

Using Heart Rate to Predict Students' Academic Performance



Mu Lin Wong, S. Senthil, L. Robert

Abstract: *Timeliness was a missing factor in many studies on Academic Performance Prediction to identify at-risk students. This study embarked on a search to evaluate the feasibility of predicting students' performance based on heart rate data collected during classes. This dimension of data was collected in the first four weeks after semester commencement to validate accurate prediction that will enable educationists to introduce remedial intervention to at-risk students. Another aim of this study is to determine the best threshold values for the different types of heart rate fluctuations that can be used in predicting academic achievements. The threshold values were tested further to verify whether the prediction model for individual course or combined courses was more accurate. Results revealed that heart rate data alone can achieve a maximum prediction accuracy of 88% and recall of 100%. Threshold values calculated in derived heart rate fluctuation types produces the best results. Prediction models for individual courses outperform the model using average threshold values of all courses.*

Index Terms: *At-Risk Students, Educational Data Mining, Heart Rate Analysis, Physiological Sensors, Students' Academic Performance Prediction.*

I. INTRODUCTION

Identifying at-risk students has been the heart of student performance prediction in the domain of Educational Data Mining. Previous models developed using historical data were successful in predicting students failing or bordering failure, especially after incorporating preparatory exam results. However, there is little or no time for remedial intervention.

Therefore, this study aims to examine the feasibility of using student heart rate to add the timeliness factor into the prediction model. In another word, the prediction should be able to identify at-risk students as early as possible in order to provide educationist opportunities for early intervention. Heart rate can be used as a gauge of students' engagement in class.

This study will also evaluate different types of heart rate fluctuation to determine the best types to be used as features in

academic prediction model. The authors have derived four types of heart rate fluctuations based on four basic heart rate fluctuation types calculated. All of them will be used to arithmetically derive threshold values for the purpose of prediction.

A third aim is to evaluate whether the threshold values of the prediction model be based on the heart rate data of each individual subject or the average heart rate data of all subjects combined. This is due to the fact that generally students are not all-rounders. Therefore, it might not be scientifically viable to generalize the threshold values for prediction.

The organization of this paper is as follows: Section II presents the literature review while Section III describes the methodology carried out to analyze students' heart rate data to find the threshold values which can be used to predict at-risk students. Section IV discusses the results and the accuracy of such results. Finally, section V provides a general conclusion with the prospect of future research.

II. LITERATURE REVIEW

Marbouti et al. [1] proved using an empirical study that it is possible to predict at-risk students using only assessment data (assignments, quizzes, homework, projects, etc.) obtained from the instructor over a 5-week period and obtained an accuracy of 86.2% in identifying at-risk students. The limitation of this model is that it is accurate only if the student population is above 120 and the failure rate is less than 10% of the population. The model can only predict at-risk students within a specific course or subject. Baars et al. [2] predicted at-risk medical students with 66.7% accuracy after 6 months using personal and academic data. These medical students are assessed in an annual scheme rather than a semester scheme. Asif et al. [3] reportedly found from a population of 210 4-year undergraduate students a trend whereby poor performing students tend to perform the same throughout the four year program, while the good performing students will continue to perform well in the same period. Therefore, it's possible to flag at-risk students through a consistent evaluation of their performance since the commencement of their class. Other studies [4]-[9] also indicate the possibility of timely prediction using academic data within the academic year or semester.

Kaur et al. [10] also performed an empirical study with 152 students and the prediction of at-risk students reach 83% with personal and academic data included. The drawback was that the accuracy was achieved only after including the feature of internal assessment results, therefore, failing to provide timeliness to the prediction model.

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Many empirical studies [11]-[19], though relatively accurate, don't include timeliness in their prediction models. Therefore, the accuracy of the models didn't provide a real solution to reduce failure rate.

Zollanvari et al. [20] argued that a relatively accurate prediction model can be developed using only a set of self-regulatory learning behaviors, without using any personal, socio-economic or academic data. However,

more and more researchers are pointing out the significance of using engagement as a core feature in academic performance prediction. Cohen et al. [21] advocated that the inter-subject correlation of the electroencephalogram can be used to measure students' neural engagement in video watching, therefore would be predictive of their academic performances. Currie et al. [22] highlight the use of eye movement as a mean of gauging student engagement for predicting academic outcome. Many recent studies [23]-[25] reveal the need to use engagement data in the predictive model development. Pardo et al. [26] emphasizes the need to combine self-report data and online engagement data to develop prediction model. Whitehill et al. [27] presented a feasibility of using automated facial recognition to determine class engagement and ultimately predict academic performance.

While self-report and observation instruments were used to measure engagement in the past [28]-[30], Azevedo [31] proposes to use data from physiological sensors as they are free from bias. Sinatra et al. [32] suggested a hybrid approach of incorporating physiological data and observational data to measure engagement. D'Mello et al. [33], recognizing learning requires engagement, showcased 15 case studies of measuring engagement in digital learning environments using a combination of physiological data and aspects of environmental context.

Ainley and Ainley [34] pointed out that in their study of more than 400,000 students worldwide, enjoyment attached with studying science is directly affecting the level of engagement, ultimately predicting the level of achievement. Polattos et al. [35] indicated that there is a strong relationship between emotional stimuli and heart rate responses. Rainville et al. [36] proved that the basic human emotions are associated with distinct patterns of cardiorespiratory activity. Two studies [37], [38] suggest that heart rate variability is highly proportionate to the demand of sustained attention, more than other cognitive processes. However, it's nearly impossible to chain students to expensive cardiovascular sensors in a classroom environment. The wires would interfere with the learning process, not to mention resulting in bias being introduced to the experimentation. Therefore, wearable wireless sensors [39]-[43] are preferred to collect physiological data. They are more cost effective, non-intrusive and non-disturbing to the wearer.

Having surveyed the above literature, a gap is identified that no study has been done on using heart rate collected from physiological sensors to measure class engagement and predict academic performance. Since heart rate is proven to relate to human emotions and human emotions are related to academic performance, there is a high feasibility that heart rate can also be used to predict student achievement. The next section will discuss on the methods used to analyze the heart rate data collected and establish threshold values to predict at-risk students.

III. METHODOLOGY

The following segments will describe the detail methods used data sets creation, heart rate analysis, threshold values calculation, and parameters used in the prediction model.

A. Data Sets

In this study, the heart rate of 50 first-semester Bachelor of Computer Applications (BCA) students were recorded when they were attending lectures of three core subjects, namely C Programming (C), Digital Electronics (DE), and Mathematics (Math). Each lecture last for an hour. At the end of the first four weeks of semester commencement, there were a total of 15 hours of C lectures, 15 hours of DE lectures, and 10 hours of Math lectures.

The end semester result unveils that only 1 student failed in C and only 1 student failed in DE. The passing mark is 50%. In the spirit of recognizing at-risk students, the authors have enlisted students who just passed (scoring between 50% and 54%) to be considered as failed. The detail is shown in Table I.

TABLE I. Demographic of Students Who Passed or Failed in C, DE and Math

	C	DE	Math
Passed ($\geq 55\%$)	45	49	49
Failed ($\leq 54\%$)	5	1	1
Total	50	50	50

B. Heart Rate Analysis

The heart rate data is measured as beat per minute (bpm) and is recorded at one second interval. There will be fluctuating heart rate for every student during the one-hour lecture. The authors proposed the following six types of heart rate fluctuation as measuring engagement during lecture.

- **Up** is defined as the number of times in an hour where the student heart rate increases 10 bpm or more within a 10-second period.
- **Down** is defined as the number of times in an hour where the student heart rate decreases 10 bpm or more within a 10-second period.
- **UD** is defined as the sum of Up and Down.
- **Peak** is defined as the number of times in an hour where the student heart rate increases 10 bpm or more and then immediately decreases 10 bpm or more within a 30-second period.
- **Low** is defined as the number of times in an hour where the student heart rate decreases 10 bpm or more and then immediately increases 10 bpm or more within a 30-second period.
- **PL** is defined as the sum of Peak and Low.

C. Threshold Values

After averaging the values of the six types of heart rate fluctuation of students who passed and students who failed, Table II, III and IV show the summary for C, DE, and Math respectively.

TABLE II. Heart Rate Fluctuation and Threshold Values of C.

	Mean Passed	Mean Failed	Threshold
Up	36.76	34.20	34.46

Down	40.38	38.20	38.42
UD	77.16	72.40	72.88
Peak	13.22	11.60	11.76
Low	10.51	8.00	8.25
PL	23.67	19.60	20.01

TABLE III. Heart Rate Fluctuation and Threshold Values of DE.

	Mean Passed	Mean Failed	Threshold
Up	38.37	34.00	34.09
Down	41.90	38.00	38.08
UD	80.27	72.00	72.17
Peak	14.59	11.00	11.07
Low	11.20	10.00	10.02
PL	25.76	20.00	20.12

TABLE IV. Heart Rate Fluctuation and Threshold Values of Math.

	Mean Passed	Mean Failed	Threshold
Up	34.78	29.00	29.12
Down	38.53	29.00	29.19
UD	73.04	57.00	57.32
Peak	13.12	8.00	8.10
Low	10.47	6.00	6.09
PL	23.27	13.00	13.21

The threshold values were calculated based on the following formula.

$$T = MF + \left(\frac{FS}{TS} \times (MP - MF) \right) \quad (1)$$

T is the threshold value. MF is the mean of students who failed. MP is the mean of students who passed. FS is the number of students of failed while TS is the total number of students.

D. Prediction

Using the threshold values obtained for each subject, students are then predicted to pass a subject should their heart rate fluctuation values be higher than the threshold values. If not, they would be predicted to fail that subject.

Other parameters required in the evaluation of our prediction model include TP, TN, FP, FN, Accuracy and Precision. TP stands for True Positive, which means the number of students predicted to pass and actually passed. TN stands for True Negative, signifying the number of students predicted to fail and actually failed. False Positive (FP) is the number of students predicted to fail but actually passed, while False Negative (FN) is the number of students predicted to pass but actually failed. Accuracy (A) and Recall (R) can be defined as follow.

$$A = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

$$R = \frac{TN}{TN + FN} \quad (3)$$

Accuracy is the rate of correct prediction of both students who passed and students who failed. Since our aim is to identify at-risk students, therefore the prediction model developed must produce a low FN. In another word, the number of students predicted to pass but actually failed must be kept to the minimum. Recall is the percentage of all at-risk students predicted accurately. Consequently, a prediction model with a higher recall without compromising its accuracy is a better option.

The results of the prediction is shown and discussed in the next section.

IV. RESULTS & DISCUSSIONS

It can be seen that the threshold values in Table II and III are similar while the threshold values of Table IV are much lower. This might be due to the fact that most of the students have already learnt most of the Mathematics syllabus before pursuing BCA. Therefore, the excitement during class would be less.

Using the threshold values of Up, Down, UD, Peak, Low, and PL found in Table II, III, and IV, a prediction model was created to predict whether students are at-risk or not. The prediction results are presented in Table V, VI, and VII. Two additional features added in the tables are UD&PL and UD|PL. UD&PL refers to both the threshold values of UD and PL must be satisfied before a student is predicted to pass. UD|PL means that either the threshold value of UD or PL must be satisfied before a student is predicted to pass.

From Table V, it can be seen that the derived heart rate fluctuation types UD and PL are not better than the default types (Up, Down, Peak, and Low). However, UD&PL produces the best recall (80%) while UD|PL produces the best accuracy (60%).

By observing Table VI, it is clear that Up and Peak produce the best accuracy (66%). Overall, the basic heart rate fluctuation types are better performing than the derived heart rate fluctuation types. The recall of all heart rate fluctuation types are 100%. This may be the result of having only one student who failed in DE.

TABLE V. Prediction Accuracy & Recall for C.

	Thres-hold	TP	TN	FP	FN	Accu-racy	Recall
Up	34.46	24	4	21	1	0.56	0.80
Down	38.42	26	3	19	2	0.58	0.60
UD	72.88	25	3	20	2	0.56	0.60
Peak	11.76	25	3	20	2	0.56	0.60
Low	8.25	23	3	22	2	0.52	0.60
PL	20.01	23	3	22	2	0.52	0.60
UD&PL		23	4	22	1	0.54	0.80
UD PL		27	3	18	2	0.60	0.60
Average		25	3	21	2	0.56	0.65

Table VII reveals the same recall of 100% is achieved, probably again due to only 1 student who failed. Another observation points to the fact that derived heart rate fluctuation types produce better accuracy, with UD|PL and PL producing 80% accuracy.

TABLE VI. Prediction Accuracy & Recall for DE.

	Thres-hold	TP	TN	FP	FN	Accu-racy	Recall
Up	34.09	32	1	17	0	0.66	1.00
Down	38.08	31	1	18	0	0.64	1.00
UD	72.17	30	1	19	0	0.62	1.00
Peak	11.07	32	1	17	0	0.66	1.00
Low	10.02	21	1	28	0	0.44	1.00
PL	20.12	30	1	19	0	0.62	1.00
UD&PL		29	1	20	0	0.60	1.00
UD PL		31	1	18	0	0.64	1.00
Average		30	1	20	0	0.61	1.00



TABLE VII. Prediction Accuracy & Recall for Math.

	Thres-hold	TP	TN	FP	FN	Accu-racy	Recall
Up	29.12	32	1	17	0	0.66	1.00
Down	29.19	36	1	13	0	0.74	1.00
UD	57.32	34	1	15	0	0.70	1.00
Peak	8.10	34	1	15	0	0.70	1.00
Low	6.09	39	1	10	0	0.80	1.00
PL	13.21	39	1	10	0	0.80	1.00
UD&PL		34	1	15	0	0.70	1.00
UD PL		39	1	10	0	0.80	1.00
Average		36	1	13	0	0.74	1.00

Another model is created by averaging the threshold values of C, DE, and Math. Table VIII displays the accuracy and recall of such model. Comparing with Table V (65%), Table VI (100%), and Table VII (100%), the average recall of Table VIII is the lowest (46%). The average accuracy of Table VIII is 67%, which is better than Table V (56%) and Table VI (61%), but worse than Table VII (74%). Therefore, averaging the threshold values to produce a prediction model is an adverse move, especially when the threshold values differ greatly.

TABLE VIII. Prediction Accuracy & Recall for Combination Model.

	Thres-hold	TP	TN	FP	FN	Accu-racy	Recall
Up	32.55	95	4	48	3	0.66	0.57
Down	35.23	97	3	46	4	0.67	0.43
UD	67.45	99	2	44	5	0.67	0.29
Peak	10.31	90	4	53	3	0.63	0.57
Low	8.12	87	4	56	3	0.61	0.57
PL	17.78	105	3	38	4	0.72	0.43
UD&PL		97	3	46	4	0.67	0.43
UD PL		107	3	36	4	0.73	0.43
Average		97	3	46	4	0.67	0.46

Another way of comparing the prediction model using the average threshold values of the three subjects with the prediction model using the threshold values of each subject can be found in Table IX. Predicting students' performance based on threshold values calculated on individual subjects produces higher recall, averagely ranging from 87% to 93%. On the contrary, the prediction model based on the average threshold values of all 3 subjects produces higher accuracy, ranging from 61% to 73%.

TABLE IX. Comparison of Models Developed Using Threshold Values of Individual Subject vs. Average Threshold Values of All Subjects.

	Threshold Values of Individual Subjects		Average Threshold Values of All Subjects	
	Accuracy	Recall	Accuracy	Recall
Up	0.63	0.93	0.66	0.57
Down	0.65	0.87	0.67	0.43
UD	0.63	0.87	0.67	0.29
Peak	0.64	0.87	0.63	0.57
Low	0.59	0.87	0.61	0.57
PL	0.65	0.87	0.72	0.43
UD&PL	0.61	0.93	0.67	0.43
UD PL	0.68	0.87	0.73	0.43

V. CONCLUSION

Based on the results obtained in this study, it is highly probable to use heart rate data to predict students' academic performance. With only 4 weeks of heart rate data analyzed,

the prediction model achieved an accuracy ranging from 44% to 80%, and recall ranging from 29% to 100%, across the various heart rate fluctuation types used.

Out of eight heart rate fluctuation types, the derived types (UD, PL, UD&PL, and UD|PL) are generally better performing than the others. UD&PL tends to produce high recall, ranging from 80% to 100%, while UD|PL produces higher accuracy, ranging from 60% to 80%.

It is clear that the students' performance prediction model should use threshold values of individual subjects as they give a higher recall as compared to using the average threshold values of three subjects. In another word, a higher recall means a better prediction model in identifying at-risk students.

However, heart rate is not the only factor influencing class engagement. The heart rate of a student can be affected by the emotional and physical elements of a student. Therefore, it is imperative that other relevant academic, personal and socio-economic data can be added as features in the prediction model, in order to increase accuracy and recall. Another future scope of research is to include evaluating the heart rate of the students for a whole semester so that the longitudinal factor can be assessed.

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