THE CLASSIFICATION OF SKATEBOARDING TRICK IMAGES BY MEANS OF TRANSFER LEARNING AND MACHINE LEARNING MODELS

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SUPERVISOR'S DECLARATION

I hereby declare that I have checked this thesis, and, in my opinion, this thesis is adequate in terms of scope and quality for the partial fulfillment of the award of the degree of Master of Science.

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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 University Malaysia Pahang or any other institutions.

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ABSTRACT

The evaluation of tricks executions in skateboarding is commonly executed manually and subjectively. The panels of judges often rely on their prior experience in identifying the effectiveness of tricks performance during skateboarding competitions. This technique of classifying tricks is deemed as not a practical solution for the evaluation of skateboarding tricks mainly for big competitions. Therefore, an objective and unbiased means of evaluating skateboarding tricks for analyzing skateboarder's trick 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 camera vision and the combination of Transfer Learning (TL) and Machine Learning (ML). An amateur skateboarder (23 years of age with ± 5.0 years' experience) executed five tricks for each type of trick repeatedly on an HZ skateboard from a YI action camera placed at a distance of 1.26 m on a cemented ground. The features from the image obtained are extracted automatically via 18 TL models. The features extracted from the models are then fed into different tuned ML classifiers models, for instance, Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), and Random Forest (RF). The grid search optimization technique through five-fold cross-validation was used to tune the hyperparameters of the classifiers evaluated. The data (722 images) was split into training, validation, and testing with a stratified ratio of 60:20:20, respectively. The study demonstrated that VGG16 + SVM and VGG19 + RF attained classification accuracy (CA) of 100% and 98%, respectively on the test dataset, followed by VGG19 + *k*-NN and also DenseNet201 + *k*-NN that achieved a CA of 97%. In order to evaluate the developed pipelines, robustness evaluation was carried out via the form of independent testing that employed the augmented images (2250 images). It was found that VGG16 + SVM, VGG19 + *k*-NN, and DenseNet201 + RF (by average) are able to yield reasonable CA with 99%, 98%, and 97%, respectively. Conclusively, based on the robustness evaluation, it can be ascertained that the VGG16 + SVM pipeline able to classify the tricks exceptionally well. Therefore, from the present study, it has been demonstrated that the proposed pipelines may facilitate judges in providing a more accurate evaluation of the tricks performed as opposed to the traditional method that is currently applied in competitions.

ABSTRAK

Penilaian pelaksanaan trik papan luncur biasanya dilakukan secara manual dan subjektif. Panel hakim sering bergantung kepadapengalaman sebelumnya dalam mengenal pasti keberkesanan prestasi trik semasa pertandingan papan luncur. Teknik pemgelasan trik ini dilihat sebagai penyelesaian tidak praktikal untuk penilaian trik papan selaju terutamanya untuk pertandingan besar. Oleh itu, satu kaedah yang objektif dan adil adalah perlu bagi menilai trik papan selaju dalam menganalisis trik pemain skateboard. Kajian ini bertujuan untuk mengklasifikasikan trik permukaan rata iaitu Ollie, Kickflip, Pop Shove-it, Nollie Frontside Shove-it, dan Frontside 180 melalui penglihatan kamera dan gabungan Pembelajaran Pindah (PP) dan Pembelajaran Mesin (PM). Seorang pemain skateboard amatur (berusia 23 tahun dengan ± 5.0 tahun pengalaman) melakukan lima trik untuk setiap jenis trik berulang kali pada papan luncur HZ daripada kamera aksi YI yang diletakkan pada jarak 1.26 m di atas permukaan bersimen. Ciri-ciri dari gambar yang diperoleh diekstrak secara automatik melalui 18 model PP. Ciri-ciri yang diekstrak daripada model kemudian dimasukkan ke dalam model pengklasifikasi PM yang diselaraskan seperti Mesin Sokongan Vektor (SVM), *k*-Jiran Terdekat (*k*-NN), dan Pokok Hutan Rawak (RF). Teknik pengoptimuman pencarian grid melalui teknik pengesahan silang lima kali ganda digunakan untuk melaras hiperparameters pengklasifikasi yang dinilai. Data (722 gambar) dibahagi kepada data untuk latihan, pengesahan, dan pengujian masing-masing dengan nisbah berstrata 60:20:20. Hasil kajian mendapati bahawa VGG16 + SVM dan VGG19 + RF mencapai ketepatan klasifikasi masing-masing 100% dan 98%, pada set data ujian, diikuti VGG19 + *k*-NN dan juga DenseNet201 + *k*-NN yang mencapai ketepatan klasifikasi 97%. Bagi menilai kemantapan model saluran yang dihasilkan, sebuah bentuk pengujian bebas akan dilaksanakan dengan menggunakan gambar tambahan (2250 gambar). Didapati bahawa VGG16 + SVM, VGG19 + *k*-NN serta DenseNet201 + RF (secara purata) mampu menghasilkan ketepatan klasifikasi yang cukup tinggi dengan masing masing 99%, 98%, dan 97%, tepat. Kesimpulannya, berdasarkan pengujian bebas, didapati bahawa model saluran VGG16 + SVM boleh mengklasifikasikan trik dengan sangat bagus. Oleh itu, kajian ini telah menunjukkan bahawa model saluran yang dicadangkan dapat memudahkan para hakim untuk memberi penilaian yang lebih tepat ke atas trik yang dilakukan berbanding kaedah tradisional yang digunakan dalam pertandingan.

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