Using Machine Learning to Recognize, Classify, and Stimulate Engagement in Online Classes
(Technical Topic)

Understanding How an Online Setting Affects Learning and How to Adjust Classes Accordingly
(STS Topic)

A Thesis Project Prospectus Submitted to the

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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

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Introduction: Why Do Online Courses Need to be Studied?

Over the past year, the COVID-19 pandemic has drastically changed the state of the world, and the United States in particular – shutting down borders, businesses, public spaces, and even schools. As a consequence, educational institutions across the country have pivoted to online or hybrid learning as solutions to educate students while minimizing risks to public health. While online learning has been a mainstay in education for quite some time, such a dramatic and unprecedented shift has led to massive readjustment efforts on the parts of administrators, faculty, and students.

This readjustment is not without growing pains – faculty report that it is harder to maintain student engagement and develop personal connections in an online setting, and students feel that classes are less organized, less effectively taught, and that they learn less than how they would in a face to face (FTF) environment (Hetrick, 2019, p. 27; Slaydon, 2020). This may be exacerbated by studies that show that the human brain digests information entirely differently from online sources rather than physical documents; reading from an online source leads to less comprehension, development of critical analysis skills, and empathy (Wolf, 2018).

In light of these issues, this prospectus will detail two projects designed to address problems with online learning. One will be technical-based, and use facial and emotional recognition classification powered by machine learning to detect student engagement during class. The other will focus on analyzing the differences in information comprehension in an online classroom compared to a FTF environment, and will aim to promote a better understanding of how to design courses that are more compatible with these differences. Together, these projects aim to provide comprehensive improvements to the online learning experience.

Technical Project: Using Machine Learning to Recognize, Classify, and Stimulate Engagement in Online Classes

In online classes, teachers report that students are less engaged and it is more difficult to develop personal connections (Hetrick, 2019, p. 27). This is a critical flaw – student engagement is shown to be a primary indicator of their achievement (Carvalho, 2018, p. 418). Luckily, several tools are proven to help improve student engagement; textbook readings, informative videos, quiz questions, and other interactive media are shown to have a positive impact on learning (Carvalho, 2018, p. 422). Unfortunately, the benefits offered by these resources are not guaranteed. When offered in the wrong context, students interact with these sources solely for completion and do not reap their benefits. This is an issue in FTF and online classrooms alike; however, the decreased ability of teachers to make formative assessments in an online setting inhibits their ability to determine if a student is learning to their full potential (Pierce, 2018, p. 63).

This project proposes using facial and emotional recognition classifiers trained by neural networks to solve this problem. Classifiers take in data points – in this case, headshots of a student during class – and assign them labels – engaged or unattentive. This project will take advantaged of the prevalence of computer-installed cameras that are a necessary component of a large number of online classes to train a classifier that will first distinguish a student's face, then classify their emotion and eye focus. By doing so, a student's attentiveness (in other words, their level of engagement) will be able to be detected, measured, and recorded.

Significant research has already been done on facial recognition and emotional detection that can help facilitate the development of this project. In 2001, Paul Viola and Michael Jones published a seminal paper "Rapid Object Detection using a boosted cascade of simple features", which set the industry standard for facial recognition with machine learning. Since then, others have expanded their work to detect emotions, body position and posture, and eye focus (Raheja, 2010; Zhenguo, 2020). The strategy for this project is to build two classifiers – one that will detect the face (drawing primarily from the work of Viola & Jones, 2001), and another that will measure attentiveness. The basic process for image input and classification is detailed below in Figure 1. Measuring attentiveness will be the more significant challenge; a number of factors go into determining engagement that will have to be trained into the classifier. Eye focus and emotion will be two primary determinants of a student's level of attentiveness.

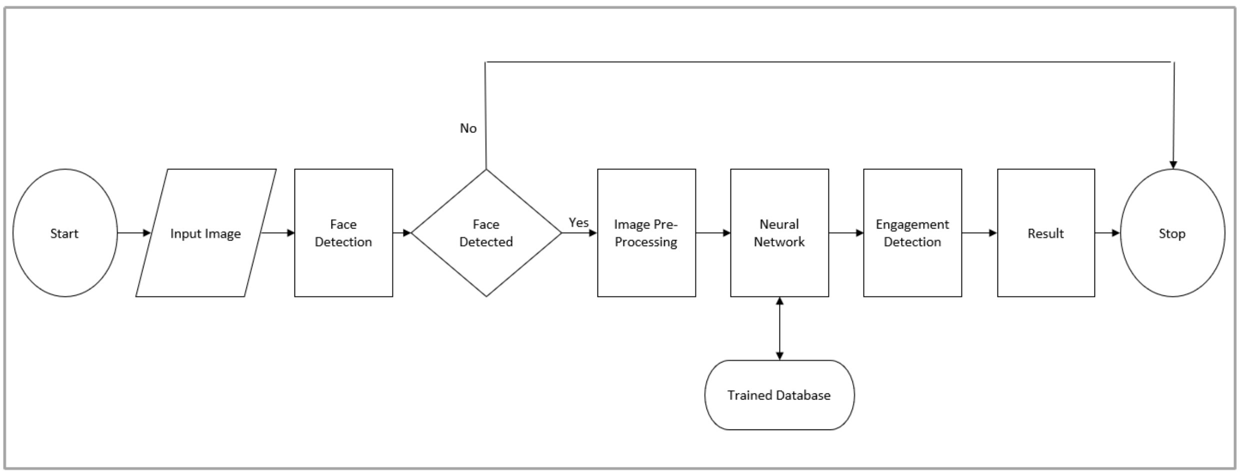

Figure 1: This model will receive images as input, and build on past work to detect if the image includes a face. If so, the image will go through pre-processing (centering, adjusting shadows, scaling, etc.), then be classified as engaged or unattentive by a trained neural network. Results will be logged (Created by author, but adapted from a similar chart from (Raheja, 2010, p. 117)).

The model will be coded in Python, with training data obtained from the Extended Cohn-Kanade (CK+) dataset, a well-established collection of headshots used to train emotion classifiers (Lucey, 2010). Figure 2, shown below, contains a breakdown of the model's decision making process once training is complete. During each class, the classifier will be fed frames taken from the webcams of student computers during their online classes at a rate of approximately .5 frames per second, generating 30 engaged or unattentive labels per minute. In the interest of privacy, the frames themselves will not be preserved, only the labels. Once the amount of unattentive labels surpasses a certain threshold – the value of which will be calibrated during testing, but initial estimates will be at one to two minutes of 80% unattentiveness – the teacher will receive a notification of the student’s status, and if the teacher has pre-registered an automatic response – such as a discussion question, link to source material, or other learning tool – that will be sent to the student.

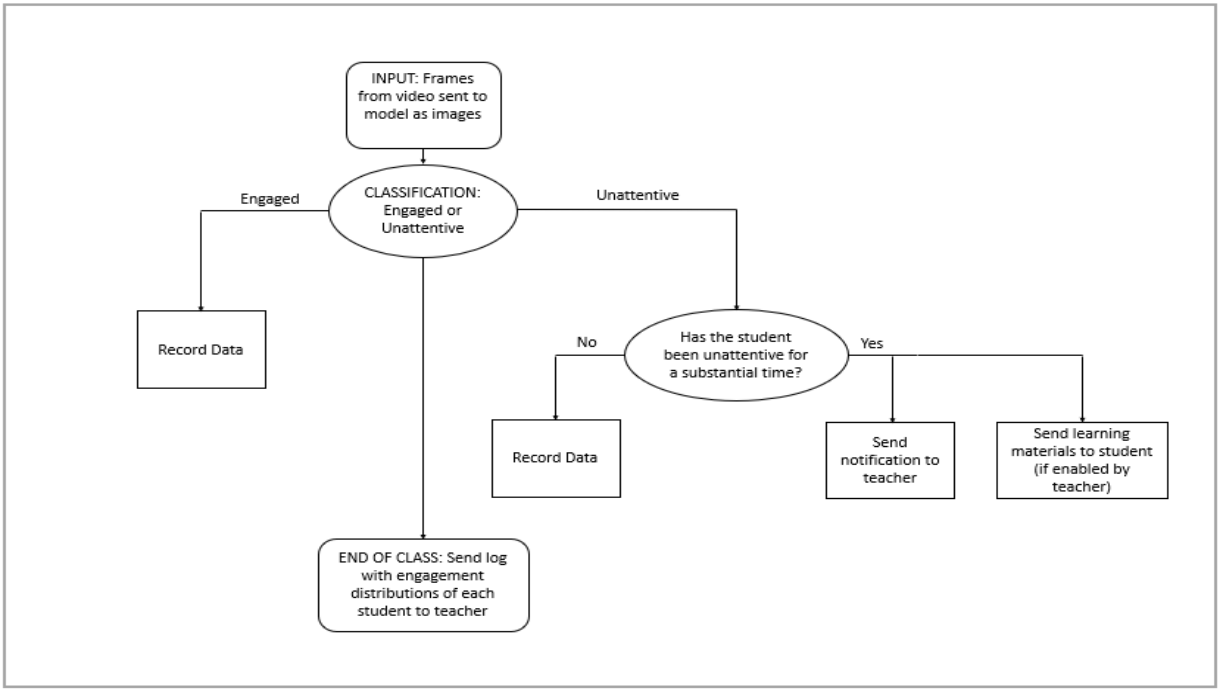

Figure 2: The model will take in images, use the trained classifier to detect whether the student is engaged or unattentive, and record the result. Once a student has been unattentive for sufficiently long, notice will be sent to the teacher and learning materials will be sent to the student to regain their attention (Created by author).

This has several potential applications:

i. Teachers can keep track of students who are attentive in class, giving them the opportunity to reach out to students who may need further guidance.

   a. This has the dual effect of facilitating a better personal relationship between the teacher and student as well as providing the teacher with the opportunity to offer more individualized assistance, which is proven to be more effective than group instructions (Angiello, 2010, p. 59).

ii. The product can prompt inattentive students with an encouraging reminder to regain focus, possibly in the form of a discussion question, informative video, or other relevant Web 2.0 resource.

iii. Recordings of student levels of attentiveness throughout the class can be analyzed for future iterations of the class to develop lesson plans aimed to optimize student engagement.

STS Project: Understanding How an Online Setting Affects Learning and How to Adjust Classes Accordingly

The technical portion of this paper focuses on providing a solution for a symptom of online classes: lower student engagement. However, it is equally useful to understand *why* online classes lead to less student attentiveness, and address those underlying causes. Problems with online courses manifest themselves through more factors than merely engagement. One study looked at two identical courses, taught by the same teacher with the same content – the only difference was that one course was FTF and the other was online. An end of semester surveyed showed at the 99% confidence level that students in the FTF class felt that their course was better designed, more effectively taught, and more likely to lead to them achieving their learning objectives as compared to the online course (Slaydon, 2020). As a result, even though enrollment in online classes has been steadily increasing over the past decade, student retention is lower in online classes comparted to their FTF counterparts (Bawa, 2016, p. 1).

This discrepeancy can perhaps be explained in the context of our brain's comprehension. A study conducted on the note-taking process of graduate students showed that those who took notes online provided less annotations, performed less critical analysis, and experienced "fragmented and disengaged reading" (Qayyum, 2008, p. 591). Likewise, it has been shown that students vastly prefer print textbooks over their online counterparts, and that they are more likely to read captions and figures, spend more time reading, and engage deeper with printed material than digital (Woody, 2010). If a screen is enough to limit reading comprehension, how severe are the effects of information ingestion through a screen when not just a reading, but the entire course's content?

It is not this project's aim to paint online courses in a negative light; as a matter of fact, substantial data shows that online learning carries significant advantages. Online classes offer more flexibility in scheduling and location, which studies have shown are valued greatly by both students and teachers (Hetrick, 2019, p.12). Moreover, and perhaps surprising given the evidence of the previously mentioned research, online classes do not negatively affect student performance (Angiello, 2010, p. 57). One meta-study analyzed the results of sixteen different comparisons of online courses and their FTF counterparts, and found online learning, when utilized properly, actually enhances results. Online classes in the study that utilized "static, non-interactive learning resources that largely resembled offline learning" had no difference in grades between online and FTF students, but classes that optimized their structure, such as one that offered "rich feedback and guidance [and] matched task difficulties to students' developmental level" had very high levels of student performance (Pei, 2019). It is clear that when the benefits of online learning are understood and implemented properly, students are able to flourish, even in a virtual setting.

In "Skim Reading is the New Normal", Maryanne Wolf calls for a thorough understanding of the effects technology has on the learning process, saying "If we work to understand exactly what we will lose, alongside the extraordinary new capacities that the digital world has brought us, there is as much reason for excitement as caution" (Wolf, 2018). This project aims to justify her optimism; over its course, both the varying structures of online classes

– such as synchronous versus asynchronous – and the nature of digital learning will be examined. By analyzing how students best ingest information in both physical and online settings, the relative strengths and weaknesses of online courses will become apparent. This deeper understanding will be invaluable to the two primary stakeholders in any classroom environment: students and teachers. Teachers will be able to structure their courses so that they are tailored specifically towards the advantages of an online setting, which will not only ease their teaching process but allow students to be able to better achieve their learning objectives and learn in an optimal environment.

Conclusion: Online Learning is Not A Temporary Need

Over the past two weeks alone, the University of Virginia has announced that it will continue online courses throughout the January and Spring terms, and the amount of new COVID-19 cases reported daily has increased by 43% (Times, 2020). It is clear that the reliance on online classes to provide safe, contactless instruction is not a passing fad, and will remain in effect for the foreseeable future. As such, it becomes ever the more necessary that steps are taken to optimize online learning and ensure that students receive the best possible education, even under extraordinary circumstances. This project will achieve this in two ways. Firstly, the problem of decreased student engagement will be addressed by providing a classifier that will detect and classify student engagement and report it back to the teacher, while also taking steps to re-engage the student with learning materials. Secondly, the nature of learning and how it relates to online classes will be researched in order to understand the ideal online structure, and how teachers and administrators can better structure their classes in order to maximize the advantages of an online setting while mitigating the potential drawbacks. The joint effort of these two projects will address the drawbacks of online learning by increasing student engagement, and provide understanding to systemically change how online courses are taught, improving the education experience for all.

~ 1,859 words

References:

Angiello, R. (2010). Study Looks at Online Learning vs. Traditional lnstruction. *Education Digest: Essential Readings Condensed for Quick Review*, *76*(2), 56–59. Retrieved from http://proxy01.its.virginia.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ903522&site=ehost-live&scope=site

Bawa, P. (2016). Retention in online courses: Exploring issues and solutions—a literature review. *SAGE Open*, *6*(1), 215824401562177. https://doi.org/10.1177/2158244015621777

Carvalho, P. F., Gao, M., Motz, B. A., & Koedinger, K. R. (2018). Analyzing the Relative Learning Benefits of Completing Required Activities and Optional Readings in Online Courses. *International Educational Data Mining Society*. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=ED593230&site=ehost-live

Hetrick, B., Marcum, D., & Council of Independent Colleges. (2019). Teaching the Humanities Online: Lessons from a Consortium of Liberal Arts Colleges. In *Council of Independent Colleges*. Council of Independent Colleges. Retrieved from http://proxy01.its.virginia.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=ED597928&site=ehost-live&scope=site

Lucey, P., Cohn, J. F., Kanade, T., Saragih, J., Ambadar, Z., & Matthews, I. (2010). The Extended Cohn-Kanade Dataset (Ck+): A complete dataset for action unit and emotion-specified expression. *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops*, 94–101. https://doi.org/10.1109/CVPRW.2010.5543262

Pei, L., & Wu, H. (2019). Does online learning work better than offline learning in undergraduate medical education? A systematic review and meta-analysis. *Medical Education Online*, *24*(1), 1666538. https://doi.org/10.1080/10872981.2019.1666538

Pierce, S. P. (2018). Web 2.0 in the Online Learning Environment: A Basic Qualitative Study to Define Best Practices [ProQuest LLC]. In *ProQuest LLC*. Retrieved from http://proxy01.its.virginia.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=ED583908&site=ehost-live&scope=site

Qayyum, M. A. (2008). Capturing the online academic reading process. *Information Processing & Management*, *44*(2), 581–595. https://doi.org/10.1016/j.ipm.2007.05.005

Raheja, Jagdish & Umesh, Kumar. (2010). Human Facial Expression Detection From Detected in Captured Image using Back Propagation Neural Network. *International Journal of Computer Science & Information Technology*. 2. Retrived from https://www.researchgate.net/publication/41447855_Human_Facial_Expression_Detection_From_Detected_in_Captured_Image_using_Back_Propagation_Neural_Network

Slaydon, J., Rose, D., & Allen, L. (2020). Quantifying the Personal Factor of FTF in an Online World. *Journal of Instructional Pedagogies*, *23*. Retrieved from http://proxy01.its.virginia.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ1241960&site=ehost-live&scope=site

Tanis, C. J. (2020). The seven principles of online learning: Feedback from faculty and alumni on its importance for teaching and learning. *Research in Learning Technology*, *28*, 1–25. https://doi.org/10.25304/rlt.v28.2319

Times, T. N. Y. (2020, July 20). Covid in the u. S.: Latest map and case count. *The New York Times*. https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html

Wolf, M. (2018. August 25). Skim reading is the new normal: The effect on society is profound. *The Guardian.* Retrieved from https://www.theguardian.com/commentisfree/2018/aug/25/skim-reading-new-normal-maryanne-wolf.

Woody, W. D., Daniel, D. B., & Baker, C. A. (2010). E-books or textbooks: Students prefer textbooks. *Computers & Education*, *55*(3), 945–948. https://doi.org/10.1016/j.compedu.2010.04.005

Zhenguo Yuan, "Face Detection and Recognition Based on Visual Attention Mechanism Guidance Model in Unrestricted Posture", *Scientific Programming*, vol. 2020. https://doi.org/10.1155/2020/8861987