CLASSIFICATION OF SKATEBOARDING TRICKS BY SYNTHESIZING TRANSFER LEARNING MODELS AND MACHINE LEARNING CLASSIFIERS USING DIFFERENT INPUT SIGNAL TRANSFORMATIONS

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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

Sukan papan selaju telah membuat penampilan pertama di Sukan Olimpik Tokyo 2020. Kebiasaannya, dalam situasi pertandingan, pemarkahan dijalankan secara manual dan subjektif tertakluk kepada pemerhatian juri-juri terhadap trik yang dilaksanakan. Dengan sebab itu, kerumitan trik membawa kepada kesulitan pemarkahan yang boleh menjurus kepada kesilapan manusia dan berat sebelah. Oleh yang demikian, matlamat kajian ini adalah untuk mengklasifikasikan lima trik papan selaju iaitu *Ollie*, *Kickflip*, *Shove-it*, *Nollie* dan *Frontside 180*. Ini dicapai dengan menggunakan tiga model pembelajaran mesin yang dioptimumkan iaitu *k-Nearest Neighbor* (kNN), *Random Forest* (RF), dan *Support Vector Machine* (SVM) dari ciri yang diekstrak melalui lapan belas model pembelajaran pemindahan. Enam pemain papan selaju amatur melakukan lima trik pada papan luncur ORY yang disesuaikan. Data mentah daripada unit ukuran inersia (IMU) yang dibenamkan pada peranti yang dibangunkan yang dipasang pada papan selaju telah diekstrak. Perlu diingat bahawa empat jenis gambar input diubah melalui *Fast Fourier Transform* (FFT), *Continuous Wavelet Transform* (CWT), *Discrete Wavelet Transform* (DWT) dan *synthesized raw image* (RAW) dari isyarat berdasarkan IMU yang diperoleh. Bentuk pengkelasan yang dioptimumkan diperoleh dengan melakukan teknik pengoptimuman *GridSearch* pada set data latihan dengan pengesahan silang 3 kali pada pemisahan data dengan nisbah 4:1:1 untuk latihan, pengesahan dan pengujian dari 150 gambar yang telah ditransformasi. Kajian ini telah menunjukkan bahawa imej CWT dan RAW yang digunakan dalam model pembelajaran pemindahan *MobileNet* ditambah dengan pengelas SVM dan RF yang dioptimumkan mempamerkan ketepatan ujian sebanyak 100%. Untuk mengenal pasti kaedah terbaik untuk keseluruhan gabungan, masa pengiraan digunakan untuk menilai pelbagai model. Disimpulkan bahawa pendekatan RAW-*MobileNet*-dioptimumkan-RF adalah yang paling berkesan dengan masa pengiraan 24.796875 saat. Hasil kajian mendedahkan bahawa pendekatan yang dicadangkan boleh meningkatkan klasifikasi trik papan selaju.

ABSTRACT

Skateboarding has made its Olympic debut at the delayed Tokyo 2020 Olympic Games. Conventionally, in the competition scene, the scoring of the game is done manually and subjectively by the judges through the observation of the trick executions. Nevertheless, the complexity of the manoeuvres executed has caused difficulties in its scoring that is obviously prone to human error and bias. Therefore, the aim of this study is to classify five skateboarding flat ground tricks which are Ollie, Kickflip, Shove-it, Nollie and Frontside 180. This is achieved by using three optimized machine learning models of k-Nearest Neighbor (kNN), Random Forest (RF), and Support Vector Machine (SVM) from features extracted via eighteen transfer learning models. Six amateur skaters performed five tricks on a customized ORY skateboard. The raw data from the inertial measurement unit (IMU) embedded on the developed device attached to the skateboarding were extracted. It is worth noting that four types of input images were transformed via Fast Fourier Transform (FFT), Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT) and synthesized raw image (RAW) from the IMU-based signals obtained. The optimized form of the classifiers was obtained by performing GridSearch optimization technique on the training dataset with 3-folds cross-validation on a data split of 4:1:1 ratio for training, validation and testing, respectively from 150 transformed images. It was shown that the CWT and RAW images used in the MobileNet transfer learning model coupled with the optimized SVM and RF classifiers exhibited a test accuracy of 100%. In order to identify the best possible method for the pipelines, computational time was used to evaluate the various models. It was concluded that the RAW-MobileNet-optimized-RF approach was the most effective one, with a computational time of 24.796875 seconds. The results of the study revealed that the proposed approach could improve the classification of skateboarding tricks.

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