A Sophisticated Platform for Learning Analytics with Wearable Devices

Z.X. Zhou, V. Tam, K.S. Lui and E.Y. Lam
Department of Electrical and Electronic Engineering
The University of Hong Kong
Hong Kong, China
email:zxchow@connect.hku.hk

Xiao Hu, Allan Yuen and Nancy Law
Faculty of Education
The University of Hong Kong
Hong Kong, China
email:xiaoxhu@hku.hk

***Abstract*—With the rapid development in wearable technology, wearable devices integrating with various sensors have been broadly applied in different areas. Yet there is seldom any previous study which focuses on applying wearable devices and deep learning in learning analytics. This paper considers a sophisticated real-time learning analytics platform for analyzing students' learning states and learning activities with wearable devices and deep learning. During the experimental period of this platform, students will receive instant notifications from an intelligent mobile application when their heart rate are out of their normal range so that the actual learning activities conducted by students can be collected to train deep learning models for recognizing their learning activities. At the same time, students can enjoy the sleeping monitoring and the exercise monitoring functionalities provided by the smart watches in this platform. The results of the interviews conducted after the experiment for this platform demonstrate that 89% of students think that this platform is useful for their daily lives and 65% of students report that this platform brings positive effects on their learning in different aspects. More importantly, this work sheds lights on the possibility of applying wearable devices in learning analytics to improve the learning effectivenesses and life qualities of students.**

***Index Terms*—learning analytics, wearable devices, deep learning**

I. INTRODUCTION

Wearable devices, such as Fitbit smart watches and Google smart-glasses, have become increasingly popular in our daily lives and different types of data can be collected through the rich sensors integrated in the wearable devices. In general, the data provided by the wearable device have two main categories: movement data and physiological data. For movement data, such as three-axis accelerometer and gyroscope data, researchers mainly applied it for pose estimation [3] and activities recognition [4]. While the researches in physiological data, such as heart rate, mainly focus on diseases detection [2] and emotion prediction [1]. In addition, with the rapid development in sensor technology, wearable devices are more affordable for both research propose and daily usage than before.

As the growing concerns over students' learning effectiveness, learning analytics has become one of the most promising areas to explore the potential usage of wearable technology. Therefore, different studies and experiments have been conducted by researchers to realize an effective learning analytics with wearable devices. However, most of these studies suffer from two important limitations. Firstly, nearly all of them relied on rule-based model. In this case, the learning analytics results can be biased and subjective as it is significantly affected by the rule-design. Secondly, none of them considers the potential functionalities provided by the wearable devices to students after school. As a matter of fact, except for collecting data from wearers, there are still many other functionalities provided by the latest wearable devices, such as sleeping quality measurement and physical exercise monitoring. These functions can improve the spirit and energy of students so that they can achieve a better learning performance.

Therefore, to address these issues, this paper considers an empirical study of applying wearable devices together with deep learning model in learning analytics. The scientific contributions of this work can be listed as follow. Firstly, we proposed a learning analytics platform which can analyze the data collected from students and provide feedbacks to students in a real-time manner. Secondly, the objectiveness and veracity of the learning analytics results in this platform are improved by adopting deep learning model for data analysis. Lastly, the proposed platform can not only bring positive impact to students' learning, but also improve their life qualities by providing the functionalities of sleeping quality measurement and physical exercise monitoring.

To guarantee the effectiveness and reliability of the proposed platform, Fitbit Versa smart watches were selected in this work [5], [6]. During the experimental period, each student was equipped with a smart watch during their lectures so that the heart rate of them could be captured and analyzed by the proposed platform. Meanwhile, students needed to report their current learning activities once abnormal heart rate patterns were found by the proposed platform. The detailed structure and design of this platform will be introduced in Section III. Based on the data collected from wearable devices and the learning activities reported by students during the experiment, two deep learning models are proposed and trained for recognizing students' learning states and specific learning activities. The details of these two models will be presented in Section IV. After the experiment, interviews were conducted to more than 70% of the students under a relaxing environment. During the interviews, students evaluated the proposed platform in three dimensions, including effectiveness, user-friendliness and interestingness, and described how did this platform affect their learnings. The interview results will be detailed in Section V.

The rest of this paper is organized as follows. Some related works will be discussed in Section II. In Section III, the overall system design and some important devices of the proposed learning analytics platform will be introduced. Section IV describes the two deep learning models for recognizing learning activities and states. In Section V, the interview results will be presented in detail. Lastly, concluding remarks and future directions will be provided in Section VI.

II. Related Work: Learning Analytics Based on Wearable Devices

Inspired by the rapid development of wearable technology and the growing concerns over students' learning performance, some researchers have tried various methods in applying wearable devices for learning analytics. In 2017, a machine learning approach, which was named as learning plus, was designed by Mitri et al. [7] to estimate the learning performance of students according to the data collected from their smart watches and computers. However, their method was not suitable for traditional lecture-based learning and the sample size of their experiment, composed of only 9 students, was too small to get a convincing results. Different from Mitri et al.'s method [7], Zhang et al. [8] predicted students' learning states in class through wearable devices. But the wearable devices adopted by Zhang et al. [8] may probably cause some disturbance to the involved students.

To reduce the disturbance caused by the wearable devices on students, Lu et al. [9] applied commodity wearable devices in their learning analytics framework to remind students if they were recognized as inactive by their framework. Yet both of the frameworks proposed by Zhang et al. [8] and Lu et al. [9] predicted the learning states of students based on some pre-defined rules. Thereby, the effectiveness of their frameworks could not be ensured since it would be deeply influenced by the design of the rules. Moreover, the students' learning states in Lu et al.s' framework were labeled by teachers rather than students themselves. This might lead to a subjective and incorrect labelling as students may have various learning habits. Furthermore, all of work mentioned above applied the wearable devices directly in school while none of them took into account the positive effects, caused by the extra functionalities in the latest wearable devices, to students' daily lives.

Therefore, to address the aforementioned problems, this manuscript innovatively considers to adopt two end-to-end deep learning models to avoid the subjectivity in rule-designing. The involved deep learning models would be trained according to the data captured from the students by our proposed platform during the experimental period. In addition, students were encouraged to wear the smart watches not only in lectures but also after school during the experiment to consider the possible effects on students' daily lives caused by our platform. All the details regarding to this platform will be described in Section III.

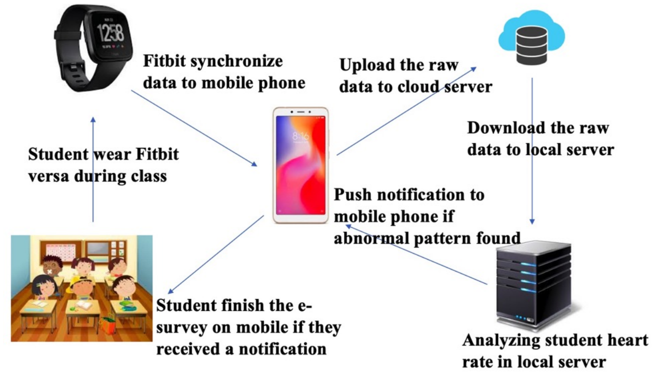


Fig. 1: The system design of the real-time learning analytics platform using wearable devices

III. Real-Time Learning Analytics Platform

Figure 1 shows the detailed structure of the proposed learning analytics platform. There are three major components in this platform: a back-end local server, a cloud server and a pair of smart watch and mobile phone for each involved student. During the experiment, the smart watches will firstly collect the data from students and then send it to the cloud server via the mobile phone. After that, the data will be downloaded into the local server from cloud server for further analysis. During the data analysis, if there is any unusual data pattern found by the local server, an instant notification will be sent to the corresponding students so that students can report their latest learning activities in their mobile phones. The information of each element in this platform will be provided in the following subsection.

A. Mobile Phone: Xiaomi Redmi 6

The Xiaomi Redmi 6 mobile phone is chosen as the smart phone used in this work and it plays two important roles in the proposed platform which can be explained as follows.

1) Data Transfer Platform: mobile phone can act as a data transfer platform between the smart watches and the cloud server. The raw data captured from the smart watches will be firstly transfered to the mobile phone before being further uploaded to the cloud server.

2) Intelligent Mobile Application Platform: except for data transfer platform, the mobile phone is also used as an intelligent mobile application platform. To verify learning activities conducted by students, an intelligent mobile application is prepared and pre-installed on the mobile phone. If there is any unusual data pattern found by the our local server, this application will trigger the vibration of the mobile phone and display an e-survey form for students to choose their present learning activities. In this e-survey form, five choices are provided for students to select, including **"writing"**, **"talking and discussing"**, **"listening to teacher"**, **"mind-wandering and sleeping"**, and **"others"**.

B. The Fitbit Versa Smart Watch

In the latest Fitbit Versa smart watch, four types of data are provided, including:

1) Heart Rates: the Fitbit Versa smart watch estimates the heart rate of each person according to the photoplethysmographic signal. The raw time-series heart rate data with a 0.2Hz sample rate can be collected via both the web application programming interface (API) and also the device API developed by the Fitbit [10] development team.

2) Calories: by default, Fitbit Versa smart watch will automatically measure the calories consumption of each wearer. Slightly different from heart rate data, the raw calories data can only be collected through the web API [10] with a sample rate of one data point per minute.

3) Accelerometer and Gyroscope Data: each Fitbit Versa smart watch provides the three-axis accelerometer and gyroscope data through its device API [10]. However, the recording of the three-axis accelerometer and gyroscope data is not a built-in functionality. Therefore, a specific Fitbit application is needed to collect the raw data from the device API.

C. The Cloud Server

In the proposed learning analytics platform, the cloud server serves as a data transfer station between the smart watches and the local server. In other words, after synchronizing with the smart watches, the mobile phone will firstly upload the raw data to the cloud server. After that, the cloud server will further transfer data to the local server for thorough analysis.

D. The Local Back-end Server

In the proposed framework for the real-time learning analytics, there are mainly two functions of the local back-end server which can be explained as follows.

1) Data Analytics of Heart Rates: During the experimental period of this platform, as there is insufficient data for training the deep learning models, a new algorithm is designed for detecting the abnormal data pattern of students. In this algorithm, each student was asked to wear the smart watch for the first two hours in a relaxing environment at the beginning stage and the standard deviation of their heart rate per minute in these two hours would be computed. The top decile and the bottom decile of these deviation values were considered as the upper bound and the lower bound, respectively. After the first two hours, the standard deviations of each student's heart rate per minute would be calculated continuously by the local server. If the computed results were out of the range between the upper bound and lower bound, it would be regarded as an unusual data pattern.

2) Pushing Notification: After finding the unusual data patterns in students' heart rate, the local server would automatically send notifications to the mobile phones of the involved students so that students can report their current learning activities on their mobile phone.

E. Extra Function of Learning Analytics Platform

As Fitbit Versa smart watch is an important component in this platform, students who participated in platform are encouraged to not only wear the smart watches during the school time but also after school so that they can enjoy all the extra functionalities provided by the smart watches.

1) Sleep Quality Monitoring: One of the most important functionalities of smart watch is the sleep quality monitoring. If students wear the smart watches during their sleep, the smart watches can monitor your sleeping and report to you all the details regarding to your sleep, such as the exact time you fall asleep and the duration of deep sleep. With this function, students can understand their sleep better and realize the importance of a good sleep quality.

2) Exercise Monitoring: In addition to sleep quality monitoring, one of the most popular and essential functionalities of smart watch is exercise monitoring. Based on the various types of data collected from the sensor, smart watches can estimate the amount of your exercise, such as the steps you walk and the floors you climb. With this function, students can understand their exercise better and encourage themselves to do more sports.

F. The Implementation of Experiment

Two different groups of students participated in this experiment of the proposed learning analytics platform for one week in Hong Kong. The first group consisted of 32 third-year high school students while the second group was made up of 20 first-year high school students

Before the experiment, all students together with their parents were informed of the details about this experiment and have signed an agreement for allowing us to collect and analyze their data. During the experiment, each student was equipped with a Fitbit Versa smart watch together with a mobile phone. All students were asked to wear the smart watches and also carry the mobile phone not only during the lecture but also after school. However, although the proposed learning analytics platform would continuously analyze the data collected from the smart watches for the whole day, students would only receive notification to report their learning activities if their heart rates were considered to be in an abnormal pattern during school time.

After the experiment, totally 499 responses of learning activities were collected from students, in which 90 were **"writing"**, 101 were **"talking and discussing"**, 138 were **"listening to teacher"**, 35 were **"mind-wandering and sleeping"**, with the remaining 135 reported activities being classified as **"others"**.

IV. Deep Learning Model for Analyzing Students' Learning Activities and States

To study the potential relationship among the physiological data, the movement data and students' learning activities, both physiological and movement data are used to analyze and predict students' activities with deep learning models in this section. After considering the trade-off between the convenience in collecting data and the accuracy in recognizing learning activities, two deep learning models are proposed in this work. The first one is the Long-short term memory(LSTM) model which can reach an accuracy of 95% in predicting the students' learning states as active or inactive and relies on only physiological data. The second one is the hybrid deep learning model integrating LSTM and CNN which can obtain an 74% accuracy in recognizing the specific learning activities but requires both physiological and movement data. More details regarding to the model structure and the differences between two models are presented in [11]

A. The Long Short-Term Memory Model

The long short-term memory (LSTM) is one of the most commonly used recurrent neural network (RNN) models for predicting the time-series data. In this proposed LSTM model, there are two LSTM layers and one fully-connected layer before the last softmax layer. Before training the LSTM model, all learning activities reported by students are recategorized into two learning states: the first three learning activities, including **"writing"**, **"talking and discussing"** and **"listening to teacher"**, are clustered as active state while **"mind-wandering and sleeping"** is considered as inactive state. Learning activity of **"others"** is ignored to avoid ambiguity. During the training process of the LSTM model, 70% of data is used as training data while the rest *30%* is reserved for testing.

After 750 epochs for training, the proposed LSTM model reaches an accuracy of 95.6% in predicting the students' learning state with a 71.4% precision and 90.0% recall rate and its $F1$ score is 0.8. This is a very impressive result for classifying students' learning states with only their physiological data. However, although the LSTM model can accurately predict students' learning states, it reaches only 68.0% accuracy in recognizing specific students' learning activities given all the physiological and movement data. Thus a hybrid model integrating LSTM and convolutional neural network(CNN) is proposed in next subsection to improve the recognition accuracy in specific learning activities.

B. The Hybrid Model for Learning Analytics of Students' Activities

A hybrid deep learning model combining both the LSTM and convolutional neural network (CNN) is proposed to increase the unsatisfactory accuracy in predicting students' learning activities by solely using the LSTM model in the earlier investigation. Different from the LSTM model considered in last subsection, this hybrid model can predict students' specific learning activities according to their physiological and movement data. In this hybrid model, there are two major routes for processing the input data. The first one applies LSTM layers for processing the physiological data, which is very close to the LSTM model discussed in last subsection. The second route processes the students' movement data through two consecutive CNN layers followed by one LSTM layers. At the end, a fully-connected layer together with a softmax layer are adopted to integrate the results from these two routes and output the final prediction.

After 750 epochs for model training, the proposed hybrid model increases the recognition accuracy dramatically from 68.0% to 74.0% with the availability of students' movement data. This phenomenon can be explained as students' learning activities are often related to their hand movements which can be easily inferred from their movement data.

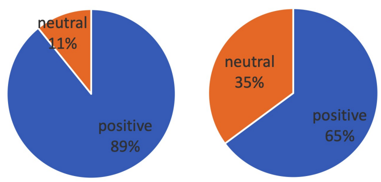
Although the hybrid model combining both the physiological and movement data can attain a higher accuracy in predicting students' learning activities, it is more difficult and less convenient in collecting the movement data due to some technical limitations of Fitbit Versa. Therefore, both the LSTM model and the hybrid model have their own strengths and weaknesses. Accordingly, the proposed learning analytics platform may adopt different models based on the different situations.

V. Interview Results

After the experiment on this platform, 37 out of 52 students who participated in this platform are interviewed to express their feelings on this platform. Their voices were recorded during the interview and were transcribed into documents for statistical analysis after getting the approvals from students and their parents. Students were asked to evaluate this platform in three dimensions: effectiveness, user-friendliness and interestingness. In the dimension of effectiveness, students were also asked to report the impact from this platform to their daily lives and learnings respectively. Interview results of each dimension is summarized in Figure 2 to Figure 4 below.

Figure 2 shows that 89% and 65% of students thought that this platform caused positive effect to their daily lives and learnings, respectively. Among these 65% students who considered this platform as a helper for their learning, as demonstrated in Figure 3, when came to the question of how could this platform affect your learning, 37% of them reported that this platform can improve their sleeping qualities thus improve their learning performance while 21% students thought that their learning efficiency was raised because this platform encouraged them to do more physical exercise by setting a minimum amount of physical exercise per day. In addition, 25% of them believed that they got a better learning experience during the experiment not only because they had a better sleeping quality and got more exercise but also the notification they received during the lecture which helped them to concentrate again on their learnings. Most importantly, during the experiment, all the notifications were pushed according to the heart rates of students which may not able to reflect their learning state accurately. However, with the two pre-trained deep learning models mentioned in last section, the students' learning states can be recognized with an impressive accuracy of 95% and the notification can be pushed to students when they are in an inactive states which can improve the learning effectiveness of students to a greater extend in the future.

In addition to effectiveness, this platform also got a positive response in the dimension of user-friendliness and interestingness. As exhibited in Figure 4(a), 59% of students held the idea that this platform has a good user-friendly characteristic while the rest of the students reported that it was not convenient to carry an extra mobile phone with them. With regards to interestingness, as elaborated in Figure 4(b), 43% of students were interested in participating in this platform with only 22% of students considering this platform as a boring thing. The interview results strongly prove that the proposed learning analytics platform can effectively improve the learning performance of students and provide them with a better learning experience



(a) Daily Life (b) Learning

Fig. 2: Impact on Daily Life and Learning

VI. Concluding Remarks

Wearable devices have been broadly adopted in various areas, such as health monitoring and motion detection. However, there is rarely any prior work which attempts to explore the possibility in applying wearable devices and deep learning in learning analytics. In this paper, a sophisticated learning analytics platform is proposed to accurately recognize the learning activities and states of students based on their physiological and movement data with the help of two deep learning models. In the interview conducted after the experiment for this platform, 89% of students expressed that this platform was useful for their daily lives and 65% of students agreed that this platform facilitated their learning. This obtained interview results clearly show the effectiveness and practicability of the proposed platform which combines both wearable devices and deep learning approaches for learning analytics.

More importantly, this work opens up a lot of possible directions for future investigation. First, it is worthwhile to examine other deep learning models in recognizing the students' learning activities for learning analytics. Second, the possible usages of different wearable devices to facilitate the learning process of students and improve their learning experiences is worth investigating. Last but not least, students can benefit more from the proposed platform if more extra functionalities can be developed and provided from the wearable devices.

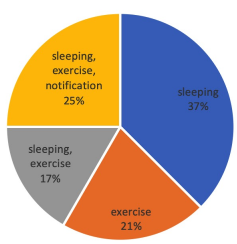
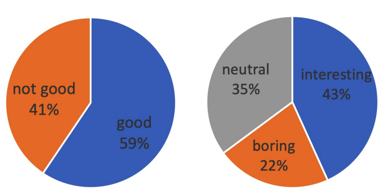


Fig. 3: Reason for Improving Their Learnings



(a) User-friendliness (b) Interestingness

Fig. 4: User-friendliness and Interestingness of Proposed Platform

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