UR-59

Analyzing Concentration Levels in Online Learning with Facial Values

Abstract

This project aimed to utilize a webcam during an online study session to detect the concentration levels of students and potentially help them improve their learning efficiency. In short, we utilized deep learning technologies to analyze students' facial expressions, including eye movements, to detect whether the students are focusing on the contents or not.

Introduction

In order to develop a deep learning model, our team created a shared data set of videos that were categorized as focused or distracted. The data set consisted of 400 total deepfake videos, of which 200 were focused and 200 distracted.

In order to make use of the data set, open-source eye tracking software was analyzed and evaluated. The first order model was implemented to deepfake along with the GazeTracking program to extract eye movement coordinates for each video. Once videos were deepfaked and eye movement data was extracted, the videos were inputted into trained deep learning models, which predicted the level of concentration.

The end goal was to develop deep learning models that are trained for maximum accuracy and low loss. The machine learning technology utilized in the models includes 1D, 2D, and 3D convolutional neural networks (1DCNN, 2DCNN, 3DCNN) along with a recurring neural network (RNN) or gated recurring units (GRU).

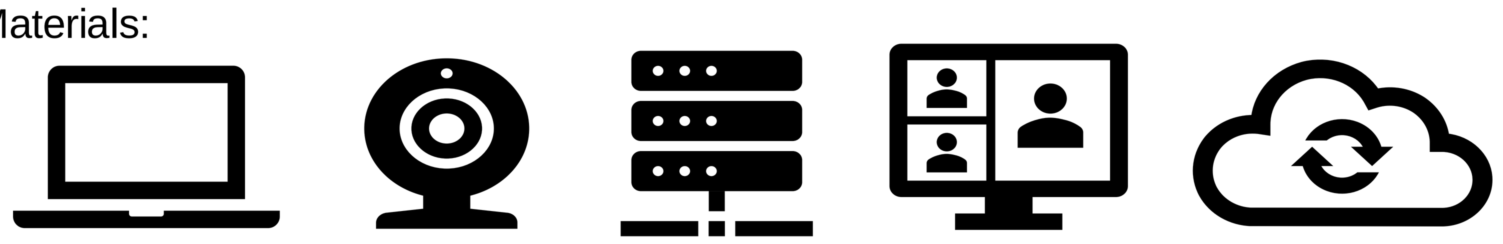
Research Question(s)

Can deep learning models accurately predict whether an individual is focused or distracted on a task in order to improve learning efficiency?

Our data collection focused on creating deepfake videos while emulating distraction or focus:

Materials and Methods

Materials:



Desktop/PC | Webcam | Server | Open-Source Software | Office 365

Methods:

- Record and collect video data (Focused or Distracted)
- Deepfake recorded videos to project individual privacy
- Generate eye tracking coordinate data from open-source software package
- Gather 4 types of model data by integrating videos with eye movement data to predict outcomes
- Employ facial and eye movement data into 5 different final model architectures

Results

The data for the final models below includes both facial and eye data from the deepfake videos. The first model includes eye data modeled with DNN and facial data with 2DCNN. The second model includes eye data modeled with 1DCNN and the facial data with 3DCNN. Utilizing both facial and eye data, the 2 models employed, after training, produced loss and accuracy values that were lower than expected. It is important to note that these models are just experimental. Typically, the deep learning models that we have been employed would generate output from thousands and tens of thousands of instances of data. This project employs the use of 400 different instances of data, hence the inaccuracies in the results of each model. Loss hovered around mid to high 3's with the 2DCNN. The 3DCNN results were significantly better with a much lower average loss, however average accuracy remained the same. Our accuracy numbers indicated a model accuracy of about 50%. The numbers suggest that the model is inaccurate due to insufficient data and/or inaccurate data.

2DCNN + GRU LR: 0.0001

Model:	CNN Face Layers:	DNN Eye Layers:	GRU Size:	MH:	Out Density:	Avg Loss:	Avg Accuracy:
1	[[16,4,4], [8,4,4]]	[32,32]	128	4	[128]	3.8136	0.5250
2	[[32,8,8], [16,8,8]]	[64,64]	64	5	[64]	3.7478	0.4858
3	[[8,2,2],[4,1,1]]	[16,16]	32	3	[32]	3.1046	0.5208
4	[[32,8,8],[16,4,4]]	[16,16]	32	4	[64]	3.4661	0.4880
5	[[32,8,8],[32,4,4]]	[64,64]	32	5	[64]	3.3424	0.5248

3DCNN + 1DCNN LR: 0.0001

Model:	CNN Face Layers:	CNN Eye Layers:	GRU Size:	MH:	Out Density:	Avg Loss:	Avg Accuracy:
1	[[16,2,4,4], [8,2,4,4]]	[[32,2], [16,2]]	128	4	[128]	3.6982	0.5051
2	[[32,2,8,8], [16,2,8,8]]	[[32,2], [32,2]]	64	5	[64]	2.6625	0.4999
3	[[8,3,2,2], [4,3,2,2]]	[[32,3], [32,3]]	64	5	[64]	0.7358	0.5267
4	[[32,4,4,4], [16,4,4,4]]	[[64,4], [32,4]]	128	4	[128]	1.1877	0.4683
5	[[32,3,6,6], [16,3,6,6]]	[[64,3], [32,3]]	64	5	[64]	0.6990	0.5188

Conclusions

After running the models and gathering results, the models gave a semi-accurate results of concentration detection to our dataset. The machine learning models could only provide partially useful optimization. Areas that needed further attention include the loss rates and average accuracies of the simulations.

To further improve this, training the data with more historical data, more videos, and using more models that have been trained with various results could advance the concentration awareness results to be more than a 50% chance accuracy.

Employing AI, with machine learning, for students/teachers to use creates a simple metric to analyze individual performance. Concentration awareness data can then be analyzed to establish learning strategies and effective methods to boost individual productivity by improving concentration retention.

Acknowledgments

We would like to thank Dr. Ying Xie and Dr. Linh Le for sponsoring this research project. For our GazeTracking program: Antoine Lame. First Order Model: Aliaksandr Siarohin, Stephane Lathuiliere, Sergey Tulyakov, Elisa Ricci, and Nicu Sebe.

Contact Information

Website: https://www.acp59.tech/
Jakeira Askew: jaskew8@students.kennesaw.edu
Jonathan Dicks: jdicks3@students.kennesaw.edu
Steven McGuire: Smcgui14@students.kennesaw.edu
Jacob Walton: jwalto28@students.kennesaw.edu
Jonah Witherell: ewithere@students.kennesaw.edu

References

[1]Y. Xie and L. Le, "Capstone Projects." Kennesaw State University, Marietta, 14-Jan-2021.

[2]Y. Xie, "Milestone 3." Kennesaw State University, Marietta, 30-Mar-2021.

[3]Antoinelame,"antoinelame/GazeTracking,"*GitHub*,20-Oct-2019.[Online].Available: https://github.com/antoinelame/GazeTracking. [Accessed: 22-Apr-2021].

[4]A. Siarohin, S. Lathuiliere, S. Tulyakov, E. Ricci, and N. Sebe, "AliaksandrSiarohin/first-order-model," *GitHub*, 23-Mar-2021. [Online]. Available: https://github.com/AliaksandrSiarohin/first-order-model. [Accessed: 22-Apr-2021].

KENNESAW STATE UNIVERSITY
COLLEGE OF COMPUTING AND SOFTWARE ENGINEERING

Authors: Jakeira Askew, Jonathan Dicks, Steven McGuire, Jacob Walton, Jonah Witherell
Advisors: Dr. Ying Xie, Dr. Linh Le