A Design Study of the Artificial Intelligence-Augmented Motivation Indicator System

Nam Ju Kim* & Min Kyu Kim** *University of Miami ** Georgia State University

INTRODUCTION

Many online learning programs have faced the challenge of students' low motivation and limited participation, which often resulted in learners' low performance and high attrition rates.

There has been no satisfactory way to detect real-time learners' motivation levels at a particular moment.

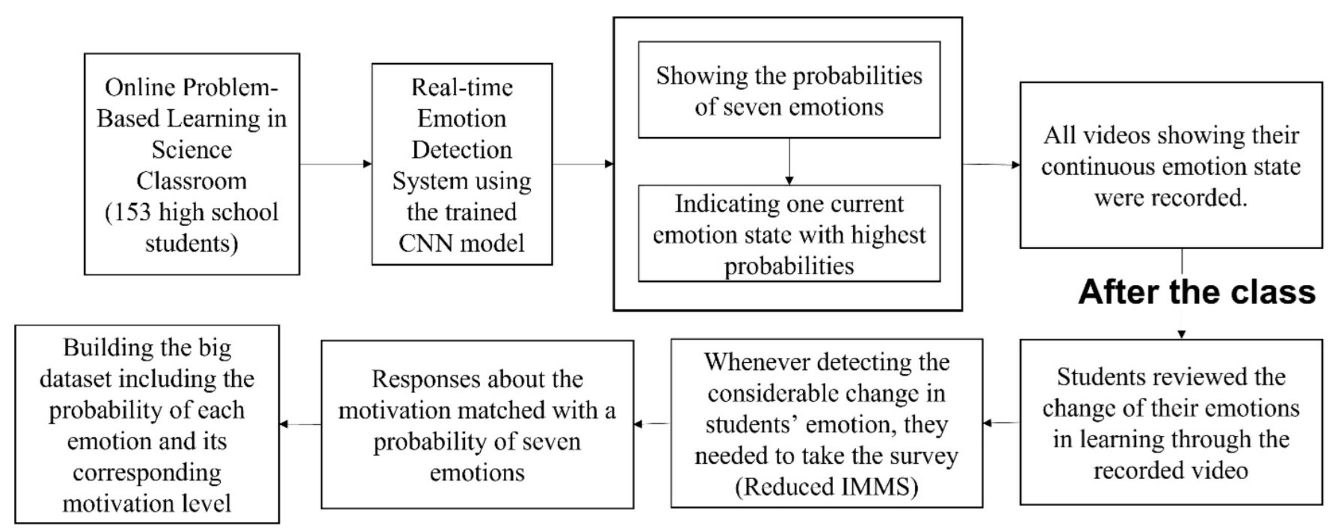
Educational scholars have demonstrated that learner's current emotions and motivation mutually influence each other when learning occurs (Atkinson, 1964; Deci & Ryan, 1985; Weiner, 1985; Ford, 1992; Ho, 2016; Jackson-Kersey & Spray, 2016). Also, recent neuroscience studies have proven that emotions and motivation share neural systems and are tightly intertwined with each other (Cromwell et al., 2020).

We developed **Artificial Intelligence-Augmented Motivation Indicator (AIMI) system,** leveraging ML techniques and building on theories of the relations between emotions and motivation.

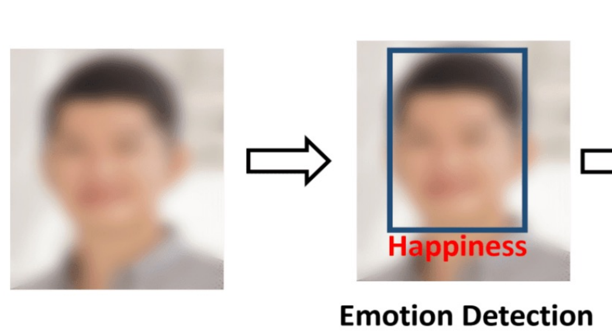
METHOD

Data Set to Build a ML Model

To build the dataset including students' emotions and related motivation level data



- Data were created indicating the relationship—or pattern—between each student's motivation level and the respective probabilities of each emotion associated with it



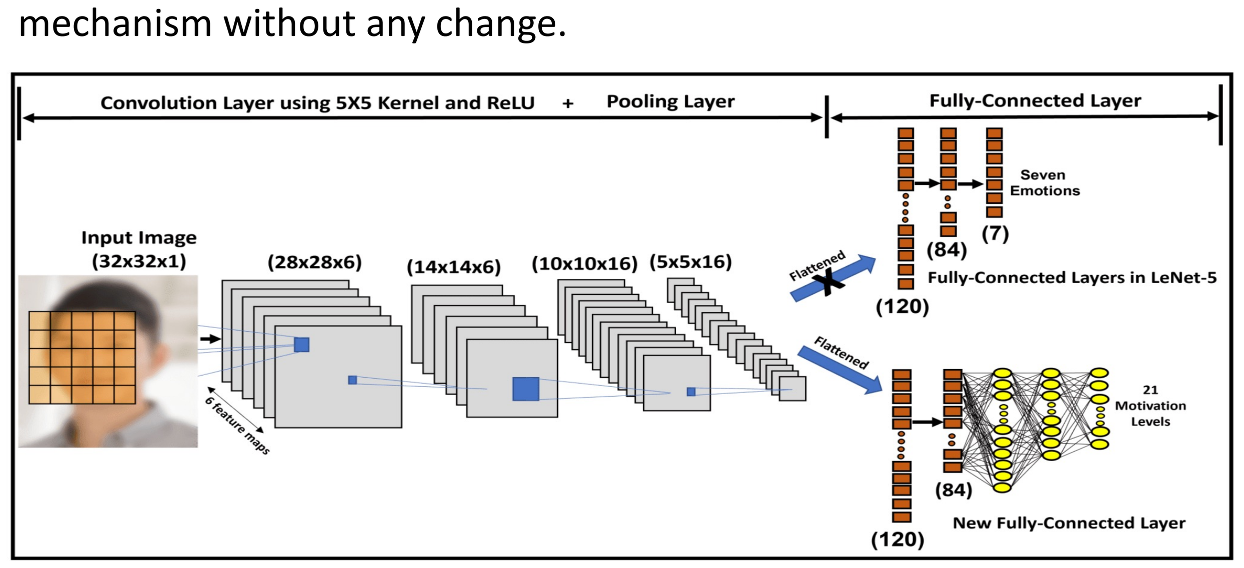
Emotions	Probability
Anger	0.05
Disgust	0.02
Fear	0.01
Happiness	0.75
Sadness	0.05
Surprise	0.07
Neutral	0.05

Probability of Each Emotion

Motivation: 17

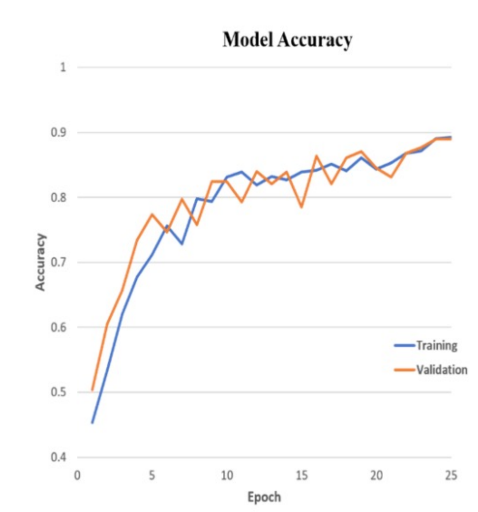
Motivation Indicator: Range from 0 to 20

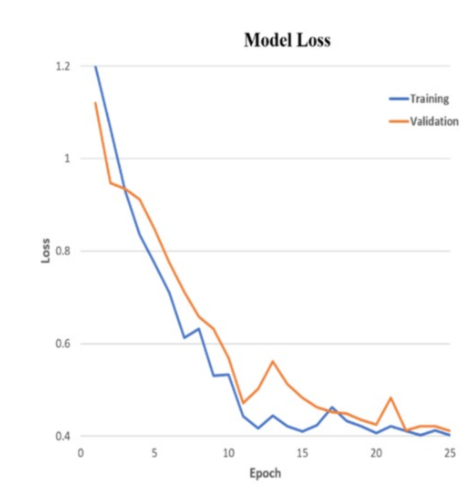
- Transfer Learning - a way to re-training only classifiers that extract motivational features from emotion data by adding some of the existing fully-connected layers, continuing to utilize the convolutional base of the existing LeNet-5 architecture as a feature extraction mechanism without any change.



METHOD (CONT'D)

- The model accuracy was 74.69%, meaning that the algorithm could correctly classify around 75 out of 100 test samples. Also, overfitting did not occur until the epoch reached 25 (learning rate 0.001, batch size 32).



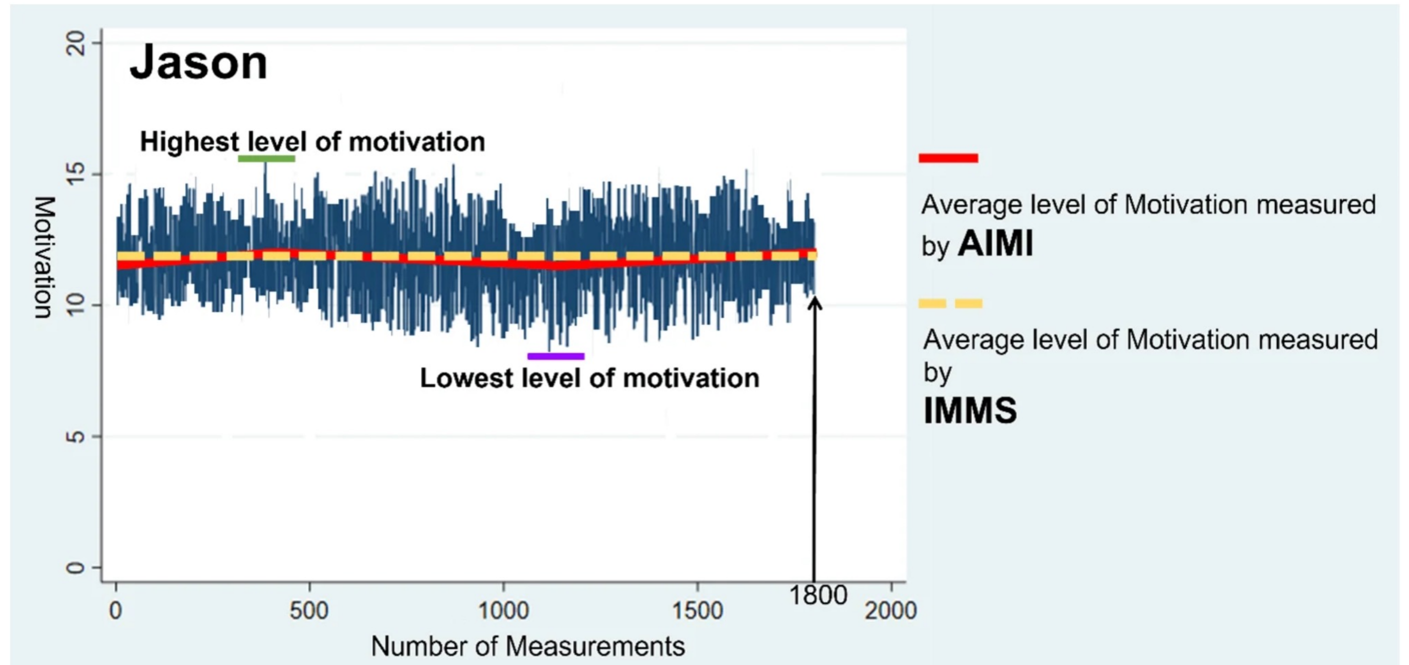


RESULTS

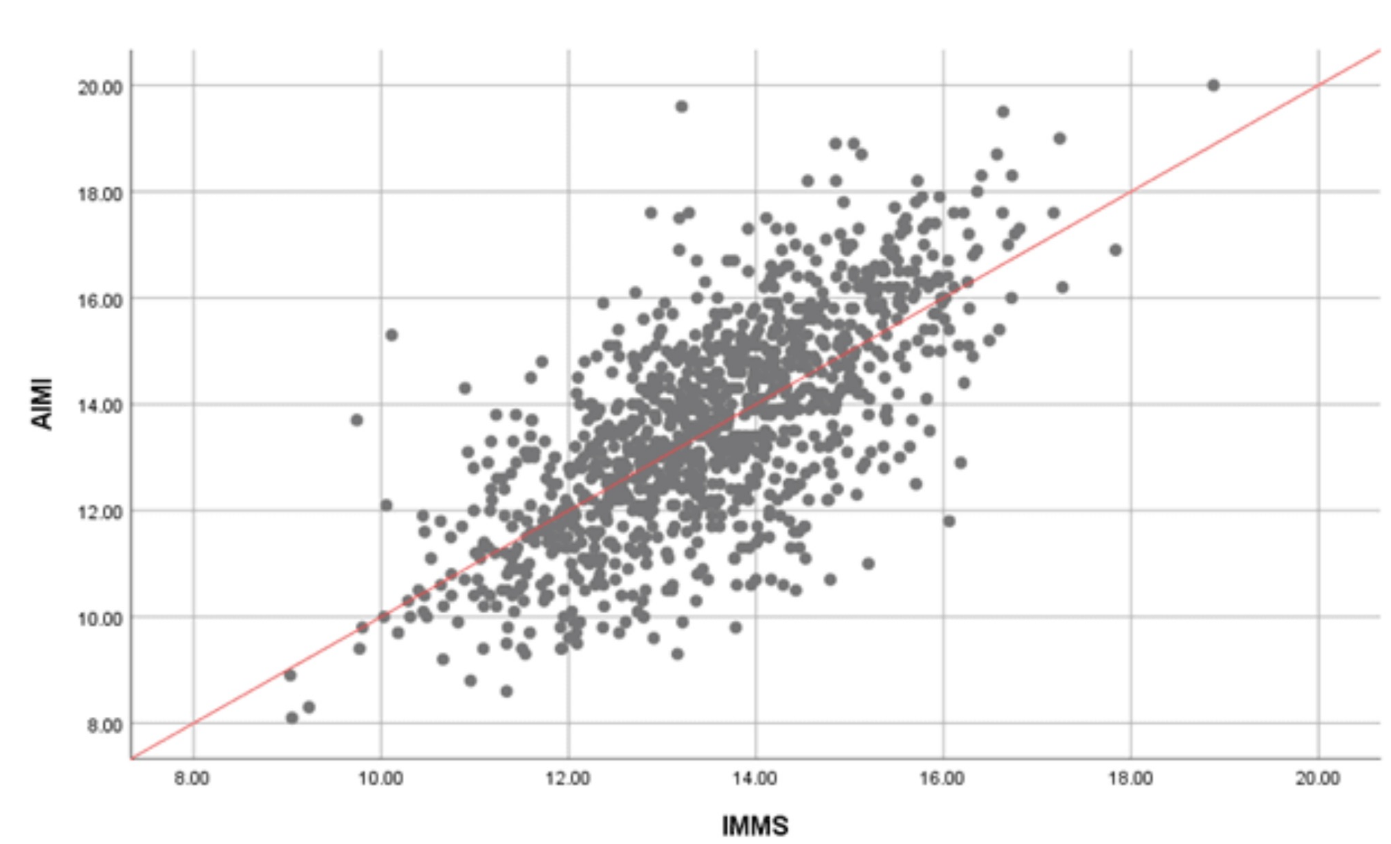
From a total of 1,073 students, ranging from kindergarten to 12th grade, at three schools located in the southeastern United States:

Comparison of Motivation level between AIMI and Written Motivation Survey (IMMS)

One student's Case



- A positive and strong correlations between the students' motivation levels measured by AIMI and IMMS (r = 0.71, n= 1073, p < 0.01)



RESULTS (CONT'D)

- There was no statistically significant difference between AIMI (M = 13.61, SD = 1.97) and IMMS (M = 13.52, SD = 1.40), t(1072) = 1.862, p = .06

Descriptive data for AIMI System and IMMS surveys

	Mean	N	Std. Dev	Std. Error
AIMI	13.61	1073	1.97	.06
IMMS	13.52	1073	1.40	.04

Paired Samples Statistics

	Mean	Std. Dev	Std. Error	95% CI Lower	95% CI Upper	*T*	*df*	*p*
AIMI-IMMS	.08	1.41	.04	-.01	.16	1.862	1072	.06

DISCUSSION

- **Findings of the present study demonstrate the potential of the AIMI System to automatically measure students' motivation in real time and help educators to respond to the motivational needs of individual learners.**

- **(a) measuring individual students' motivation in real-time and reporting the status of at-risk learners to the teacher/instructor. The teacher can then provide individualized support in an online learning environment, where it might otherwise be extremely difficult to check individual students' learning pace and difficulties.**

- **(b) identifying what learning contents, activities, and instructional methods significantly undermine learners' motivation through the data provided by AI. This additional information can enable educators to revise instructional materials and activities to improve learner engagement.**