ORIGINAL ARTICLE

USM ExerHunt: A Building Image Recognition-Based Exergame

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ABSTRACT

Introduction: Exergames is defined as a technology-driven physical activity, which is an innovative way of physical activity that integrates interactive gameplay in the exercise process. The exergames may provide enjoyable experiences that could motivate people to participate and continue playing the game play, while also exercising at the same time. **Methods:** This article presents a treasure hunt-based walking exergames on android platform with the implementation of intelligence-based image recognition. The exergame, termed USM ExerHunt uses images of Universiti Sains Malaysia buildings as the hints. The participant of the game supposes to find a building shown in the hint, and once reaching the destination captures the image of the building. Then, the application will calculate the total steps taken and calories burnt by the participant using an implementation of accelerometer from the mobile phone. **Results:** The developed USM ExerHunt application is able to achieve accurate image recognition of USM building, with the accuracy rate of 92%. Besides that, the application is capable of calculating the number of total steps and calories burnt after an exercise routine is completed. **Conclusion:** This android application has shown a proof of concept in incorporating machine intelligence into an exergame application, with pilot study within the USM community.

Keywords: Deep Learning, Exergame, Image Recognition

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INTRODUCTION

Obesity has raised a major concern worldwide, which leads to noncommunicable diseases including cardiovascular disease, insulin resistance and musculoskeletal disorders. According to World Health Organization, 39% of adults aged 18 years and over were overweight, and 13% were obese in 2016 (1). The rising prevalence of obesity is mainly contributed by the current sedentary lifestyle, where human tend to be more inclined to desk jobs or activities. It is estimated that there is approximate 12 hours of physical inactivity in a day, excluding sleeping.

The advancement of technology has contributed to sedentary lifestyle, which can be observed through the majority use of mobile gadgets rather than physical activity. It is very common that people are more inclined to be hooked up to mobile applications most of their time. Hence, medical practitioners are having difficult times at promoting healthy lifestyle through physical activities such as running, walking or working out in the gym. This is because physical activities are seen to be less attractive when compared to mobile games, which can attract million online users to be engaged in virtual activities. According to Digital Report 2019 by DataReportal, there are 58% of mobile phone users connected with internet technology (2).

Hence, as a drive in motivating the current technologically driven community to be actively more involved in physical activities, the *Exergame* was established. Exergame is defined as technology-driven physical activity, which designs exercises as gameplay routines (3). Several studies have investigated and demonstrated the benefits of Exergames among children and adolescents (4,5). With vast majority of population more inclined to mobile phones, the exergame is found to be an efficient solution to promote physical activities.

Some of the smartphone applications that promote exercise through exergame is widely available and already been used by the community. Runkeeper is an example of exergame that encourages physical activities, such as walking, running, cycling or even yoga (6). Users can track their exercise routine, including their pace, distance and calories burnt. This application is dependent upon Global Positioning System, that tracks the location being travelled. The Runkeeper implemented the exercise as a challenge, in which the users may get a medal after an exercise challenge is completed. Besides that, the users may also share their achievements with other friends through social media. A recent study by Ormel et. al. (2018) has investigated the effectiveness of Runkeeper in increasing physical activity among cancer patients (7).

Another mobile application known as Zombies, Run! is an exergame for running activity (8,9). Players will be registered as characters, and running activity is designed as set of missions through audio narrations. This application forces the players to run using the zombies chase concept, in which the players are supposed to run away from the zombies that are chasing them. After a mission is successfully completed, information of distance, time, pace and calories burnt will be recorded. This application uses GPS to track the route travelled during the mission.

Besides exergames that are based on GPS technology, another type of exergame uses virtual reality-based applications. One such example is VRun, proposed by Yoo and Kay (2018) (10). This game promotes running through a virtual world, in which the players wears a virtual reality headset, and perform running within an enclosed environment. The environment is simulated through a virtual world, in which the player physically walks or run on the spot to the finishing point, and the activity is recorded through the accelerometer from a handphone. However, player finds exergame using virtual reality-based application involves fatigue and uncomfortable feeling due to the requirement of wearing the headset and inclined to a single physical room throughout the exercise routine.

Most of the exergames that is available in the mobile market are based on GPS or virtual reality technology. As an alternative exergame solution this article presents a treasure hunt based exergame, named USM ExerHunt. Aimed at integrating gameplay into exercise routine, the work presented in this article focuses at integrating intelligence into the exergame through building image recognition method. As a pilot study, an exergame based on android platform is developed with Universiti Sains Malaysia's building images for the image recognition module. This exergame was motivated inline with Universiti Sains Malaysia (USM) initiative of having healthy community, mainly for the deskjob staffs of USM.

MATERIALS AND METHODS

System Architecture

USM ExerHunt is an android-based mobile application aimed to promote exercise among USM staffs. This application consists of three main modules, including the android-based mobile application, a database management of USM buildings' images, hints and players information, and server integrating a deep learning model for USM building image recognition. Fig. 1 illustrates an overview of the architecture of USM exergame.

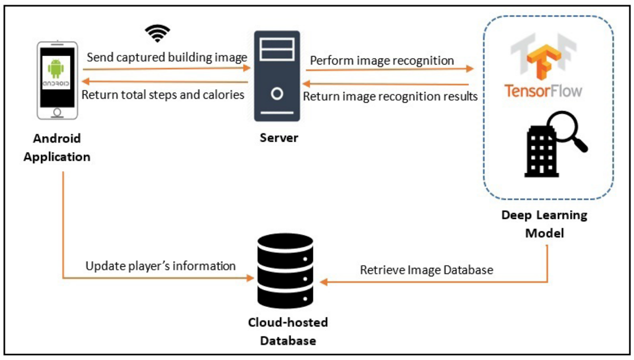

Figure 1: Overview of USM exergame architecture

Firstly, the application will load USM building image-based hints from Firebase and display the hints for the player to initiate the exergame. The player is required to find the specified building based on the hint shown. Upon reaching the destination, the player will capture the image of the guessed building. Then, the captured image will be sent to the server that contains the image recognition model to verify the correctness of the captured building image against the given hint. The image recognition model is a deep learning model trained with USM building image dataset, aimed to recognize USM buildings used as hints.

If the building image is captured accurately by the player, the application will calculate the total steps taken and calories burnt by the player and shown to the player. The player may then continue his exergame by choosing the next cue. The database will also store the exercise information of each player and keeps updating it during every exercise routine.

Functional Requirements

The main functionalities involved in this USM exergame application is summarized in Table I. The illustration of these main functionalities is also given as in use case diagram shown in Fig. 2.

Table I: Main functionalities of USM exergame

Functional Requirement	Descriptions
Request image-based hints	Displays image-based hints that are loaded randomly from the database
Capture building image photo and image verification	Captures building images, and verified by the deep learning model
Display total step taken and calorie Burnt	The system must be able to display the total step taken and calorie burnt after user get the correct location
Display ranking board	Displays ranking among registered players
View History	Stores and display players exercise history

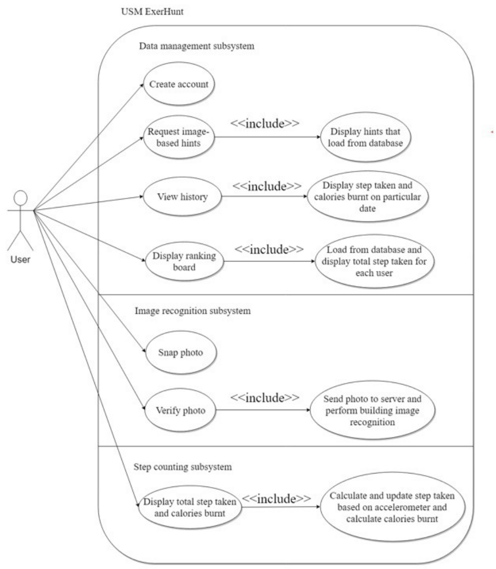

Figure 2: Use case diagram of USM exergame

Data Management Module

The data management module allows player to register accounts and login into the application using the player's phone number as their unique identification number. All players' information is updated into a cloud-hosted database at Firebase (12). Besides that, all the exercise routines information such as the totals steps and calories burnt by each player is stored in the database. This allows the exercise information to be retrieved for the ranking purpose of retrieval of history of the exercise routine. In addition, the data management module also involves in storage and retrieval of the image-based hints and USM building images, which will be used by the image recognition module.

Image Recognition Module

The image recognition module is developed based on a deep learning model using Convolutional Neural Network (CNN) algorithm. This CNN model requires USM building image as the input dataset. The server in the USM exergame architecture, contains this CNN model which performs two main tasks, including (i) training of the CNN model using USM building images, and (ii) perform image recognition.

The CNN model is implemented using Inception version 3(v3) architecture, which has been proven with high classification accuracy on the ImageNet dataset (12). A classification is aimed to classify a data according to a set of predefined categories. Since then, the Inception v3 has been widely applied in various domains such as natural image classification (13), audio classification (14) and medical image classification (15,16). In this work, the image recognition model is trained using transfer learning technique (17,18). Generally, the training of a model requires a very large number of dataset and extensive computational resources. Transfer learning is an inexpensive and timesaving training technique, which uses pre-trained CNN model from a general dataset, such as the ImageNet. It removes the last fully-connected layer and replaces it with a custom fully-connected layer for the USM building images. Hence, the pre-trained CNN model serves as a feature extractor module for the USM building image dataset and achieve a new CNN model accustomed for the USM building image recognition problem.

Dataset

The image dataset is collected by capturing all possible angles of the USM buildings. The dataset contains approximately 2000 USM building images, comprising of 5 targeted building covering School of Computer Sciences, USM mosque, Eureka, Pusat Sejahtera and USM museum. There are approximately 400 images for each type of the building, taken at various time of the day, and varying cloud conditions. Fig. 3 shows examples of images captured for USM mosque.

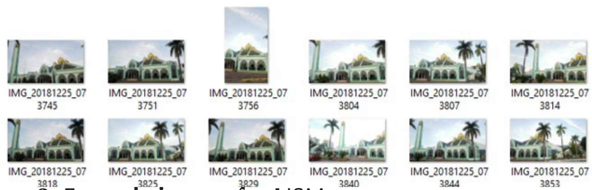

Figure 3: Example images for USM mosque

RESULTS

Image Recognition Module Testing

Two types of testing have been performed to measure the accuracy of USM ExerHunt application, involving testing of (i) training of the proposed CNN model and (ii) real-time USM building image recognition.

During the training of the CNN model, the dataset is divided into three groups, comprising of 80% of images for training set, 10% of images for validation set and 10% of images for testing set. After the final round of validation testing, 100% of accuracy rate is achieved. For the testing phase, an accuracy rate of 98.9% of accuracy has been achieved. Fig. 4 shows a snapshot of the training, validation and testing phases of the CNN image recognition model.

```
INFO:tensorflow:2019-04-13 12:55:08.425707: Step 3999: Train accuracy = 100.0%
INFO:tensorflow:2019-04-13 12:55:08.426706: Step 3999: Cross entropy = 0.006603
INFO:tensorflow:2019-04-13 12:55:08.560629: Step 3999: Validation accuracy = 100.0% (N=100)
INFO:tensorflow:Final test accuracy = 98.9% (N=366)
```

Figure 4: Snapshot of the training, validation and testing phases of the CNN image recognition model

A second experiment was carried out to further validate the performance of the USM building image recognition model performance in real-time. In this experiment, a player is chosen to capture the building image from the 5 target group of USM buildings using the USM ExerHunt application. Then, the image recognition is performed through the module in the application of the captured image. Each USM building is tested 5 times, totaling to 25 image recognition tests. From this total of 25 image recognition tests, the image recognition module is able to perform 23 accurate recognition, which with the accuracy rate of 92%.

USM ExerHunt Application

The USM ExeHunt application comprises main functionalities such as providing image-based hints, image recognition module based on CNN model, calculation of total steps and calories burnt using built-in accelerometer in the mobile phone, review of exercise history and ranking board. Fig. 5 shows example snapshots of these functionalities that have been developed in the USM ExerHunt application.

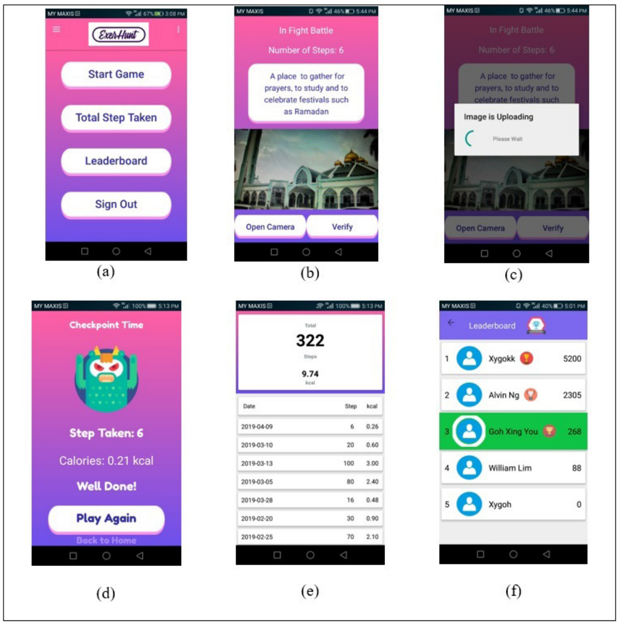

Figure 5: (a) Main menu of USM ExerHunt, (b) image-based hints, (c) image recognition module based on CNN model, (d) calculation of total steps and calories burnt, (e) review of exercise history and (f) Ranking board.

Table II summarizes the comparisons between the existing exergame applications and USM ExerHunt. USM ExerHunt is one of the first exergame that have included an intelligent based image recognition into the exercise routines. In addition, it has been customized to cater the local community of USM as its pilot study. Besides that, it provides a ranking board that may encourage the community to compete each other and promote continuous exercise practice.

On the contrary, Runkeeper, Zombies, Run! and VRun is more focused at interval based exercise routines and

Table II: Comparisons between the existing exergame applications and USM ExerHunt

	Runkeeper	Zombies, Run!	VRun	USM ExerHunt
Exergame Technology	GPS	GPS	Virtual Reality	Deep Learning-based Image Recognition
Functionality	Interval-based exercise Medal collections Ranking board	Mission oriented exercise	Single spot interval-based exercise	Treasure hunt-based Ranking board
Drawback	Less motivation due to unavailability of target mission or challenges	Unavailability of ranking board	Fatigue due to virtual reality wearables	Limited to USM environment

completing a mission. Players may not find motivation to continue to exercise after certain timeframe due to unavailability of competition among multiple players. In addition to that, VRun creates fatigue from the use of virtual reality wearables and being inclined to a closed room.

CONCLUSION

The work in this article presented an exergame, termed USM ExerHunt which integrated intelligence technology into the exercise routines on android platform. Currently, the pilot study in the USM ExerHunt is aimed at USM community. Future possibilities are seen to customise the application beyond USM buildings, which may cater the public community.

Besides that, currently the USM ExerHunt only runs on android platform. Hence, efforts will be carried out to enable the application to run on multiple operating systems. It is also envisioned to include multiple exercise routines such as cycling and hiking.

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