The Classification of Skateboarding Tricks: A Support Vector Machine Hyperparameter Evaluation Optimisation

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Abstract The growing interest in skateboarding as a competitive sport requires new motion analysis approaches and innovative ways to portray athletes' results as the conventional technique of the classification of the tricks is often inadequate in providing accurate and often biased evaluation during competition. This paper aims to identify the suitable hyperparameters of a Support Vector Machine (SVM) classifier in classifying five different skateboarding tricks (Ollie, Kickflip, Frontside 180, Pop Shove-it, and Nollie Frontside Shove-it) based on frequency-domain features extracted from Inertial Measurement Unit (IMU). An amateur skateboarder with the age of 23 years old performed five different skateboard tricks and repeated for five times. The signals obtained then were converted from time-domain to frequency-domain through Fast Fourier Transform (FFT), and a number of features (mean, kurtosis, skewness, standard deviation, root mean square and peak-to-peak corresponding to x–y–z axis of IMU reading) were extracted from the frequency dataset. Different hyperparameters of the SVM model were optimised via grid search sweep. It was found that a sigmoid kernel with 0.01 of gamma and regularisation, C value of 10 were found to be the optimum hyperparameters as it could attain a classification accuracy of 100%. The present findings imply that the proposed approach can well identify the tricks to assist the judges in providing a more objective-based evaluation.

Keywords IMU sensor · Machine learning · Skateboard · Classification · Trick

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1 Introduction

Skateboarding is a sport that falls under the category of extreme game, where someone rides a wooden deck with four wheels. Through the tracking foot momentum and weight in short intervals, the skateboarder could execute different tricks. Therefore, foot rotation is an integral part of skateboarding. Skateboarding is worth approximately USD 4.8 billion in the sports industry. The sport was confirmed in 2016 for its first appearance at the Tokyo Summer Olympic Games 2020 (now shifted to 2021 due to COVID-19 pandemic). Due to the increasing popularity of the sport, the early development of talent is no longer an option.

The recent development of activities detection technologies has resulted in an increased interest in Machine Learning (ML) [1]. This expected to offer specifically detailed information on physical moves in a dynamic situation, such as skating, to help an individual understand and analyse the physical movements [2]. In several studies, factors that have influenced skateboarding tricks have been studied. Nevertheless, it is important to bear in mind, that judges have often subjectively judged the skateboarding tricks based on their past experiences which could lead to biases if incorrect judgments are made.

Hitherto, there is limited literature available in the classification of skateboarding tricks. Basic tricks were carried out for some investigation in order to ease the collection of data and understanding the basis of signal processing on fundamental tricks. Groh et al. [3] performed a study to predict six different tricks namely, Ollie (O), Nollie (N), Kickflip (K), Heelflip (H), Pop Shove-it (PS), and 360-Flip (360) with the involvement of seven male skateboarders (age: 25–29 years old, stance: 3 regular and 4 goofy). Each correctly performed trick was repeated five times. In a similar study on recognition of skateboarding tricks, an earlier investigation was carried out to observe performance while skateboarding through Graphical User Interface (GUI) and to differentiate two skateboarding tricks specifically, Ollie and Frontside 180. Only two tricks were performed in order to ensure the skater can reproduce the tricks consistently. The trick was repeated 20 times each [4].

Groh et al. [3] used a miPod sensor system with built-in of IMU with a 16-bit axis resolution and 200 Hz sampling rate. The sensor has a synchronous timestamp of 150 ms. The IMU comprises ± 16 g and $\pm 2000\circ$/s of the 3D accelerometer and 3D gyroscope to classify manoeuvres skateboarding tricks. In extensive research, Groh et al. [5] integrated a miPod sensor (IMMU) with number of bit axis, sampling rate, and measurement ranges are similar to previous study. The range of 3D Magnetometer is ± 1200 μT. On the contrary, Park et al. [2] used a Arduino kit fromKytronix namely, snowboard for sensing pressure matrix and 160 data points were collected from pressure data.

Apart from time-domain features, researchers have also employ frequency-domain features. For instance, Ashqar et al. [6] conducted a research with different classifiers of machine learning using smart phone application to detect transportation modes of walking, running, bus, cycling and as a passenger in a car. The extraction of useful features in order to provide details for classifying the training model of the machine learning algorithm with an understanding of the skateboard's trick is essential. Groh et al. [3] invert the x-axes and z-axes for all goofy rider stance data in the data pre-processing method in order to distinguish tricks for both stance types of skaters. From the time-domain features, relationship between *x*–*y*-axis, *x*–*z*-axis and *y*–*z*-axis were obtained such as the kurtosis, variance, skewness, bandwidth and dominant frequency, resulting in a total of 54 new features were obtained. Additionally, a total of 345 features were extracted from time series and frequency series data based on measure of 10 variability (similar with the 8 derivative variance with additional energy and spectralEntropy) and 8 derivative variability which is the range, inter-quartile range and standard deviation as well as value distribution of max, min, mean, variance and the difference between positive and negative [6].

Machine learning algorithms have shown as a powerful method for classifying not only skateboarding tricks but also be able to distinguish between two stances, goofy and regular. As an illustration, Anlauff et al. [4] utilised a Linear Discriminant Analysis (LDA) and shrinkage method was applied to improve the accuracy of classification by regularise the covariance matrices using lemma. A 10-folds CV was employed to the classifier resulting in correct rate and sensitivity with 96.0% and 97.0% respectively for Ollie trick and 86.0% of correct rate and 90.0% of sensitivity for Frontside 180. Four classifiers: NB, PART, SVM and kNN were compared. The evaluation of all four classifier were based on a leave-one-subject-out cross-validation. NB and SVM were the best classifier with accuracy of 97.8% [3]. Five classifier of supervised classification: NB, RF, LSVM, RB-SVM and kNN were used to divide all the event detection into 11 tricks classes, 1 bail class and 1 rest class. The evaluation of all five classifier were based on a leave-one-subject-out cross validation. RB-SVM was the best classification accuracy with 89.1% for only correctly landing tricks. Classification accuracy of all events, RF was the best classifier with 79.8% [5]. Furthermore, the study on identification of five different transportation modes has shown that the RF-SVM have a maximum classification accuracy of 97.02% [6].

It is interesting to note that although minimal studies have been done with respect to skateboarding, many sports activities and simple daily activities utilising IMU sensors (time-domain and frequency-domain datasets) as well as machine learning have also been well acknowledged and documented [7–13]. This paper intends to evaluate the improvement that could be made on the classification accuracy of SVM model by performing hyperparameter optimisation on a number of extracted frequency-domain features. The present study is an extension from a previous work that equipped with the sk8pro device [14]. This result of this study can be beneficial for a more accurate evaluation by judges and to enhance the skateboard athletes' performance further.

2 Methodology

2.1 Instrumented IMU Device

CATIA software was used to design the architecture of the computer modelling of the IMU device. A Zortrax M200 Plus 3D printer was utilised to print out the device's casing with Acrylonitrile Butadiene Styrene (ABS) as its material. The ABS material was chosen because of its advantageous as in, elevated force resistance and excellent absorbing nature as the device is prone to shock from the tricks presented. The Arduino Pro Mini act as the microcontroller with equipped of signal detection sensor (MPU6050) and a Bluetooth Module (HC-06) which powered by 3.7 V Lithium Polymer battery. The signals obtained from the tricks are derived from the acceleration (m/s2), and the angular velocity (°/s) haul out from the 6D-IMU sensor with a sampling time of 50 ms (Fig. 1).

Figure 2 illustrates the location on the skateboard of the instrumented IMU unit.

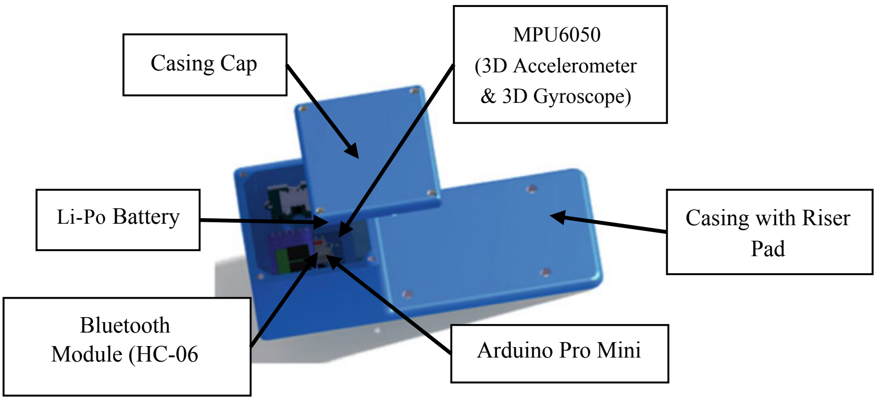

Fig. 1 Sk8pro device

Fig. 2 The sk8pro device attached at bottom front of the board **a** the 3D printed sk8pro device **b** attachment of the sk8pro to the skateboard

Table 1 Executed tricks

Name	Rotation (angle and axis)
Ollie (O)	Nose liftoff (about 45° + x)
Nollie FS Shuvit (NFS)	Incline spin on the vertical (about 180° − z)
Frontside 180° (FS180)	Vertical spin about (180° − z)
Pop Shove-it (PS)	Clockwise turn on vertical axis (180°+z)
Kickflip (K)	Turn whole the board clockwise about longitudinal axis (360° + y)

It is positioned at the bottom front of the skateboard (Nose), and behind the front truck is the unit actually set. As the device is built alongside with riser pad, it easy to mount the device on the deck using the existing fastener to ensure the device's stability. The choice of the device's location is non-trivial as it does not impede the skateboarders' movement when executing a particular trick. In fact, the location of the device reduces the risk of damage to the system throughout the process of data collection.

2.2 Data Collection

A 23 years old amateur skateboarder with 170 cm tall and a weight of 54 kg from University Malaysia of Pahang was requested to execute five sundry tricks (as shown in Table 1) and to be repeated for five times of each trick as previously investigated [15]. The tricks of the skater carried out were chosen based on his competence and comprehensiveness. All of the tricks performed were in goofy stance direction. In the preprocessing stage, the identification event was done to filter noisy and unnecessary data points. Figure 3 shows an executed trick diagram plus its accelerometer and gyroscope signals.

2.3 Data Processing

The time-domain data acquired from the IMU sensor from sk8pro device. Transforming the time domain to frequency domain was applied through Fast Fourier Transform (FFT). We are interested in the magnitude of amplitudes in the frequency responses. Just half the sampling rate (N/2) can be used for frequency signals based upon a Nyquist-Shannon sampling theorem, in order to scrutinise the frequency signals. Each signal has decreased to 10 Hz in frequency. Figure 4 displays the frequency signals of the trick.

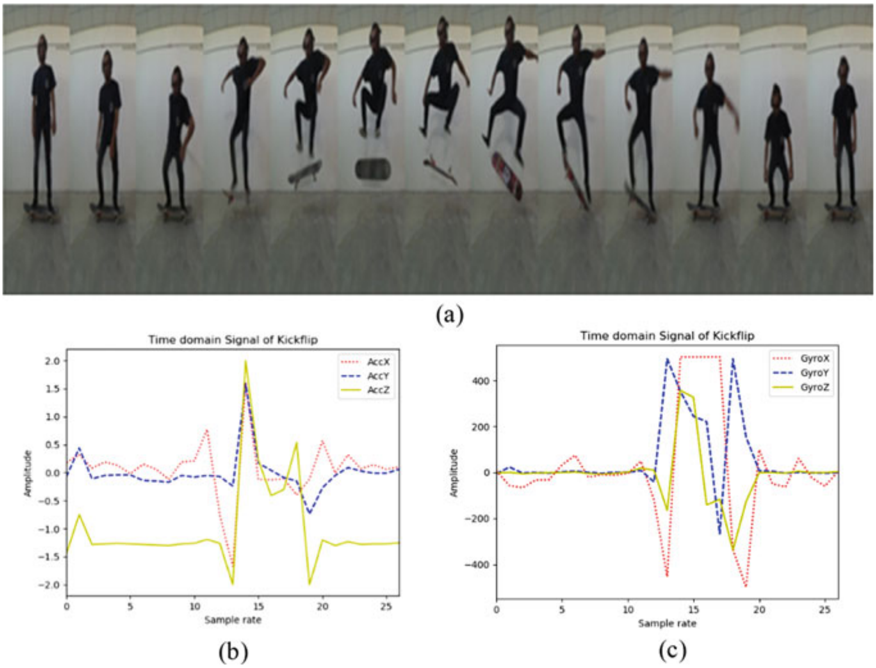

Fig. 3 **a** A Kickflip (K) trick was executed and **b**, **c** its corresponding signals

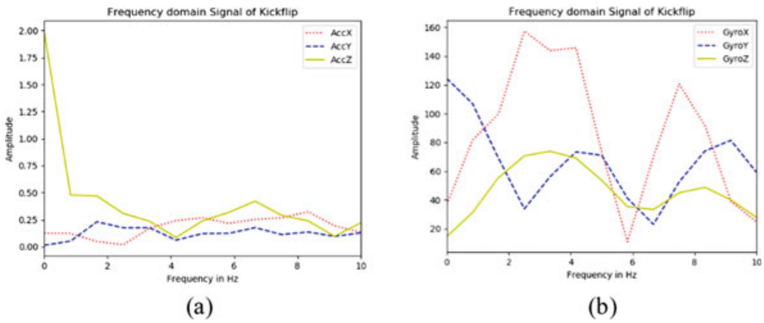

Fig. 4 Converted acceleration and gyro signal for Kickflip

2.4 Machine Learning

The absolute FFT data (frequency domain) are then analysed using MATLAB 2016b for the resulting features in all six degrees of freedoms, of standard deviation, kurtosis, mean, peak to peak, skewness, root mean square and all readings. This is resulting in 36 new features were generated. An SVM with Radial Basis Function (RBF) kernel was initially used in this investigation towards its efficacy in classifying the tricks.

Table 2 Hyperparameter tuning for SVM model

Parameter			
Kernel	RBF	Sigmoid	Linear
Gamma, γ	$1e^{-5}$, $1e^{-4}$, $1e^{-3}$, $1e^{-2}$		No
C (regularisation)	0.001, 0.10, 0.1, 10, 25, 50, 100, 1000		

It should be noted that the classifier default settings are taken from the scikit-learn library [16]. The machine learning models were assessed to determine the accuracy, precision, recall, and the F1 score calculated according to the confusion matrix. In the current study, the leave-one-out (LOO) cross-validation technique was implemented to train the model from the total successful dataset recorded.

A total of 40 successful tricks were recorded, nonetheless, and only 25 tricks were found to be effective as it landed to the standard action of each foot stays on the board. Hence, the collected data were used to train the classifiers' algorithm. A stratified split with 68% for training and 32% for test, respectively was carried out prior invoking the LOO on the training dataset. In order to improve the classification accuracy, the model's hyperparameters were then optimised using grid search sweep in which the twofold technique was used to evaluate the hyperparameters. Three parameters have been taking into account to evaluate its efficacy. The parameter used in grid search is shown in Table 2.

3 Results and Discussion

It is evident that an overfitting phenomenon could be observed on the default SVM model. A drop of 25% could be seen in the testing accuracy, as depicted in Fig. 5. Nonetheless, upon evaluating the features based on the optimised hyperparameters, the 'Optimised' model could attain a classification accuracy (CA) of 100% on both the train and test dataset. The optimised hyperparameters identified is the sigmoid kernel with 0.01 of gamma and regularisation, C value of 10. Table 3 tabulates the comparison between the default SVM and SVM with optimised hyperparameter in terms of CA, F1 score, precision and recall.

Further analysis can be demonstrated on the confusion matrix of default SVM and optimised SVM trained models in Fig. 6a, b respectively and showed that there is no misclassification of tricks (highlighted in blue). Furthermore, the confusion matrix of test results as in Fig. 7a, b illustrate that the misclassification (highlighted in red) reported by the tested default SVM model resulted from the NFS and O tricks which were misclassified as FS180 and K tricks respectively, while there is no misclassification recorded by the tested optimised SVM model. From this investigation, a fair classification performance to predict skateboard tricks can be achieved by tuning the hyperparameter of the model.

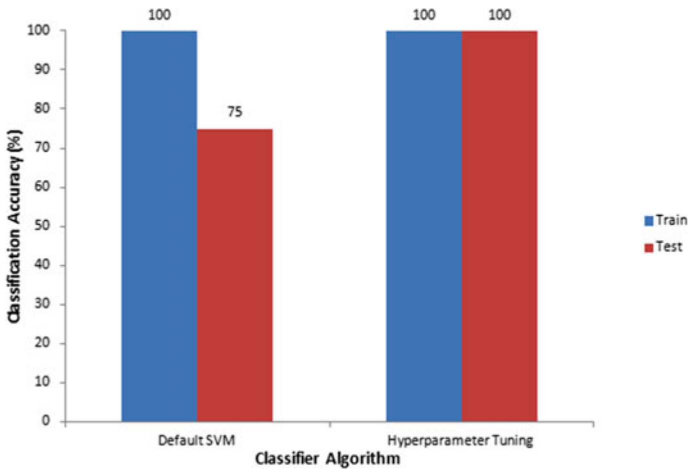

Fig. 5 Graph of comparison of classifiers performance

Table 3 Evaluation of the developed classifiers

Classifier	Evaluation	CA	F1-score	Precision	Recall
RBF-SVM	Train	1.000	1.000	1.000	1.000
	Test	0.750	0.740	0.850	0.750
Hyperparameter Tuning SVM	Train	1.000	1.000	1.000	1.000
	Test	1.000	1.000	1.000	1.000

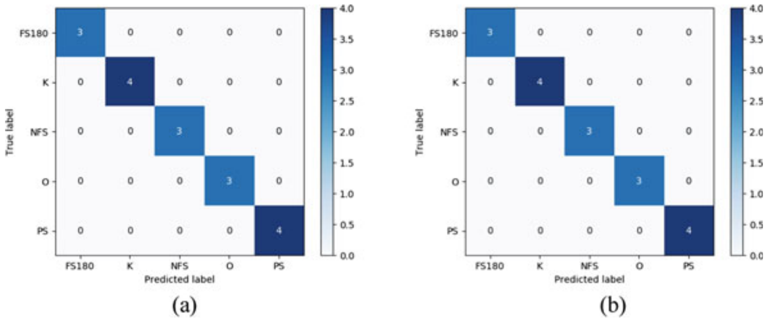

Fig. 6 Confusion matrix of the training of **a** default SVM and **b** optimised hyperparameter SVM model

4 Conclusion

This study investigates the influence of hyperparameter optimisation towards the classification accuracy of skateboarding tricks. It was demonstrated that from the

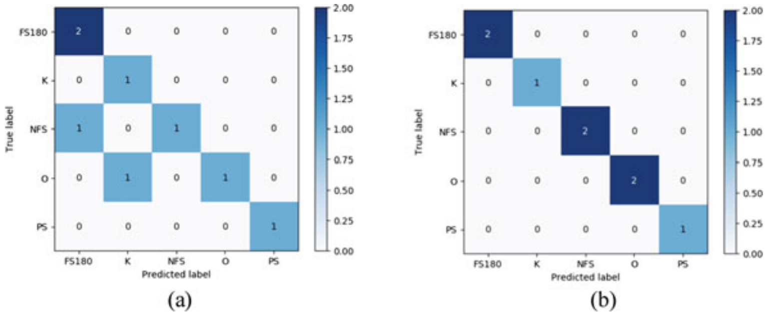

Fig. 7 Confusion matrix of the testing of **a** default SVM and **b** optimised hyperparameter SVM model

frequency domain features extracted from the instrumented IMU device mounted on the deck, that the optimised SVM model is able to predict accurately both on the train and test dataset, unlike the default SVM model which could not predict well on the test dataset. Future study will be conducted to include more subjects, considering other features, as well as exploiting other feature selection techniques. The findings of the present study could provide a more comprehensive and accurate based appraisal of the tricks performed.

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