have yielded high classification accuracy. Bagheri-Khaligh *et al.*[8] studied the efficacy of SVM classification for shot classification in soccer. Other applications include the detection of sports fatigue.[11] Major headings should be typeset in boldface with the first letter of important words capitalized.

To measure the performance of a classifier in making accurate predictions on new datasets, the F_1 score is usually implemented.[11] The F_1 score can be defined as the harmonic mean of precision and recall, which can be directly accessed from a confusion matrix.[12] Cross-validation can be defined as a "model assessment technique" used for evaluating the performance of a machine learning algorithm by partitioning a dataset.[13] Cross-validation uses one data subset to *train* and the second subset to *test* the algorithm. The issue of overfitting amidst the period of training is prevented as model-building using cross-validation does not use the whole data. Meanwhile, the Nelder–Mead method is one of the most commonly used mathematical technique for calculation of the maximum or minimum of an objective function in a high-dimensional space. To apply the Nelder–Mead method in this research, output parameters C (Capacity constraint) and K (Kernel scale) were subjected to logarithmic scale conversion to incorporate their entire range in whole real numbers by numerical computation using a selected dataset (as per Eq. (1)). The Nelder–Mead method determined the best combination of C and K for maximizing the objective function:

$$\max_{C,K} F_1 \left\{ \sum_{i=1}^{N} \{\mathrm{ConMat}[\mathrm{SVM}_{C,K}(\mathrm{Train}_i, \mathrm{Test}_i)]\} \right\} \tag{1}$$

The function "F_1" and "ConMat" determines the "F_1 score" and the "confusion matrix," respectively.[14] SVM is the "classifier" trained by the training set Train_i and vaulted by testing set Test_i under the parameters "C" and "K".[14] It has to be noted that "N" ($N = 20$ in this study) is the number of SVM that the cross-validation is performed on. The development and optimization of the classification model has been depicted in Fig. 1.

1.2. *Table tennis motion data*

Playing racket sports effectively requires complex spatial movement of the racket and associated coordination of the human body segments and joints.[9,14] For example, a forehand stroke in table tennis is the accumulation of sequential movements from the human trunk, shoulder, elbow and wrist to hand, and finally to the translational and rotational movement of the racket. A table tennis trainee may spend a large amount of time practicing, ultimately aiming to replicate the way experts control

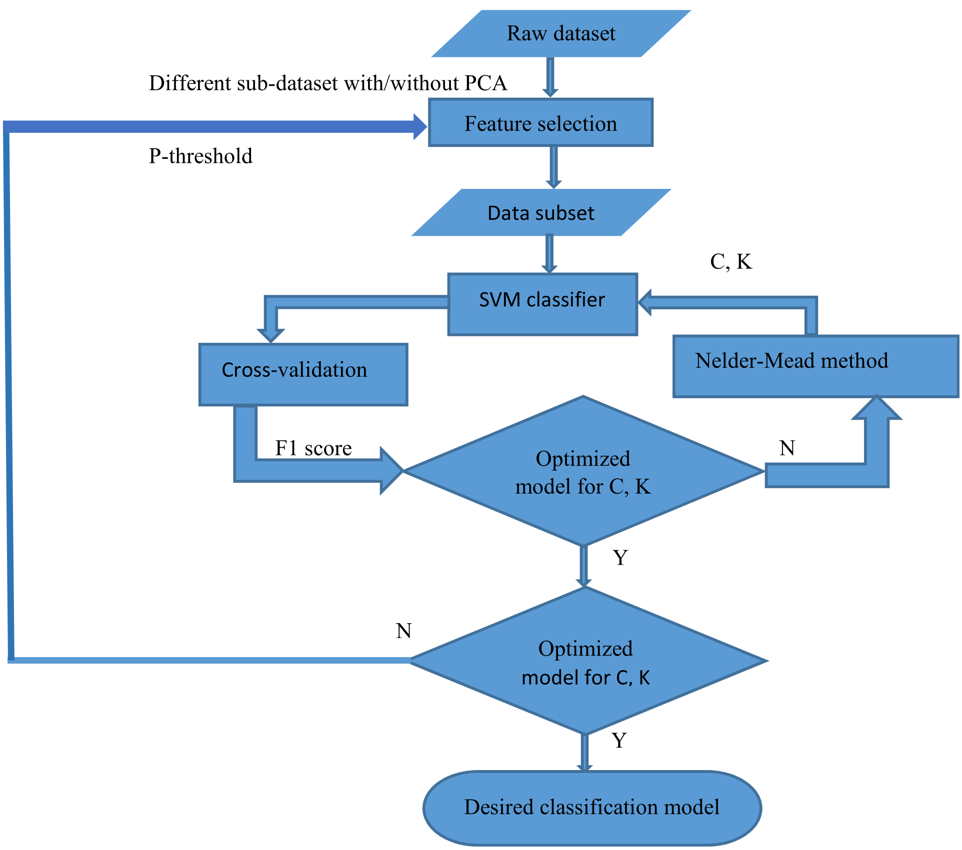


Fig. 1. Flowchart of the classification model development and optimization.

their racket. A coach can help to evaluate the movement of a trainee followed by providing feedback in order to rectify the trainee's motion patterns. However, such evaluation requires an expert's experience in addition to substantial human interaction. Both of these things are relatively expensive to realize and may be prohibitively so for the typical recreational player.

The automation of human performance evaluation using increasingly low-cost/high-performance vision-based data acquisition systems and computer-based processing may therefore be advantageous. Instead of human observation, an intelligent, automated coaching system may use motion data, for example, from a motion capture system, automatically processed by the evaluator prior to generating feedback to give to the player.[15,16] In this study, therefore, a classification model based on SVM to automatically evaluate the motion quality of table tennis players is proposed. The racket and human body motion of a group of expert and novice players, observed and extracted from video data, were used as the input data and the model performance was cross-evaluated.[14,17]

2. Experimental Work

2.1. *Raw dataset*

The velocity and displacement data of the racket center (RC), trunk center and the rotational displacement of the trunk, racket, shoulder, wrist and elbow are the variables in the raw dataset[14,17]; the raw dataset has been tabulated below (Table 1). The normalization of variables was conducted by means of "time-series variables" from the "phase time $T1$" (start of the back-swing) to $T4$ (end of the follow-through). The various degrees-of-freedom (DOF) under every specific joint and segment and

Table 1. Variables in the raw dataset.

Joint/segment	Each DOF	DOF	Abbr.
Racket center	along global x	3	RC
	along global y		
	along global z		
Racket (rotational)	with respect to global x-y	3	RR
	with respect to global y-z		
	with respect to global x-z		
Trunk center	forward (+)/backward (−)	3	TC
	upward (+)/downward (−)		
	leftward (−)/rightward (+)		
Trunk (rotational)	flexion (−)/extension (+)	3	T
	lateral left (−)/right (+)		
	rotation right (−)/left (+)		
Shoulder joint	plane of elevation	3	S
	elevation (−)		
	internal (+)/external (−) rotation		
Elbow joint	flexion (+)/hyperextension (−)	2	E
	pronation (+)/supination (−)		

were combined as one set and not separated.[17] For example, the displacement of RCx, RCy and RCz was regarded as one set of features, however, each DOF was regarded as one feature for SVM classification.[17] At each phase time, data was formed in the matrix such that each row and each column represented one stroke observation and one feature, respectively. The study yielded twenty observations for twenty study subjects. For optimization of computational resources, a gap of T0.2 was selected such that only data at five equally distributed phase times were used within each phase.

The following abbreviations have been used: "D" for displacement, "V" for velocity, and "ALL" (where ALL = (RC + RR + TC + T + S + E + W). For example, the velocity data of the racket center is represented by "(RC) V"; "(RC + RR) $(D + V)$" represents both displacement and velocity (including angular displacement and velocity) data of the racket rotational motion racket and centre translational. If a data subset includes the entire raw dataset, then it would be denoted as "(ALL) $(D + V)$".

2.2. *Selection of features*

The generation of data subsets for the classification model was implemented using different strategies. The first technique used simple extractions to obtain a wide range of feature combinations from the raw dataset. The manual selection of combinations relied on the various segments and physical quantities (Table 2).

The next method used principal component analysis (PCA) and involved the orthogonal transformation of the original features into linearly uncorrelated components and the selection of principal components. Standardization was applied prior to using PCA such that each feature was centered to mean "0" and scaled to the standard deviation "1". To determine the number of principal components to

Table 2. Basic feature combinations.

Category		Displacement	Velocity	Displacement + Velocity
All	ALL	(ALL)D	(ALL)V	(ALL)$(D+V)$
	RC	(RC)D	(RC)V	RC$(D+V)$
Racket	RR	(RR)D	(RR)V	RR$(D+V)$
	RC+RR	(RC+RR)D	(RC+RR)V	(RR+RR)$(D+V)$
	TC	(TC)D	(TC)V	TC$(D+V)$
	T	$(T)D$	$(T)V$	$T(D+V)$
	S	$(S)D$	$(S)V$	$S(D+V)$
	E	$(E)D$	$(E)V$	$E(D+V)$
	W	$(W)D$	$(W)V$	$W(D+V)$
Human	TC+T	(TC+T)D	(TC+T)V	(TC+T)$(D+V)$
	$T+S$	$(T+S)D$	$(T+S)V$	$(T+S)(D+V)$
	$S+E$	$(S+E)D$	$(S+E)V$	$(S+E)(D+V)$
	$E+W$	$(E+W)D$	$(E+W)V$	$(T+W)(D+V)$
	$T+S+E+W$	$(T+S+E+W)D$	$(T+S+E+W)V$	$(T+S+E+W)(D+V)$
	TC $+T+S+E+W$	(TC $+T+S+E+W$)D	(TC $+T+S+E+W$)V	(TC $+T+S+E+W$)$(D+V)$

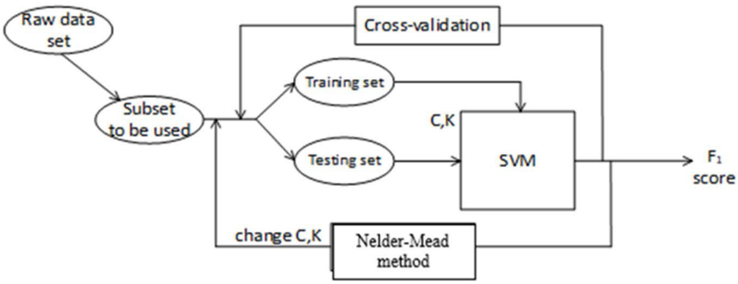


Fig. 2. Model training and validation.

reserve, a threshold of 90% was set; a minimum of 90% and just above 90% of principal components were selected. This method was applied to each data subset in Table 2.

2.3. *SVM training and cross-validation*

In this study, the model is designed by integrating a binary SVM (as shown in Fig. 2) with the design and relevant experimentation being conducted using MATLAB. The SVM uses the "Radial Basis Function (RBF)" kernel, one of the most common kernel types. The raw dataset for the model included racket movement data collected from 10 expert and 10 novice players under a controlled experiment, as detailed in a previous research study.

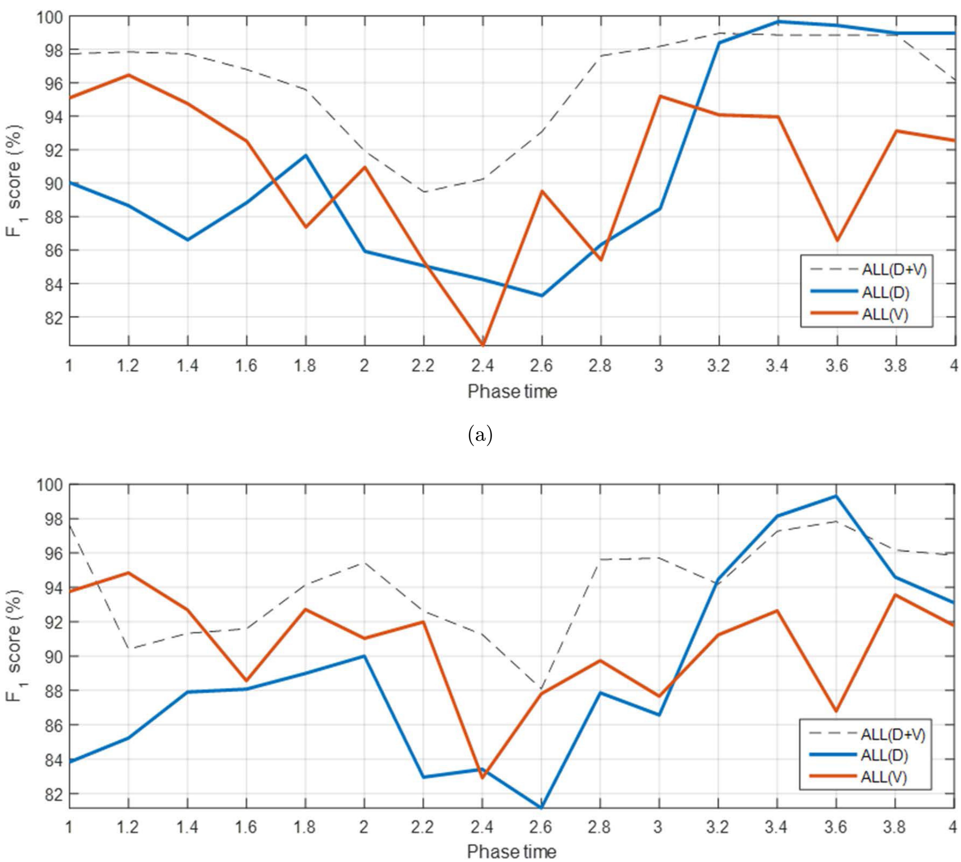
Prior to training, a data subset was selected followed by partitioning into a training set and a testing set. The data of 19 players were selected as the training set while that of the one remaining player was used as the testing set. For any given C and K, each training set was used to train the model with the testing set being used for model validation. The model performance F_1 score was calculated based on the 20 different results generated by cross-validation, i.e. one result for each one of the 20 participant's data used as the test data subset. The Nelder–Mead method computed the best F_1 score by changing C and K parameters. To apply the Nelder–Mead method, C and K were converted into log scale. The objective function was formulated through cross-validation. This was followed by the Nelder–Mead method to determine the best combinations of C and K for maximizing the objective function. Upon completion of these tests, a pair of initial values "$C = e^\wedge 2$ and $K = e^\wedge 2$" were selected for parameter tuning for all the data subsets.

3. Results

3.1. *Performance of "ALL" dataset*

The performance of the "ALL" dataset is investigated in this section. It has to be noted that the maximum number of features were naturally contained in "(ALL) $(D + V)$". Such a combination was used as the benchmark for results associated to the human and racket motion. Both sets of results, as shown in Fig. 3 for a typical example, used a basic feature selection with those in (b) also using PCA. As observed, the $D + V$ generally performs equivalently or more effectively at all phase times but is particularly effective, relative to only D or V, during phase 2, the forward swing. In this case, the inclusion of PCA in general has a detrimental effect. This is a typical example that represents the precision, accuracy and recall of the model results (with and without PCA) for all data subsets.

Figure 4 shows the corresponding results for different combinations of features, here with the displacement and velocity parameters used in (a), only the velocity in (b) and only the displacement in (c). In all cases, PCA was not utilized. These results can be used to see the importance of the relative contributions of the body segments at the different phases of the stroke with, for example, the trunk center and trunk (rotational) making a greater contribution during phase 2, the forward swing, as



(a)

(b)

Fig. 3. Results for using the "ALL" dataset (a) without and (b) with PCA.

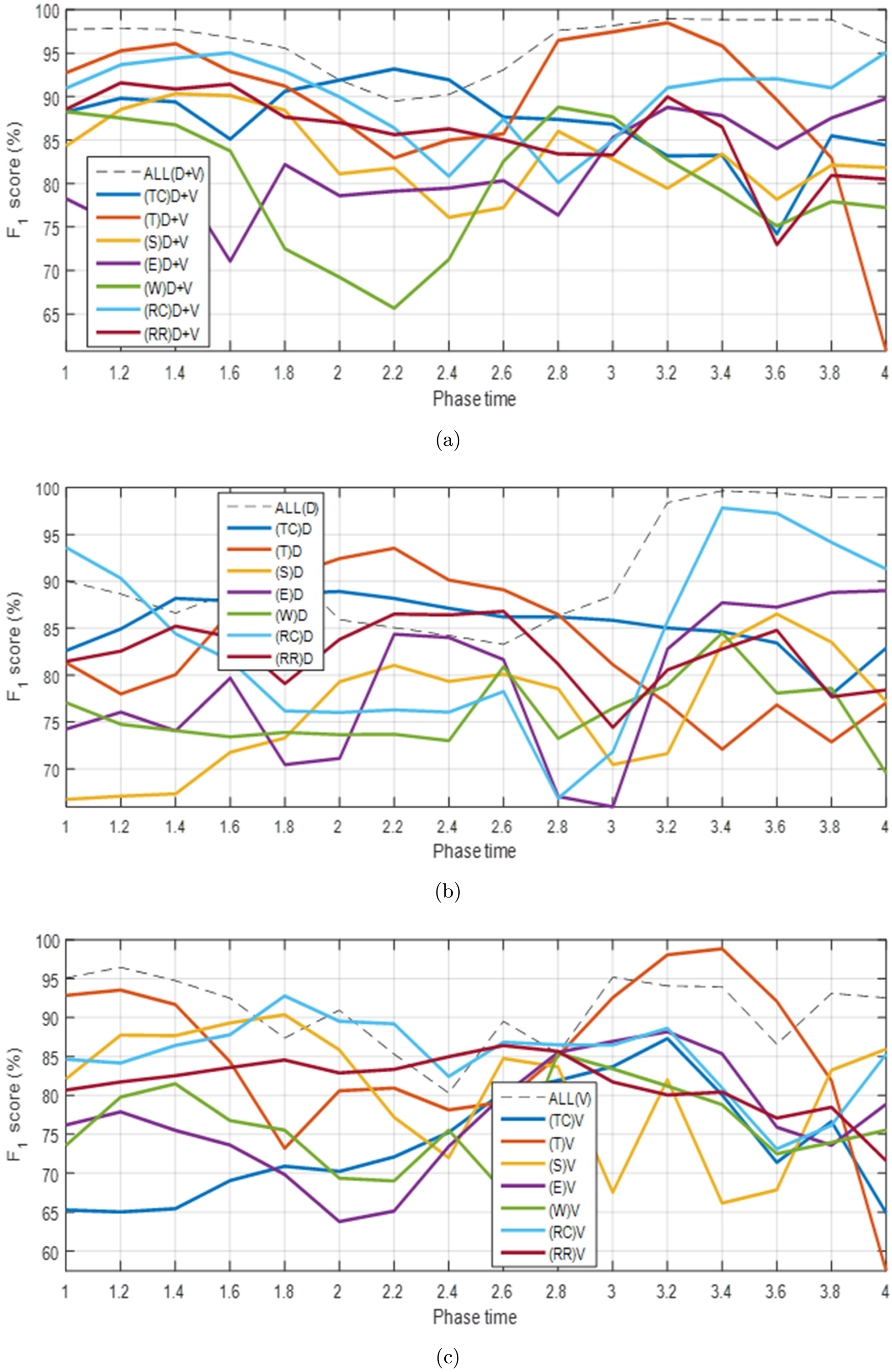


Fig. 4. Results for some dataset $(D + V)$ (a), D (b) and V (c) without PCA.

expected. For better comparison and analysis, the data have been converted to a score table.

3.2. *Score table*

In order to filter and facilitate enhanced data visualization, a score table using the "80–80%" rule was generated.[17] The baseline is fixed at F_1 score of 80% such that if the F_1 score at a phase time or mean F_1 score during a phase is less than 80%, it is marked as "×";[17] if less than 80% of the phase is higher than F_1 score 80%, it is marked as "—"; otherwise the score or mean score is represented by the actual number.[17] The results have been tabulated (Table 3) with conditional formatting — the darker the color, the higher the number. It has to be highlighted that "×" denotes the worst results, "—" highlights reasonable results (normally with large variation in values), whereas the numbers symbolize good results (filtered). The

Table 3. F_1 score table with all the results.

	without PCA							with PCA						
	1	1—2	2	2—3	3	3—4	4	1	1—2	2	2—3	3	3—4	4
(ALL) D	90	89	86	86	88	97	99	84	87	90	85	87	94	93
(ALL) V	95	93	91	88	95	93	93	94	92	91	89	88	91	92
(ALL) (D+V)	98	96	92	93	98	98	96	98	93	95	93	96	96	96
(RC) D	94	—	×	×	×	90	91	94	—	×	×	×	90	91
(RC) V	85	88	90	87	86	—	85	89	88	89	85	87	83	86
(RC) (D+V)	91	93	90	85	85	91	95	92	92	90	—	82	92	96
(RR) D	81	83	84	83	×	×	×	82	84	86	84	×	×	×
(RR) V	81	83	83	84	82	×	×	82	84	86	85	81	×	×
(RR) (D+V)	89	90	87	85	83	82	80	89	91	88	87	83	83	×
(RC+RR) D	93	91	86	83	×	90	92	90	—	85	—	×	90	92
(RC+RR) V	87	89	90	86	83	86	98	89	90	93	88	87	87	97
(RC+RR) (D+V)	92	94	96	87	83	91	96	90	93	92	86	81	90	96
(TC) D	83	87	89	87	86	83	83	82	86	89	88	89	85	83
(TC) V	×	×	×	×	84	×	×	×	×	×	×	84	×	×
(TC) (D+V)	88	89	92	90	87	83	84	87	90	91	91	91	—	86
(T) D	81	85	92	89	81	×	×	×	×	×	—	81	×	×
(T) V	93	86	81	—	93	87	×	87	83	81	83	94	90	×
(T) (D+V)	93	93	87	89	97	88	×	×	×	×	—	92	87	×
(S) D	×	×	×	×	×	×	×	×	×	81	×	×	×	×
(S) V	82	87	86	×	×	×	86	×	×	×	×	×	×	86
(S) (D+V)	84	87	81	—	83	—	82	×	—	×	×	88	83	82
(E) D	×	×	×	×	×	84	89	×	×	×	×	×	84	89
(E) V	×	×	×	×	87	—	×	×	×	×	×	87	—	×
(E) (D+V)	×	×	×	×	85	87	90	×	×	84	84	88	88	90
(W) D	×	×	×	×	×	×	×	×	×	×	×	×	×	×
(W) V	×	×	×	×	83	×	×	×	×	×	×	83	×	×
(W) (D+V)	88	—	×	×	88	×	×	×	×	×	×	83	—	×
(TC+T) D	86	86	82	90	85	88	86	86	86	82	89	91	93	92
(TC+T) V	95	—	×	86	97	90	×	92	83	86	83	90	84	×
(TC+T) (D+V)	92	91	86	89	88	90	88	91	90	87	91	92	91	88
(T+S) D	×	—	96	91	82	×	×	×	×	×	86	80	×	81
(T+S) V	91	91	92	87	95	93	80	85	85	82	—	93	94	83
(T+S) (D+V)	90	92	93	93	99	92	×	×	91	89	89	95	91	83
(S+E) D	82	×	80	×	×	88	90	×	×	83	×	×	87	89
(S+E) V	91	88	82	—	87	83	81	91	—	×	—	89	×	×
(S+E) (D+V)	86	83	×	—	91	91	91	82	85	89	85	88	90	89
(E+W) D	82	—	82	×	×	86	91	83	—	81	×	×	85	87
(E+W) V	×	×	×	×	89	—	×	×	×	×	×	89	—	×
(E+W) (D+V)	×	×	×	—	91	90	91	81	×	×	—	87	88	90
(T+S+E+W) D	89	86	85	86	85	91	93	×	—	87	89	83	91	96
(T+S+E+W) V	95	91	80	86	96	93	84	92	—	×	85	92	93	84
(T+S+E+W) (D+V)	94	93	87	91	98	95	90	90	87	87	90	93	94	95
(TC+T+S+E+W) D	82	83	85	89	89	95	95	83	—	84	87	86	90	92
(TC+T+S+E+W) V	97	90	×	—	97	93	85	94	—	×	×	91	91	85
(TC+T+S+E+W) (D+V)	97	94	91	92	94	96	97	96	—	94	90	93	96	95

greater the number, the better the model performance. The SVM classification model was able to classify the existing data with relatively high performance. When all the raw data of "(ALL) $(D + V)$" was used, the model generated the best scores varying from 92% to 98% without PCA and 93–98% with PCA. When the subset features were selected, the overall performance decreased.

The reservation of principal components exhibited substantial variations depending on the combinations of features. In general, with a higher number of features, components with reduced importance could be removed. This is because the greater number of features raised the possibility of features being linearly correlated. The reservation of the principal components could be as high as 100% for some data subsets (e.g. elbow and wrist), which indicated the importance of including all the dimensions. In fact, the model performance shows that these principal components are insufficient and generated lower F_1 scores. Overall, the application of PCA generally presented comparatively similar performance compared to experiments without PCA. Therefore, the application of PCA may benefit if the data has more features (e.g. more kinematic variables involved), since PCA reduces both the number of features in addition to the data processing time.

In addition to the ALL dataset, the RC velocity also presented good performance. However, the F_1 score for the RC displacement could typically not differentiate the experts from the novices. The racket rotations (RR) were similarly not able to yield good results being marginally over 80%. When PCA was not applied, use of the displacement led to the prediction of relatively good outcomes, whereas velocity did not. Both displacement and velocity of the trunk rotation (T) seemed applicable at most phase times. The shoulder (S), elbow (E) and wrist (W) were not leading to good results. A combination of the trunk center motion and trunk rotational motion showed better results using displacement as opposed to velocity. Conversely a combination of trunk and shoulder rotations showed better results in velocity. The combination of elbow and wrist alone did not lead to good results. The other combinations in the table (e.g. $(T + S + E + W)D$), on the other hand, were able to present good model performance. Overall, these results can be interpreted as showing that experts can be differentiated from novices in their additional use of the trunk and in their higher racket velocities generated. This would be consistent with common belief.

3.3. *Classification model*

The technique was applied to model building and classification of experts and novice players. The model development encompassed three different SVM kernels (polynomial, linear, RBF), three different feature selection methods (PCA, p-threshold and diverse subset,) and two different SVM parameters (C and K) for determination of the best model performance (F_1 score) by means of the Nelder–Mead and cross-validation methods. The results clearly indicate that the linear kernel performed the least well whereas the polynomial kernel and RBF kernel had comparable

Table 4. Selected feature combinations.

Selected combinations	Average performance (%)
RC($D+V$)	89.7
RR($D+V$)	85.7
(RC + RR)($D+V$)	90.7
TC(D), TC($D+V$)	85.7
$T(D+V)$	90
(TC + T)D, (TC + T)($D+V$)	88.0, 90.0
$(T+S)V$, $(T+S)(D+V)$	90.3, 92.3
$(T+S+E+W)D$, $(T+S+E+W)V$, $(T+S+E+W)(D+V)$	87.7, 90.0, 93.0
(TC $+T+S+E+W$)D, (TC $+T+S+E+W$)($D+V$)	89.0, 94.0
ALL(D), ALL(V), ALL($D+V$)	90.7, 91.3, 95.7

performances, with the ultimate selection of the RBF kernel. The p-threshold feature selection technique was devoid of any advantage because of the relatively small dataset size, therefore from over-reduction of the data dimensions or number of features. The application of PCA generated similar results to SVM without applying PCA when the data dimensions are large, however, this could be worse for a smaller da-taste size. Hence, the model with basic feature selection methods and RBF kernel was preferred (without PCA) for the biomechanical data pertaining to table tennis strokes. The PCA could potentially be considered on using the higher dimension of data.

Numerous combinations of good features (without PCA) were chosen. The selected feature combinations have been tabulated below (Table 4). The average performance for all the phases was calculated for 18 combinations. The "grand average performance" of these 18 combinations is 90.2%. It has to be emphasized that the SVM distinguished the biomechanical motion data of novice and expert players with notable efficiency.

4. Discussion

In this study, a classification model has been designed and evaluated based on the racket and human body motion of table tennis players. Results showed that the model presented good performance ($>90\%$) on distinguishing racket motion of experts and novices on displacement and velocity although the study used a relatively small dataset. Contemporary and past research studies have reported varying accuracy levels of SVM classification techniques, especially in human biomechanics-based applications. Wu and Wang3 reported 90% accuracy levels for SVM; this was comparable to the findings of this research study. Comparable accuracy levels for SVM were also reported by Begg and Kamruzzaman,[18] Powers,[5] Acikkar *et al.*,[6] Chen *et al.*,[9] Anik *et al.*[10] However, Igiri[18] reported limited accuracy for SVM (53.3%) in the prediction of football match results.

The study conducted by Araújo *et al.*[20] has emphasized the use of artificial intelligence in sports performance analysis. The application of various methods such as

SVM in creating training plans, strategies, sports management and athlete performance has also been highlighted by Araújo *et al.*[20] Claudino *et al.*[21] conducted a systematic literature review based on prediction models in sports, utilizing SVM and AI. Similar to our study, the research by Oytun *et al.*[22] explored the application of machine learning to predict athletic performance metrics in female handball players. Oytun *et al.*[22] compared various models such as linear regression and multiple forms of neural networks. The radial-basis function neural network was found to be the most effective, achieving R^2 scores ranging from 0.86–0.97. This research highlighted the significant potential of machine learning in optimizing training and performance strategies in sports. Xu and colleagues[23] proposed a model based on AI, including SVM, to facilitate enhancement of the accuracy of sports training management evaluations, demonstrating the integration of technology in sports training. By applying SVM, the model by Xu *et al.*[23] aimed to provide more precise and data-driven insights into sports performance and training needs, thereby optimizing training strategies and outcomes in competitive sports. SVM application in sports analysis aims at leveraging advanced computational techniques for addressing complex problems in sports science.

Future applications include developing a table tennis coaching system capable of monitoring and providing feedback to players. The proposed system includes components for motion capture, classification model, database, and feedback.[14] Such a system may also comprise of Wi-Fi-based recognition of table tennis keystrokes, gestures as proposed by Chen *et al.*[9] The SVM model has ample potential to facilitate continuous monitoring and prompt correction of the motion patterns for novice table tennis players in addition to offering valuable evidence on the player's training status.[14] The classification model processes the data by phase alignment, normalization, and feature selection followed by classifying the data into expert patterns or novice patterns by giving a score.[14] The coaching system could be equipped with a feedback component generating feedback to players using real-time feedback sensors (haptic LED or voice), or posting performance overview through web/mobile interfaces.[14] The database could store the training outcomes and allow the progressive assessment of players.[14] Such a coaching system has the ability to provide feedback to trainees and aid the improvement of their technical skills.

5. Conclusions

This research study has successfully implemented SVM technology in evaluating the performance of table tennis players. A classification model based on the racket and human body motion of table tennis players has been developed and evaluated. The SVM model exhibited good performance ($> 90\%$) on distinguishing racket motion of novice and expert players. SVM technology can be exploited in sports science and biomechanics research, for example, to assist with the automation of performance evaluation and decision making because of its accuracy and consistency. SVM technology could be developed into coaching systems for assessment of player performance like a coach.

Acknowledgments

The authors wish to acknowledge the support of the Institute for Sports Research, Nanyang Technological University and the Sports Technology Institute, Loughborough University.

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