

THE CLASSIFICATION OF SKATEBOARD  
TRICK MANOEUVRES THROUGH THE  
INTEGRATION OF INERTIAL  
MEASUREMENT UNIT (IMU)  
AND MACHINE LEARNING

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We hereby declare that we have checked this thesis and in our opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Master of Science.



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## STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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## ABSTRAK

Minat yang semakin meningkat dalam sukan papan selaju sebagai sukan kompetitif memerlukan pendekatan analisis gerakan baharu dan cara inovatif bagi menggambarkan prestasi atlet kerana klasifikasi teknik aksi sebelum ini sering dianggap tidak mencukupi dalam memberikan penilaian yang tepat semasa pertandingan. Oleh itu, kaedah yang objektif dan adil bagi menilai aksi papan selaju dibangunkan untuk menganalisis aksi pemain papan selaju adalah bukan remeh. Kajian ini bertujuan untuk mengklasifikasikan aksi tanah rata, iaitu *Ollie*, *Kickflip*, *Pop Shove-it*, *Nollie Frontside Shove-it*, dan *Frontside 180*, melalui penggunaan *Inertial Measurement Unit (IMU)* dan model pembelajaran mesin. Enam pemain amatir papan selaju melakukan lima jenis aksi yang diulangi sebanyak lima kali bagi setiap jenis aksi. Data papan selaju input domain siri masa (*TS*) telah diubah kepada dua jenis domain kekerapan yang berbeza, iaitu *Fast Fourier Transform (FFT)* dan *Discrete Wavelet Transform (DWT)*. Oleh itu, kedua-dua ciri domain masa dan kekerapan digunakan bagi menilai enam model pembelajaran mesin, *Logistic Regression (LR)*, *Random Forest (RF)*, *k-Nearest Neighbors (k-NN)*, *Artificial Neural Network (ANN)*, *Naïve Bayes (NB)*, dan *Support Vector Machine (SVM)*. Sebagai tambahan, dua jenis kaedah pemilihan ciri yang dikenali sebagai kaedah *Wrapper* dan *Embedded*, telah digunakan untuk mengenal pasti ciri-ciri penting. Set data dibahagikan kepada nisbah 70:30, 70 untuk latihan dan 30 untuk ujian. Daripada kajian menunjukkan bahawa RF-TS (Semua), RF-TS (*Wrapper*), RF-TS (*Embedded*), RF-DWT (Semua), RF-DWT (*Wrapper*), dan RF-DWT (*Embedded*) menghasilkan ketepatan klasifikasi sebanyak 100%. Namun begitu, RF-TS (*Wrapper*) ditetapkan sebagai yang terbaik kerana ia menggunakan bilangan ciri yang paling sedikit (empat puluh satu dan bukannya lima puluh empat), yang seterusnya mengurangkan kerumitan model untuk mengklasifikasi aksi yang dinilai. Oleh itu, pendekatan yang dicadangkan dapat mengenal pasti aksi papan selaju secara munasabah bagi membantu para juri menilai prestasi aksi dengan lebih tepat berbanding teknik subjektif dan tradisional yang digunakan pada masa ini.

## ABSTRACT

The growing interest in skateboarding as a competitive sport requires new motion analysis approaches and innovative ways to portray athletes' performance as previous classification of tricks techniques was often deemed inadequate in providing accurate evaluation during competition. Therefore, an objective and fair means of evaluating skateboarding tricks were developed to analyze skateboarder's tricks is non-trivial. This study aims at classifying flat ground tricks, namely Ollie, Kickflip, Pop Shove-it, Nollie Frontside Shove-it, and Frontside 180, through the use of Inertial Measurement Unit (IMU) and machine learning models. Six armature skateboarders executed five tricks for each type of trick repeatedly by five times. It is worth noting that the time-series (TS) domain input skateboard data were transformed to two different types of frequency domains, namely Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT). Therefore, both the time and frequency domain features were used to evaluate six machine learning models, Logistic Regression (LR), Random Forest (RF),  $k$ -Nearest Neighbors ( $k$ -NN), Artificial Neural Network (ANN), Naïve Bayes (NB), and Support Vector Machine (SVM). In addition, two types of feature selection methods known as Wrapper and Embedded methods, were applied to identify the significant features. The datasets were split into 70:30 ratios for training and testing, respectively. It was shown from the study, that the RF-TS (All), RF-TS (Wrapper), RF-TS (Embedded), RF-DWT (All), RF-DWT (Wrapper), and RF-DWT (Embedded) yield 100% classification accuracy. Nevertheless, the RF-TS (Wrapper) is established to be the best as it utilises the least number of features (forty-one instead of fifty-four), which in turn reduces the complexity of the model for the classification of the tricks evaluated. Therefore, it is opined that the approach proposed can reasonably identify the tricks of the skateboard to help the judges evaluates the trick performances more precisely as opposed to the currently used subjective and traditional techniques.

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