The Classification of Skateboarding Tricks by Means of Support Vector Machine: An Evaluation of Significant Time-Domain Features

Muhammad Amirul Abdullah, Muhammad Ar Rahim Ibrahim, Muhammad Nur Aiman Shapiee, Anwar P. P. Abdul Majeed, Mohd Azraai Mohd Razman, Rabiu Muazu Musa, and Muhammad Aizzat Zakaria

Abstract This study aims to improve classification accuracy of different Support Vector Machine (SVM) models in classifying flat ground tricks namely Ollie, Kickflip, Shove-it, Nollie and Frontside 180 through the identification of significant time-domain features. An amateur skateboarder (23 years of age ±5.0 years' experience) executed five tricks for each type of trick repeatedly on a customized ORY skateboard (IMU sensor fused) on a cemented ground. From the IMU data a total of 36 features were extracted through statistical measures. The significant features were identified through two feature selection methods, namely Pearson and Chi-Squared. The variation of the SVM models (kernel-based) was evaluated both on all features and selected features in classifying the skateboarding tricks. It was shown from the study that all classifiers improved significantly in terms of training accuracy, prediction speed, training time and test accuracy. The Cubic-based SVM and Quadratic-based SVM demonstrated a 100% accuracy on both the test and train dataset, however, the Cubic-based SVM model provided the fastest training time and prediction speed between the two models. It could be concluded that the proposed method is able to improve the classification of the skateboarding tricks well.

Keywords Skateboarding · Machine learning · Classification · Feature selection

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M. A. Abdullah · M. A. R. Ibrahim · M. N. A. Shapiee · A. P. P. Abdul Majeed (✉) · M. A. Mohd Razman · M. A. Zakaria
Innovative Manufacturing, Mechatronics and Sports Laboratory, Faculty of Manufacturing and Mechatronic Engineering Technology, Universiti Malaysia Pahang, 26600 Pekan, Pahang, Malaysia
e-mail: amajeed@ump.edu.my

R. M. Musa
Department of Credited Co-Curriculum, Centre for Fundamental and Continuing Education, Universiti Malaysia Terengganu, Kuala Nerus, Terengganu, Malaysia

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1 Introduction

In the 2020 Tokyo Summer Olympics, skateboarding will make its debut due to its popularity and the traction that this sport has made over the years. It is worth noting that in 2010, the net worth of the skateboarding industry is approximately $USD 4.6 billion [1]. As the evaluation of the tricks executed are literally subjective, which is carried out by a panel of judges, that could be open for bias and imprecise assessment. Therefore, an innovative approach should be proposed in addressing the aforesaid issue and it is expected that is the use of machine learning is able to provide the solution.

Machine learning has been employed for many type of sporting events [2–8] whilst in skateboarding, Groh et al. [9] in classified six different skateboarding tricks, i.e., OLLIE, NOLLIE, KICKFLIP, HEELFLIPM POPSHOVE-IT and 360-FLIP through the use of Naïve Bayes (NB), Partial Decision Tree (PART), Support Vector Machine (SVM) with a radial basis kernel and *k*-Nearest Neighbour (*k*NN). A total of 54 features were extracted combining both statistical time and frequency features including the x-y-correlation, the x-z-correlation and the y-z-correlation. The feature selection was carried out using Embedded Classification Software Toolbox (ECST) but, the number of features selected were undisclosed. The feature selection method used in the ECST was the best-first forward selection. The best overall accuracy was achieved for Naïve Bayes and SVM with a classification accuracy of 97.8%.

Groh et al. [10] further improvised the study by classifying 13 classes: the 11 trick classes, 1 class for bails and 1 rest class for all other detected events that did not contain a trick. Five (5) different classifiers, namely, Naïve Bayes (NB), Random Forest (RF), Linear Support Vector Machine (LSVM), Support Vector Machine with a radial-basis kernel (RB-SVM) and *k*-Nearest Neighbour (*k*NN) were evaluated. The best performing classifier reported for only the correctly performed tricks was the RB-SVM with a classification accuracy of 89.1%. Conversely, for the classification of all events, the Random Forest model demonstrated the best result with an accuracy of 79.8%.

Correa et al. [1] developed different Artificial Neural Networks (ANN) models by considering different axes as the input features in classifying five (5) skateboarding trick classes: NOLLIE, NSHOV, FLIP, SHOV and OLLIE. It was shown from the study that the ANN model that utlilised statistical features from the Z-axis could yield a classification accuracy (CA) of 98.7%. Anlauff et al. [11] used Linear Discriminant Analysis (LDA) in classifying three (3) classes, i.e., the two (2) trick classes (OLLIE & OLLIE-180) and one (1) class for events that did not contain any trick. The 10-fold cross-validation technique was employed in the investigation. It was shown that the classifier could provide a 97% true positive classification for the OLLIE trick.

In a recent study, Abdullah et al. [12] investigated the efficacy of different machine learning models, viz. Support Vector Machine (SVM), k-Nearest Neighbour (k-NN), Artificial Neural Network (ANN), Logistic Regression (LR), Random Forest (RF) and Naïve Bayes (NB) in classifying five (5) skateboarding trick classes, i.e.,

Table 1 Short summary of machine learning application on skateboarding

References	No. of target	No. of tricks	No. of features extracted	Features selection	No. of classifier	Best accuracy
[9]	6	6	54	Best-first forward, ECST	4	NB, 97.8%
[10]	13	11	–	–	5	RB-SVM, 89.1%
[1]	5	5	–	–	4	ANN Z, 98.7%
[11]	3	2	7	–	1	LDA, 97%
[12]	5	5	36	–	6	LR & NB, 95%

OLLIE, NOLLIE FRONTSIDE SHUVIT, FRONTSIDE 180, POP SHOVE-IT and KICKFLIP. A total of 36 statistical features were extracted from 6 input signals collected from the tri-axial accelerometer and gyroscope embedded in the data acquisition device. The features extraction and classification were performed by using an open source platform, Orange. The leave-one-out cross-validation technique was employed in the investigation. It was established from the study that both the LR and NB models yields the highest classification accuracy of 95% against other evaluated models (Table 1).

It could be seen from the limited literature available with regards to the employment of machine learning in classifying skateboarding tricks demonstrated commendable classification accuracy [1, 9–12]. However, it is worth noting that the investigation with regards to feature selection is rather limited [9]. Therefore, this paper aims at evaluating the significance of feature selection restricted to time-domain towards the classification accuracy of different variation of SVM models.

2 Methodology

2.1 Data Collection

The acquisition of the data from the skateboarding tricks was attained via an instrumented inertial measurement unit (IMU) device developed as shown in Fig. 1. The device is attached to the bottom front of the skateboard specifically fix behind the front truck as depicted in Fig. 2. To ensure the balance of the board after adding up the device, an equal riser pad is fixed at bottom rear of the board. Both device and riser pad are fixed with hex screw bolts and nylon lock nuts (nyloc) to ensure its stability. In addition, the device is secured with a 3D-printed casing using acrylonitrile butadiene styrene (ABS) material on Zortax M200 3D printer. The ABS material

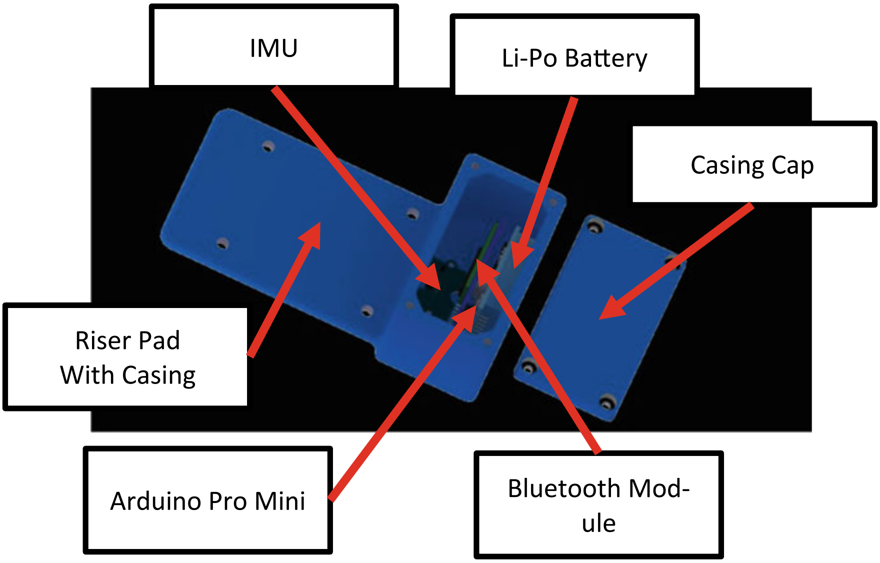

Fig. 1 The 3D model of instrumented device on CATIA

Fig. 2 Placement of the instrumented device on the skateboard

is chosen due to its desirable mechanical properties, primarily high impact strength and good absorbing as the device will be prone to impacts and shocks from the tricks. On the inside, the device consists of a MPU6050 as the IMU for raw data sensor, a Bluetooth 2.0 module (HC-05) for communication, a microcontroller (Arduino Pro Mini) for central processing unit, and a 3.7 V Lithium Polymer rechargeable battery for power supply. An amateur skateboarder (23 years of age ±5.0 years' experience) executed five tricks for each type of trick repeatedly (Table 2).

Table 2 Description of the observed activities/tricks

Trick name	Rotation (angle and axis)	No. of samples
Ollie (O)	Board incline about the x-axis ($\approx 45°$ +y)	5
Nollie FS Shuvit (NFS)	Board incline about the z-axis ($\approx 180°$ –z)	5
Frontside 180 (FS180)	Clockwise about z-axis (180° −z)	5
Pop Shove-it (PS)	Clockwise about z-axis (180° +z)	5
Kickflip (KF)	Clockwise about x-axis (360° −x)	5

2.2 Feature Selection Method

A total of 25 segmented raw signals data for five (5) different skateboarding tricks collected was used for this study. The segmented data were equally distributed for all trick which is 5 segmented raw signals per trick. The statistical features were extracted from the IMU devices, namely mean, skewness (sk), kurtosis, peak to peak, root mean square (rms) as well as standard deviation (std) for all the readings (all six degrees of freedom) which are equal to a total number of 36 features. In this study, two feature selection methods are employed, i.e., Pearson-correlation technique and chi-squared. Feature selection is non-trivial in identifying the features that significantly contributes towards the classification efficacy of the developed model, as the inclusion of irrelevant features (noises) could decrease the accuracy of the models. The features were evaluated via Spyder 3 software package in the Python 3 environment.

2.3 Classification

Different variation of SVM models are evaluated in the present investigation. The variation is based on default kernels available on the MATLAB 2016b Classification Learner toolbox, i.e., Linear, Quadratic, Cubic, and Medium-Gaussian, respectively. The five-fold cross-validation technique was employed in the study in order to mitigate the effect of overfitting on the trained models. The data was split to an 80:20 ratio for train and test, respectively.

3 Results and Discussion

By considering all features, it could be observed from Table 3, that Linear, Quadratic and Cubic SVM model yield a similar training and test accuracy of 85 and 80% with different in prediction speed and training time. Nonetheless, it is evident that the Quadratic SVM model could provide the fastest prediction speed against the other models evaluated, particularly with the best models mentioned. Through the feature selection evaluation via both Pearson and Chi-square method, the following features are identified as significant, i.e., stdgZ, skgZ, rmsgZ, rmsgX, rmsaX, meangZ, meangX and meanaX, where a, g, X, and Z, corresponds to accelerometer readings (m/s^2), gyro readings (°/s), X-axis, and Z-axis, respectively.

It could be seen from Table 4, that all the SVM classifier evaluated have improved in all performance indicators. It is apparent that the Cubic, Quadratic and Medium Gaussian based SVM models resulted in the best training and test accuracy of 100%. Nevertheless, it could be said that the Cubic-SVM model is the best, as it provided the fastest prediction speed as shown in Fig. 3. Moreover, from Fig. 4, it could be seen that the Linear, Quadratic and Cubic models exhibit an overfitting behavior before the considering the selected features, but upon the selection of the features, such behaviour no longer transpires, suggesting that the procedure of selecting significant features are non-trivial.

Table 3 Training and test results on SVM model on all 36 features

Performance indicators	Linear-SVM	Quadratic-SVM	Cubic-SVM	Medium gaussian-SVM
Training accuracy (%)	85	85	85	80
Prediction speed (obs/s)	~140	~130	~140	~180
Training time (s)	10.737	9.8779	9.747	11.541
Test accuracy (%)	80	80	80	80

Table 4 Training and test results on SVM models on 6 selected features

Performance indicators	Linear-SVM	Quadratic-SVM	Cubic-SVM	Medium gaussian-SVM
Training accuracy (%)	95	100	100	100
Prediction speed (obs/s)	~180	~170	~170	~310
Training time (s)	8.8811	8.6213	8.3247	11.482
Test accuracy (%)	100	100	100	100

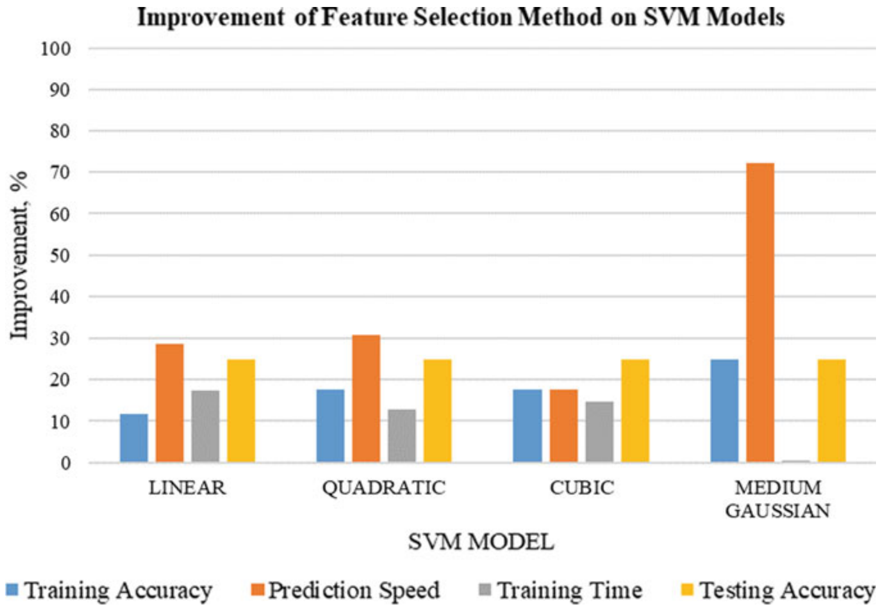

Fig. 3 Comparison of training and test accuracy before and after feature selection on SVM models

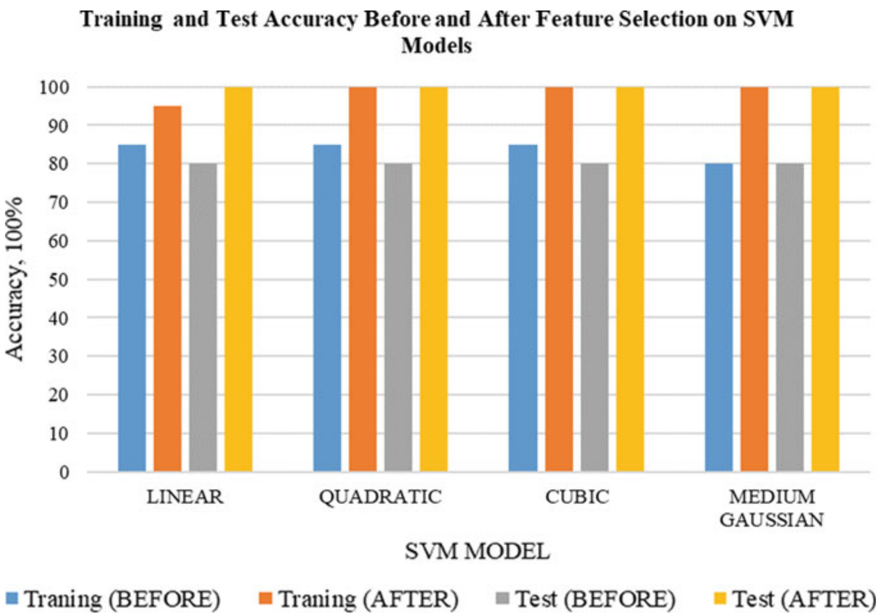

Fig. 4 Improvement of feature selection method on SMV models

4 Conclusion

It was shown in this preliminary investigation that that the features selection significantly improved the training accuracy, prediction speed, training time and test accuracy of the classification models evaluated. It was shown that the best classifier is the Cubic based SVM model as it has the fastest training time. This study suggest that the selection of the features is non-trivial in yielding a better performance of the classifiers evaluated. Future study shall evaluated other feature selection methods as well as its effect towards other classifiers that has yet been investigated in the present study.

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