Applying Deep Learning and Wearable Devices for Educational Data Analytics

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***Abstract*—In this paper, an advanced real-time learning activities analytics system based on wearable device and a deep learning model for predicting students' activities are introduced. The system contains a local back-end server, a cloud server, quantities-unlimited smart watches and smart phones. Each student participating in this system is equipped with one smart watch and one smart phone. The physiology data, including heart rate, calories, 3-axis accelerometer data and 3-axis gyroscope data that being collected from students are analyzed by this system. And the students will received a notification to report their activities if the abnormal heart rate pattern is found by the system. Based on the physiology data and the reports from the students, two deep learning models are developed to predict the student learning activities. The first deep learning model reaches 95% on discriminating the active or inactive states of students based on heart rate and calories data. The second deep learning model reaches 74% on predicting the different learning activities of the students based on the heart rate, calories, 3-axis accelerometer data and 3-axis gyroscope data.**

***Index Terms*—wearable device, smart watch, learning activities analytics, deep learning**

I. Introduction

Wearable devices, such as Fitbit smart-watch[1] and Google smart-glass[2], are getting more and more popular in our daily lives. It is very common for people to own a smart-watch nowadays. And the rich built-in sensor provides a big potential for data analytics through wearable device. The data we can get from the smart watch mainly includes two categories: physiology data, such as heart rate, and movement data, such as 3-axis accelerometer data and 3-axis gyroscope data. Many different researches have been done on these two types of data. For heart rate, it can be used as the indicator for detecting disease, such as coronary artery disease[3], and estimating emotion[4]. While the researches for movement data mainly focus on movement recognition, such as fall detection[5] and activity recognition[6]. And the fast-growing sensor technology makes the wearable affordable for daily usage. You can easily buy a latest smart watch from different branches with less than 1800HKD[1].

On the other hand, as learning is one of the most important activities in our lives, a lot of teachers and students are increasingly concerned about students' learning effectiveness. Therefore, learning analytics has become a rapidly-developed research field recent years. Different researchers have tried various methods for effective learning activities analytics. These methods can be mainly separated into two groups: vision-based analytics and sensor-based analytics. Vision based learning analytics, just as its name implies, analyzes the student learning state through images and videos[7-8]. However, to implement a valuable vision-based learning activities analytics, usually you need to install and tune the infrastructures, such as camera, before the lecture. And all learning activities are limited in this classroom. In addition, the movements of the students, such as grouping together and turning back may affect the recognition and analytics results. Also, we need to consider the related high computation time for a real-time vision-based learning analytics. On the contrary, sensor-based learning analytics does not have these weaknesses. Sensor-based learning analytics mainly relies on the wearable devices, such as the smart-watch, for data collection. And the non-intrusive characteristic of the wearable devices makes them the ideal equipments for learning activities analytics.

Therefore, to explore and verify the possibility for applying wearable devices in learning activities analytics and predicting the students' learning activities through wearable devices, a experimental study was done by this paper. To ensure the validation and reliability of the experiment, Fitbit versa was chosen as our wearable devices. Because Fitbit is one of the bellwethers in the area of smart-watch[9-10]. In this study, more than 50 students were asked to wear the Fitbit versa during their classes. And their heart rates were collected and analyzed in real time by our back-end system. If there is any abnormal heart rate pattern found, student needed to report his learning activities as soon as possible on his mobile phones. After collecting the sensor data from wearable and e-survey data from students, this paper firstly developed a LSTM-based deep learning model to predict the students' learning states and activities through physiology data, i.e. heart rate and calories data. After that, to further improve the prediction accuracy, a hybrid model was proposed which combined both physiology data and movement data, i.e. 3-axis accelerometer data and 3-axis gyroscope data. With these two pre-trained models, our learning activities analytics system can be further upgraded by combining different types of data source rather than only heart rate. And the trigger algorithm in our system can rely on the prediction results of the deep learning model, which is more objective than manually-design rule. At the end of this paper, based on the prediction results, the possible applications of applying our system and the pre-trained deep learning models in learning activities analytics and its limitation will be pointed out. The rest of this paper is arranged as following: We will first discuss some related work in section 2. And then, in section 3, the structure and required devices of our real-time learning activities analytics system will be introduced. Section 4 describes the LSTM model which is used to recognize the student learning activities through physiology data. In section 5, a hybrid model combining physiology data and movement data will be presented. And then, the conclusion and discussion are provided in section 6.

II. Related work

A. Wearable device based activities recognition

This application of wearable device mainly focuses on activities recognition. In 2015, Jiang and Yin[11] rearranged the data from accelerometer and gyroscope data into a activity image and applied deep convolutional neural networks for activities recognition. Their model reached a state-of-art level at that time. After that, Ordonez and Roggen[12] proposed a more generic deep learning framework for activities recognition. By combining convolutional neural network and the Long-short-term-memory(LSTM) recurrent units, Ordonez's model outperformed the non-recurrent networks structure 4% at that time.

In 2018, Li, Shirahama, Nisar, Koping and Grzegorzek[13] systematically compared the different performances of various models in action recognition task based on wearable devices. Their results showed that among different types of models, including MLP, CNN and others, the hybrid CNN-LSTM model reach the top performance in two public datasets. Except deep learning model, some researchers preferred traditional machine learning methods.In 2018, Acici, Erdas, Asuroglu and Ogul[14] published a dataset, called HANDY, for activities recognition based on wearable devices. And among 4 different machine learning models, they claimed random forest to be the best model in their dataset. In this paper, to avoid extracting hand-crafted features, the CNN-LSTM model, similar to Li's model[13],is adopted on both accelerometer and gyroscope data.

B. Wearable device based Learning analytics

Despite of recognizing activities, some experiments related to applying wearable device in learning analytics have been done. In 2017, Mitri et al.[15] proposed a machine learning approach, called learning pulse, for predicting the learning performance. They tried to predict the learning performance level by collecting the sensor data from wearable device and digital path data from students' laptops. But their method only works for individual learning rather traditional classroom based learning. In addition, the sample size of their experiment, 9 PhD students, is not big enough. Different from Mitri et al.'s experiment[15], Zhang, Wu, Viger, Van and Tseng[16] analyzed students' attentions in class through wearable device. But the wearable deivces of Zhang et al.[16] are not commodity wearable devices and are very likely to cause disturbance to students.

To avoid this problem, Lu, Zhang, Zhang, Xiao and Yu[17] proposed a framework for learning analytics in classroom with commodity wearable devices. Students would received warning if they were judged as inactive by Lu et al.'s framework[17]. However, both Zhang et al.'s[16] and Lu et al.'s[17] works suffered from a same question that they were all rule based model. Therefore, the design of the rule will deeply affect the model performance. In addition, Lu et al.[17] judged the students' learning states by teachers rather than the students themselves. This may led to a very subject and incorrect judgment due to the different learning habits of students.

To solve the problems mentioned below, in this paper, two end-to-end deep learning based supervised models for learning activities analytics will be introduced. To avoid the hand-crafted rule, both the sensor data and the student learning activities were collected during our experiment. All data are collected through our real-time learning activities analytics system which will be introduced in chapter 3. In addition, to reach a higher objective level, all the learning activities and states were reported by the students themselves.

In addition, most of the studies in wearable device based learning analytics utilizing different types of data source, such as physiology data[15], vision-based data[16] and movement data[17]. Less of them tried to analyze the relation between the learning state and pure physiology data, i.e. heart rate data and calories data. Therefore, to explore the possibility and limitation of analyzing through physiology data. We firstly tried to predict the students' learning state and activities through only physiology data. After that, to reach a high accuracy in recognizing and predicting the students' learning activities, the physiology data and the movement data are combined to build a hybrid deep learning model.

III. Real-time learning activities analytics system

The basic structure of the learning activities analytics system is illustrated in Figure 1. This system mainly consists three components: a back-end server, a cloud server and pairs of smart-watch and mobile phone.

A. Smart-watch: Fitbit versa

In this paper, as we mentioned in section 2, Fitbit versa was chosen as the smart-watch a. From Fitbit versa, there are four types important time-series data we can get:

1) Heart rate data: Fitbit versa measures heart rate based on PPG signal[18]. And we can access the raw time-series heart rate data through both Web API and Device API provided by Fitbit[19]. It is a built-in function for Fitbit versa to measure your heart rate. Therefore, after wearing Fitbit, you can always get your heart rate data from Web API with a 0.2Hz sample rate. While for Device API, you need to build a Fitbit application to extracted raw heart rate at whatever sample rate

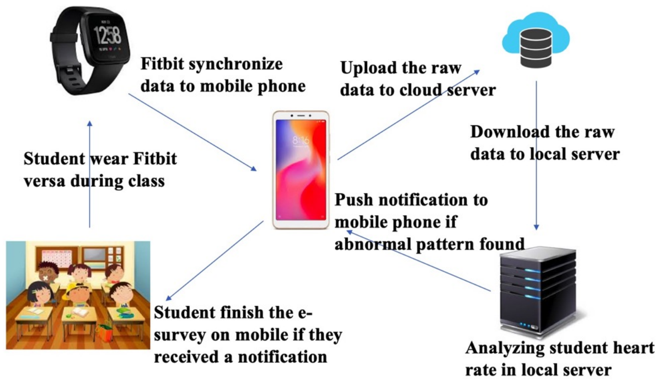

Fig. 1: the structure of the system

you want and then send the data to a cloud server to store the data.

2) Calories data: Fitbit can provide the information of your calories consumption if you are wearing it and it is also a built-in function. The calories data can only be accessed through the Web API from Fitbit[19] with one data point per minute.

3) Accelerometer data: Fitbit provides 3-axis accelerometer data through device API[21]. Different from heart rate and calories data, recording the 3-axis accelerometer data is not a built-in function. Thereby, to get the raw accelerometer data, you need to build a Fitbit application on Fitbit versa which can continuously read and send the raw data to a cloud server. The sample rate can be determined by yourself. However, during our testing, we found that the connection between the smart-watch and mobile phone will be terminated if the sample rate is too high. After several times of trying, 6Hz was chosen as the sample rate by balancing the stability of the system and the requirements of data.

4) Gyroscope data: The gyroscope data are very similar to accelerometer data. And they can only be accessed through device API.

B. Difference between physiology data and movement data

Although all the data are available to us, the difficulties of them are different. For physiology data, including heart rate and calories, because it is a built-in function, Fitbit will automatically record and store these data for you. And even you don't have a paired mobile phone during wearing the Fitbit versa, you can still recover your data by synchronizing the data later. In other words, you won't loss your data as long as you are wearing it. While for movement data, including gyroscope data and accelerometer data, you need to develop a Fitbit application to extract it. And it is necessary for your to keep your application running on the Fitbit versa on front desk to upload the raw movement data in real-time. Fitbit OS currently does not support any back-end application. Another important question about extracting raw movement data is the electricity consumption. In normal cases, Fitbit versa can work for several days without charging. However, if you need the real-time movement data, you need keep uploading the data to your mobile phone. According to our testing, the battery of Fitbit versa can only last for one day if we keep running the Fitbit application we developed and extracting the raw movement data.

C. Mobile-phone: Xiaomi Redmi 6

Due to budget limitation, we chose Xiaomi Redmi 6, which costs less than 1000HKD per one[20], as our mobile phones for experiment. There are mainly two functions of the mobile phones:

1) Data transfer platform: To extract the raw data from Fitbit versa, it is necessary to connect the watch with a mobile phone through blue-tooth so that the raw data can be further transferred to a cloud server. And Fitbit mobile application must be installed on this mobile phone so that the data from the smart watch can be synchronized to the mobile phone automatically.

2) E-survey platform: To investigate the relationship between the students' learning activities and their data from wearable devices. Students needed to finish the e-survey on their mobile phones if they received a notification from our back-end server. And then, the results of the e-survey were sent back to our cloud server. In our e-survey, there are 5 options for students to report their activities: writing, talking and discussing, listening to the teacher, mind-wondering and sleeping, and others.

D. Cloud server

In this paper, the cloud server only server as a data transfer station between our local server and the mobile phone. In other words, the data from smart-watch will be firstly synchronized to the mobile phones. And then the mobile phones send the raw data to the cloud server. Lastly, our local server downloads the data from the cloud server for further analytics. But with development of powerful cloud server. It is also workable to combine our local server and cloud server to a single cloud server.

E. Local back-end server

In this paper, the local back-end server mainly has two duties:

1) Heart rate data analytics and trigger: As a experimental study, without a pre-trained deep learning model, heart rate was chosen as the indicator of detecting abnormal pattern at the first stage. The details of the heart rate trigger algorithm can be described as followed: For each student who's wearing our smart-watch, the standard deviation of their heart rate will be calculated for the first two hours with a one-minute window. The top 10% of the standard deviation was chosen as the upper bound and the low 10% was chosen as the lower bound. After two hours, the local server continuously collected the raw heart rate data from the cloud server one time per minute. And then, the standard deviation of this one minute heart rate data was calculated and compared with the upper and lower bound. Any minute with a standard deviation higher than the upper bound or lower than the lower bound was consider as an abnormal pattern.

2) Notification pushing: After analyzing the heart rate data, if an abnormal pattern was found, the local back-end server would send a notification to the mobile phone of the corresponding student. And the student needs to finish the e-survey as soon as possible. However, to avoid affecting the normal education environment and disturbing students, the interval between two notifications was set to be at least 30 minutes.

F. Details about the experiment

Each student participating in this study was equipped with a Fitbit versa and a mobile phone. To ensure that we can get the raw accelerometer and gyroscope data, all Fitbit versas were installed our Fitbit application before the experiment. The function of this application is to call the Fitbit device API and keep transferring the raw accelerometer and gyroscope data to the mobile phone through blue-tooth. All students were asked to go to school and attend the lecture as normal but wearing our smart-watch and carrying our mobile phone. As we mentioned in section 3.A, if the student's heart rate is out of our pre-decided range, he/she would received a notification on their mobile phones and need to report their learning activities now. Our experiments were conducted in two class. The first one is a A3 class with totally 30 students and the second one is a A1 class with 20 students. And the experiment lasts for one week for each class. All participators are high school students in Hong Kong. After our experiment, we got totally 499 replies from students, in which 90 are writing, 101 are talking and discussing, 138 are listening to teacher, 35 are mind-wondering and sleeping, and 135 are others.

IV. Physiology data based student learning activities analytics

To prove the relation between the physiology data and students' learning activities, this paper firstly tried to use only physiology data for recognizing students' activities. In addition, as we mentioned in section 3, the difficulties in real-time extracting raw physiology data and movement data are different. It is easier for collecting data and more power-saving for Fitbit versa if we don't need the movement data. Therefore, in this section, only physiology data are used. The heart rate and calories data collected from Fitbit Web API are 1 data point per 5 seconds and 1 data point per minute. To create a standard input, the calories data are copied into 12 data points per second. Also, we assume that only the last 5 minutes data will be related to each reported learning activity based on the framework of Lu et al.[17].

A. Long-short-term-memory(LSTM) model

Long-short-term-memory[23], or LSTM in short, is one of the most famous and successful RNN models. There are 4 important components in a LSTM unit: a cell, an input gate, an output gate and a forget gate. The cell can work as an internal information storage and three gates can control the information income and outcome. With this special structure,

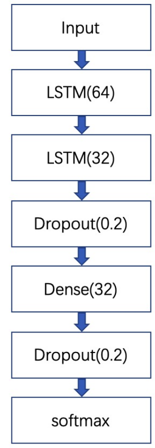

Fig. 2: the structure of the LSTM model

LSTM successful solves the long-term temporal dependencies question in traditional RNN. Therefore, to consider the sequence information hidden in the time-series physiology data, a two-layers LSTM model is proposed to predict the student learning activities. Figure 2 describes the structure of the proposed LSTM model. Before the last softmax layer, there are two lstm layers and one fully-connected layer. Also, to avoid over-fitting, two dropout layers with 0.2 dropout rate are added in the model.

B. Prediction results on different learning activities

We use 70% as training set and the rest 30% as testing set. Table I shows the best confusion matrix we can after 750 epochs and its corresponding accuracy is 62.7%. This accuracy is far away from a satisfactory level. However, from the confusion matrix, we can find that most of the error happens between option 0-2 and option 4. In other words, compared with other options, our model seems to have a high prediction accuracy on option. And it reached 90.9% recall rate on option 3 although the average accuracy is lower than 63%. According to the definition we mentioned in section 3, the learning activities that option 3 refers to is mind-wondering and sleeping. This interesting phenomenon motivated us to try a binary classification for detecting whether the students are in an inactive and mindless state. Also, in some cases, students and teachers only want to know whether students are active or inactive rather than the exact learning activities. Because as long as you are in an active learning state, you very likely to learn and absorb something from the class.

C. Prediction results on binary learning state

To prove the relation between the physiology data and students' binary learning states, a slight update was made on the existing dataset. Although we provided different learning activities options for students in our e-survey, we first clustered all the options into two categories: active and inactive. Options 0-2, including writing, talking and discussing and listening to teacher are clustered as active state while Option 3: mind-wondering and sleeping is considered as inactive state. The

TABLE I: Confusion matrix of LSTM model

actual label	predicted label				
	0	1	2	3	4
0	19	1	5	0	1
1	2	7	13	2	7
2	3	1	32	3	6
3	0	0	1	10	0
4	5	0	5	1	26

option 4: others is ignored to avoid ambiguity. And nothing is changed in our LSTM model except that the number of class become two in this situation. To minimize the imbalance sample size in active and inactive learning states, Synthetic Minority Over-sampling Technique(SMOTE)[21] was adopted on the training set before the training.

Table II shows the best confusion matrix we can get after 750 epochs and its corresponding overall accuracy is 95.6%. But for an imbalance dataset, the overall accuracy is less accurate. Therefore, for the inactive learning state, the precision and recall of our LSTM model are 71.4% and 90.9% respectively. And its corresponding F1 score is 0.8 which we think is a satisfactory level. In addition, in the situation of detecting the learning states, it seems that the recall rate is more important than the precision. Because with a higher recall rate, the students can always receive a notification or warning under an inactive state which can help them to achieve a higher learning efficiency. On the contrary, student can just ignore our notification if they think that they are already in an active state because of the relatively lower precision.

TABLE II: Confusion matrix of binary LSTM model

actual label	predicted label	
	0	1
0	98	4
1	1	10

V. Hybrid model for student learning activities analytics

As we mentioned in section 4, with only physiology data, the prediction accuracy is not satisfactory. Therefore, to further improve the prediction accuracy, a hybrid model, which combines the physiology data and the movement data, is proposed in this paper.

A. *The structure of the hybrid model*

Figure 3 demonstrates the structure of the hybrid model. In this hybrid model, there are mainly two routes. The first one is actually the LSTM model for physiology that we mentioned in section 4. The only difference is the last fully-connected network. While the second route is designed for processing the students' movement data. Inspired by Li et al.' results[13],

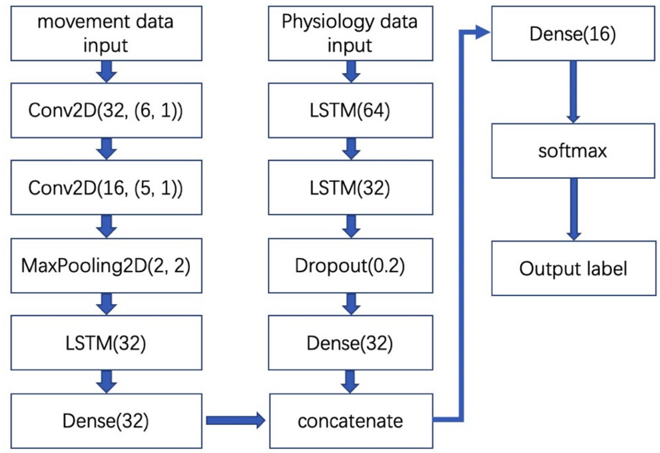

Fig. 3: the structure of the hybrid model

we applied a CNN-LSTM based structure for automatically extracting features from the raw accelerometer and gyroscope data. Finally, the output of different routes are combined together to next fully-connected layer.

B. *prediction results on different learning activities with hybrid model*

Table 3 shows the best confusion matrix we get after 750 epochs and its corresponding accuracy is 74.0%. As we can see, with the help of the movement data and the hybrid model, the prediction accuracy increased dramatically from 62.7% to 74.0% and this phenomenon can be explained easily. The students' learning activities are usually strongly related to their hand movement which can be inferred from the movement data.

TABLE III: Confusion matrix of hybrid model

actual label	predicted label				
	0	1	2	3	4
0	14	1	6	2	3
1	0	25	0	0	6
2	5	3	30	2	5
3	0	0	0	10	1
4	3	1	1	0	32

C. *Limitation of hybrid model*

Although hybrid model with physiology data and movement data can reach a higher accuracy in predicting the student learning activities, one important limitation of it is the relatively more difficult in collecting the raw data. As we mentioned in section 3, measuring and recording physiology data is a built-in function for Fitbit versa, we can easily access to these data through Web API[19] as long as we are wearing the Fitbit versas. Also, even you are in a place with no Internet connection, you physiology can be stored in the smart watch and you can re-upload the data once you get Internet connection on you phone. On the contrary, we can't get raw movement data through Web API. You need to build a Fitbit application, which can read and send the movement data, and keep running it on the front desk, which shorten the duration of the watch. Also, once you lost the Internet connection, your movement data is not retrievable.

VI. Conclusion and Discussion

In this paper, we creatively research the possibility to apply wearable device in recognizing and predicting students' activities. After collecting the experimental data, two deep learning models were trained by us to predict the students' learning states and activities. The first one is a LSTM model which can successfully predict the students' binary learning states through their physiology data. The second one is a hybrid model which combined the physiology data and movement data, and reached a 74% accuracy on predicting the students' learning activities.

During the experiment, the system takes heart rate as the indicator and rely on a rule based decision strategy to detect the abnormal pattern. And after these experiments, with these two pre-trained deep learning models, we can easily predict the student learning state and learning activities with smart watches. Therefore, by updating the triggering algorithm with the pre-trained deep learning model in our proposed system, a real-time student learning activities analytics system is proposed by us. Compared with the similar learning analytics system proposed by other researchers, such as [16-17], our system is more accurate and objective. Because our system is based on pre-trained deep learning model rather than manual-designed rule based model. Also, all our training data are labeled according to the responses on the e-survey from different students in high school rather than the observation of teachers, which can improve the objectivity of our models.

A. Possible application

There are many possible applications for our real-time learning activities analytics system with smart watch and pre-trained model. The most intuitive one is that our system can infer the students' binary learning states according to their physiology data. If the student is in an inactive state, we can push him a notification to help him improve the learning efficiency. However, if the binary learning state is not enough, our second learning model can predict the student learning activities with physiology data and movement data. For example, if we further collect the exam performance of the students, we can analyze the relation between proportion of a specific activities and students' performance. Students who keep writing notes on book may outperform the students who just sitting and listening to teacher although all of them are in an active state. Or we can also infer that one student is more active in discussing than others students. This is can be very useful for teachers to provide an individual guidance to different students. But to collect raw movement data, you need to fulfill the requirement, including running Fitbit application, enough battery life and reliable Internet connection.

B. future work

The learning activities system proposed in this paper can only predict 5 different activities categories and the prediction accuracy is only 74%. In the future, we can collect more experimental data from students with more activities categories and design a better deep learning model to improve the prediction accuracy. In addition, the learning analytic system can be further updated so that the collection of movement data is easier.

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