Milestone 4 - Team 17

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CS 6795: Introduction to Cognitive Science

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Abstract

In this Milestone paper, we are tasked to write an overview of the computational model results we have obtained after building our model. We will also discuss how it is associated with cognitive science. The problem we are attempting to solve is whether the eyes are the window to a human's internal state. Through the analysis of pupil dilation (as marked by dark pixel ratio), can a general intelligence agent recognize mood? This is a branch of artificial intelligence and will involve constructing systems to help an artificial general intelligence agent determine mood in the eyes.

Introduction

Our research question: "are the eyes a window to a human's internal state?" was examined through multiple perspectives, one of them being through the concepts defined in this course, Cognitive Science. Our computational model was inspired by the concept of a System, in which independent parts interact with one another to perform a set of actions or form an underlying mechanism. If the eyes are a system, either each eye individually or in combination with its complement (right eye + left eye), from whose images a person's mood can be derived, then it should be possible to build a computational model to do so.

The ability to predict a person's mood from photos or video footage has practical applications in the domains of public safety, healthcare, customer service, among others. With regard to public safety, security cameras at public venues can continuously monitor people's moods to detect people in distress who might need help. In the healthcare field, computerized monitoring of patients' moods during their stay at health facilities could improve medical treatment. In addition, customer service providers would benefit from computerized monitoring of their customers' moods.

Experiment design

The development of our mood-prediction tool involved multiple steps. First, we reviewed the course lessons to identify relevant cognitive concepts. Subsequently, we conducted a literature review on the identified concepts, with the focus areas being Systems. Finally, we brainstormed and discussed how these concepts can be implemented and eventually constructed into a model. The most relevant course lessons were: *Lesson 5: Analogies*; *Lesson 11: Systems* and *Lesson 13: Revisiting Representations*. The most pertinent readings so far were chapters 1 and 5 of *The Sciences of the Artificial*[4] *(Simon, 2019)* and *Knowledge Representation*[8] *(Markman, 1999)*.

After reviewing the literature, lessons, and various material sources related to our research topic, we eventually abstracted a hierarchical representation of a System to represent our model. A System, containing hierarchies in its abstractions, was observed and eventually defined to have the following high level hierarchical abstraction: Images -> DPR -> Emotions.

In our model, the most fundamental building blocks were pixels with grayscale values in the range of 0 to 255, inclusive, with 0 being the darkest black and 255 being the lightest white. With relation to Cognitive Science, pixels are the lowest-level constituents of a hierarchical system, and can be thought of as the zeroth level of abstraction. Their use as the basic building blocks of our system was justified due to human ability to perceive collections of pixels as representations of objects. The next (higher) level in our system were cropped-out, seperate images of the eyes: right eye and left eye. Our assumption was that an AI agent could discern moods based on patterns found in those images. In particular, we hypothesized that there would be sufficient information in just the eyes (as opposed to a larger area of the face) to predict mood.

In terms of measurable quantities, we expected the Dark Pixel Ratio (DPR), expressed as the ratio of dark pixels to the total number of pixels in an image, to be different for different moods (joy, anger, fear, etc.). Our hypothesis was that the biological processes that result in any given mood have a unique visual representation that can be identified via DPRs. In order to perform a mapping between the base and target, we processed the images via mathematical algorithms to determine the DPR for combinations of eye inputs; i.e., pairs of right and left eye images. In order to extract commonalities, we utilized machine learning algorithms to graph the DPRs. In the code, for a pixel to be classified as "black," the grayscale value of that pixel had to be lower than the threshold value. Given that a grayscale value of 0 is the darkest black and 255 is the lightest white, we set the algorithm to classify a pixel as "black" for values below the threshold and "white" for all values at or above the threshold. Thus, in a given image, for low threshold values, there would be less pixels in the "black" category than for high threshold values. Our computational tool was written in the python programming language and utilized the K-Nearest Neighbor (KNN) supervised learning algorithm. As an input, we used images with varying represented moods, and as an output, a prediction would be made identifying which image cluster the input image most likely pertained to. The training data consisted of 30k labeled images for the following moods: anger (2711 images), disgust (335 images), fear (2518 images), joy (5523 images), neutral (3095 images), sadness (2649 images), surprise (2381 images).

The major classes in the code were: Atom, Molecule, and Cell, each representing a level of abstraction. An atom, being an individual left or right eye cropped out of a facial image, was the first level of abstraction. A molecule, being a combination of two eyes (left and right) together, was the second level of abstraction. A cell, representing a cluster of molecules, as defined by the KNN algorithm, represented the third level of abstraction.

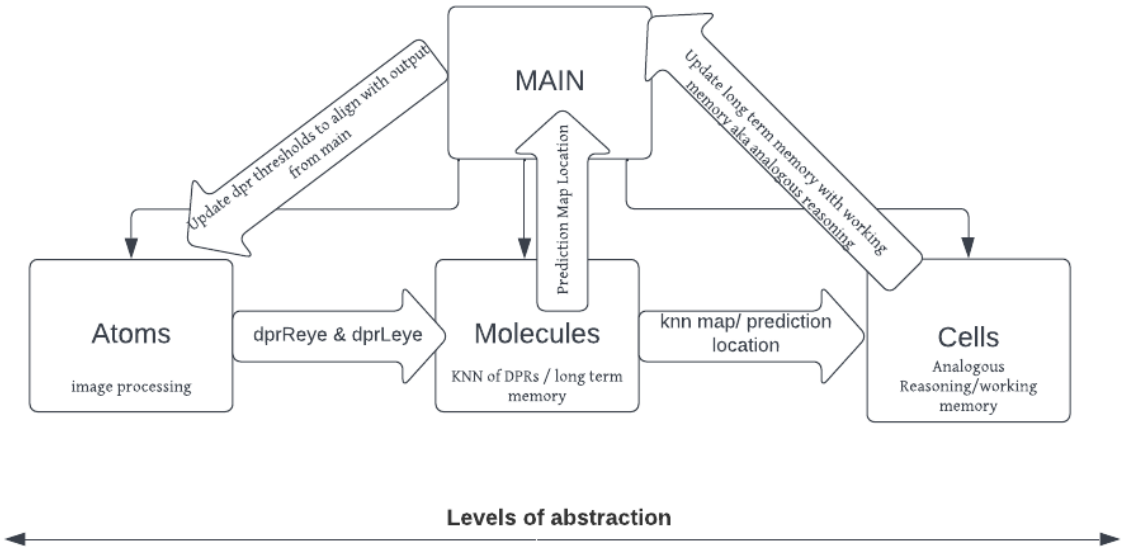


Figure 1. Schematic of computational tool processing logic.

The source code can be accessed at the following link: here (main code) and here (plotting the data).

Results

We initially plotted the DPR ratios of the left and right eyes with varying the *faceOverlap* values from 1 to 5 for *dprThreshold* values in the set {25, 50, 75, 100, 150, 200, 250}. The *knnDepth* was kept constant for all simulations with a value of 5. Appendix 1 summarizes the meaning of each variable. A selection of plots with all emotions from the training dataset as well as the algorithm's prediction, represented by a "red circle," is shown in Appendix 2. Three images were utilized as the input, as shown in figure 2. The cropped-out eyes corresponding to the input images are displayed in figure 3.

Figure 2. Input images (left to right): /happy/30.jpg, /sad/98.jpg, /surprise/438.jpg.

	/happy/30.jpg		/sad/98.jpg		/surprise/438.jpg	
faceOverlap	**Left eye**	**Right eye**	**Left eye**	**Right eye**	**Left eye**	**Right eye**
1						
2						
3						
4						
5						

Figure 3. Cropped-out eyes (left to right): /happy/30.jpg, /sad/98.jpg, /surprise/438.jpg.

As can be observed in Appendix 2, fewer emotions are rendered on the plots for DPR thresholds that are closer to both the low ("0") and high ("255") ends of the spectrum. In terms of cognitive science, this means that the AI agent's ability to process the training data is better when the thresholds are neither too low nor too high. Furthermore, we found that higher resolution images resulted in more accurate predictions. From the cognitive science perspective, this is due to the agent having less data to process and make inferences about at the pixel level of abstraction. The data in A2.1 of Appendix 2 showed that increasing the *dprThreshold* from 25 to 100 resulted in a substantially larger increase in the prediction right eye DPR than the left eye DPR. Between *dprThreshold* values of 100 and 250, the left eye DPR exhibited a greater rate of increase. On the other hand, the prediction left/right eye DPRs in A2.3 of Appendix 2 were more closely aligned in terms of their rate of increase. The numbers are summarized in figure 4 and corresponding plots are shown in Appendix 2.

	image: /surprise/438.jpg [A2.1] (faceOverlap=1)				image: /sad/98.jpg [A2.3] (faceOverlap=1)			
DPR Threshold	**Left eye DPR**	**Right eye DPR**	**Δ (Left eye DPR)**	**Δ (Right eye DPR)**	**Left eye DPR**	**Right eye DPR**	**Δ (Left eye DPR)**	**Δ (Right eye DPR)**
25	0.0	0.0	-	-	0.07143	0.03125	-	-
50	0.04	0.0667	0.04	0.0667	0.17857	0.21875	0.10714	0.1875
75	0.06	0.3167	0.02	0.25	0.25	0.46875	0.07143	0.25
100	0.14	0.6333	0.08	0.3166	0.46429	0.59375	0.21429	0.125
150	0.54	0.8667	0.4	0.2334	0.60714	0.75	0.14285	0.15625
200	0.9	0.9833	0.36	0.1166	0.82143	1.0	0.21429	0.25
250	1.0	1.0	0.1	0.0167	1.0	1.0	0.17857	0

Figure 4. Left/Right eye DPR predictions for /sad/98.jpg and /surprise/438.jpg images.

With further modifications to the code, we shifted focus by letting the AI agent modify the *faceOverlap*, *dprThreshold*, and *knnDepth* values via a feedback vector. Additionally, the code was updated to generate filtered (black-and-white) images of the eyes, as shown in figure 5.

Feedback vector	**Left eye**	**Filtered left eye**	**Right eye**	**Filtered right eye**
{'faceOverlap': 2, 'dprThreshold': 100, 'knnDepth': 7}				

Figure 5. Cropped-out eyes and their corresponding filtered images

An interesting observation was that starting with two different sets of feedback vector parameters resulted in the same output after multiple simulations. As shown in figure 6, we ran two experiments with *faceOverlap* initialized to a value of 2 for the first experiment and a value of 4 for the second experiment.

Experiment #1: Non-labeled image: kyle.jpg. Initialized values: {'faceOverlap': 4, 'dprThreshold': 25, 'knnDepth': 7}						
Feedback vector parameters			Prediction DPRs		Predicted moods	
faceOverlap	*dprThreshold*	*knnDepth*	Left eye DPR (*x*)	Right eye DPR (*y*)	Result	Confidence (*lvl*)
4	25	7	0.13	0.11	anger + joy = 0.71	0.71
4	50	5	0.36	0.34	disgust + sadness = 0.4	0.4
4	75	3	0.59	0.58	neutral + anger = 1.0	1.0
Experiment #2: Non-labeled image: kyle.jpg. Initialized values: {'faceOverlap': 2, 'dprThreshold': 25, 'knnDepth': 7}						
Feedback vector parameters			Prediction DPRs		Predicted moods	
faceOverlap	*dprThreshold*	*knnDepth*	Left eye DPR (*x*)	Right eye DPR (*y*)	Result	Confidence (*lvl*)
2	25	7	0.13	0.11	anger + joy = 0.71	0.71
2	50	5	0.37	0.34	anger + sadness = 0.6	0.6
3	50	5	0.36	0.34	anger + sadness = 0.6	0.6
4	50	5	0.36	0.34	disgust + sadness = 0.4	0.4
4	75	3	0.59	0.58	neutral + anger = 1.0	1.0

Figure 6. Two experiments with different initial parameters. Final results were the same.

Despite the difference in the initialized values for the two experiments, the results came out exactly the same after multiple iterations. See Appendix 3 for more details.

Discussion

The best way to expose the implications of our results is to analyze a number of different paths the AI agent took with a Cognitive Science lens: specifically, cognitive systems. To begin, let's look at the output produced by the agent, to understand how this system thinks, self reflects, and adapts to the input[1]. In this case, the Agent correctly identified the label, Joy, and also provided a vector rather than a single emotion.

```
[Running] python -u "/Users/kjams/Desktop/dataAnalysis2022Spring/main.py"
feedback: {'faceOverlap': 4, 'dprThreshold': 50, 'knnDepth': 8}
x: 0.5762820512820512
y: 0.5657855436081243
anger and joy make up 0.625
lvl: 0.625
feedback: {'faceOverlap': 4, 'dprThreshold': 75, 'knnDepth': 8}
x: 0.9025919732441472
y: 0.7306227598566308
neutral and sadness make up 0.75
lvl: 0.75
feedback: {'faceOverlap': 4, 'dprThreshold': 75, 'knnDepth': 6}
x: 0.9025919732441472
y: 0.7306227598566308
neutral and sadness make up 0.6666666666666666
lvl: 0.6666666666666666
feedback: {'faceOverlap': 4, 'dprThreshold': 100, 'knnDepth': 6}
x: 0.9575808249721294
y: 0.8493876941457587
joy and neutral make up 1.0
lvl: 1.0
```

Figure 7. The inputs journey through four iterations of self reflection.

Looking at the terminal output, *feedback at state 0* is the initial settings chosen by the programmer[2]. These rates determine how the outside system, the eye images, are processed

[1] For a full overview of the AI agent, please see appendix one.
[2] The initial state should be determined by the AI agent based on the outside system. This is a place for expansion.

inside the AI agent, and how the parts of the system *interact* with each other. For example, face-overlap is quite literally the size of the image to take into consideration. This can be akin to directed attention, i.e., what a human would decide to pay attention to when taking in an image, and this choice largely affects DPR as size of the image = the distribution size of pixels, and is based on case-based similarity. Higher faceoverlap, higher the detail paid attention to.

Next, the initial x,y values represent the x,y location of the current image location amongst all training images through the lens of eye DPR rates[3]. The string statement after the x,y output represents an aggregated percentage of all atoms and their respective labels, formed as molecules, where two labels are chosen based on the highest representation in said aggregations.

This is how we try to represent a working memory through generalizations based on previous cases. That is, *past experiences inform new experiences*. For example, I've seen this type of eye numerous times in our x,y variable binding knn map, and the statistically closest memories, as measured by Euclidean distance, are of emotionOne and emotionTwo. This forms a vector, as an abstraction of the current theory of mind, opening room for larger analysis as we now have a range of emotion.

Lastly, the variable *lvl* is a range between 0-1 on how confident the AI agent is in its own analysis. Based on this rate, the current *feedback* is adjusted based on heuristics, a place to experiment with our model, which takes into consideration the output, *feedback*, the abstraction of the *input*, and the relationships amongst current feedback to produce new feedback based on these self reflections[4].

The implications from this experiment are as follows:

1. Systems are hierarchical, ex., face overlap => DPR rate => KNN => emotion

[3] Appendix 1
[4] Appendix 2 contains the input and output for several paths the AI agent may take.

2. Systems parts communicate. This is in fact, how feedback is considered and constructed, i.e., at least one feedback variable per abstraction level.
3. Systems are made of abstracted parts. This is literally how the program is organized => Atom, Molecule, Cell Network, Tissue, Main, Feedback, repeat cycle x times.
4. Systems use Heuristics, this is how feedback is measured and reflected on.
5. Systems must be calibrated to the outside environment, aka the initial feedback results should not be human generated. The feedback, from state 1 on, *does use AI generated feedback* based on reflection. Very cool :)

Conclusion

In this study, we set out to determine whether it is possible to construct a computational model to identify *systems* in the eyes and make accurate predictions about a people's mood by using only images of the eyes as input. In order to do so, we developed a computational tool that takes facial images as input and makes predictions about the mood. The tool was able to make accurate predictions based on a labeled set of training data. Furthermore, the tool was able to generate the same prediction with different initialized values for *faceOverlap*, *dprThreshold*, and *knnDepth*. The main implications that we derived were (1) systems are hierarchical (2) system parts communicate (3) systems are made of abstract parts (4) systems use heuristics and (5) systems must be calibrated to the outside environment.

Limitation

Initial limitations to our study revolved around sourcing various different image datasets and the processing of the types of variations in images found in the datasets. The datasets themselves were selected on facial representation, as well as level of classification and tagging available. For an initial model and prototype, as well as the scope of the initial model iterations developed, a small controlled sample size would provide a more succinct way of validating whether a cognitive system is present within the eyes of a human being. The limitation this adds is that, should images be used that don't follow the pattern presented, it's possible the system designed and architected, may present a variation in prediction from the base model. In addition to the small sample size used, the number of emotions sourced were also limited. The scope of the model was purposely limited to attempt to design the feedback loop, than to expand into more uncertainty. Due to that, the model would need some investment to account for different emotion representations and similarities that could be identified via DPR.

In addition to the limitations presented already, the choice was made to focus on addressing a system where the facial representation/area present to the model is symmetrical. This limits the model specifically to faces that represent a broad area of either the face or the eyes. The model is therefore limited to a full surface area of the eye. The face overlap limits how much of the face is available, but still provides a symmetrical representation of the input images the model processes. If an image of a face being processed is not looking directly into the camera, if one eye has more shade than the other, or if the face is turned in one direction or another limiting the visibility to the eye, the model would need to be modified to account for variations in eye angle, and ability to use DPR appropriately.

Future studies, or expansions of this study, would focus on expanding the sample size of images, black/white images in addition to grayscale versions of color images, as well as varying angles of faces. Expanding the image datasets to consider a larger amount of emotions would be the smaller hurdle. Expanding the model to support a non-clear facial area, tilted face, or edges of the eyes, would provide a larger hurdle for implementation. Further considerations should be taken as well into model parameter variation, KNN depth, as well as DPR threshold variations while updating other impacting parameters. Overall, for a base model, our model is quite powerful and insightful, but it serves as a basis for so much more exciting work and expansion that can be made.

References

1. Woods, D. D. (1985). Cognitive Technologies: The Design of Joint Human-Machine Cognitive Systems. *AI Magazine*, *6*(4), 86. https://doi.org/10.1609/aimag.v6i4.511
2. Raymond Phang, Sierra Beck, Ohad Dar, Joanne Robertson-Smith, Christie Fyfe, Meghan Scanlan, Sophie Thomas, Rebekah Wrigley, Megan Anakin. Using Systems Thinking to Identify Staff and Patient Safety Issues in Infectious Disease Simulation Scenarios. Clinical Simulation in Nursing, Volume 61, 2021, Pages 23-32, ISSN 1876-1399. https://doi.org/10.1016/j.ecns.2021.08.026
3. Meadows, D. H. (2008). Thinking in Systems: A Primer. Chelsea Green Publishing.
4. Simon, H. A. (2019). The Sciences of the Artificial. The MIT Press. https://doi.org/10.7551/mitpress/12107.001.0001
5. A. Goel. (2022). Systems [Lesson 11 Videos]. Georgia Institute of Technology.
6. Goldstein, E. B. (1981). The Ecology of J. J. Gibson’s Perception. Leonardo, 14(3), 191–195. https://doi.org/10.2307/1574269
7. Gibson, J. J. (2014). The Ecological Approach to Visual Perception. New York: Psychology Press. https://doi.org/10.4324/9781315740218
8. Markman, A. B. (1999). *Knowledge representation*. L. Erlbaum.

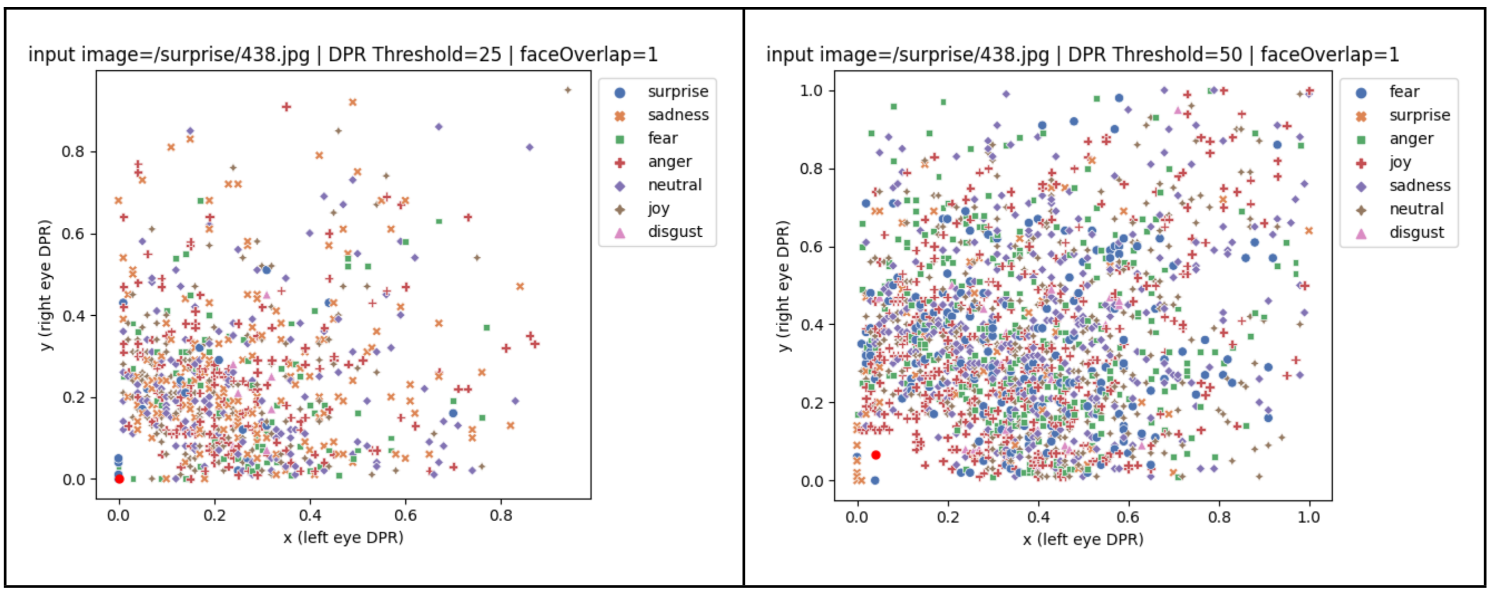
Appendix 1

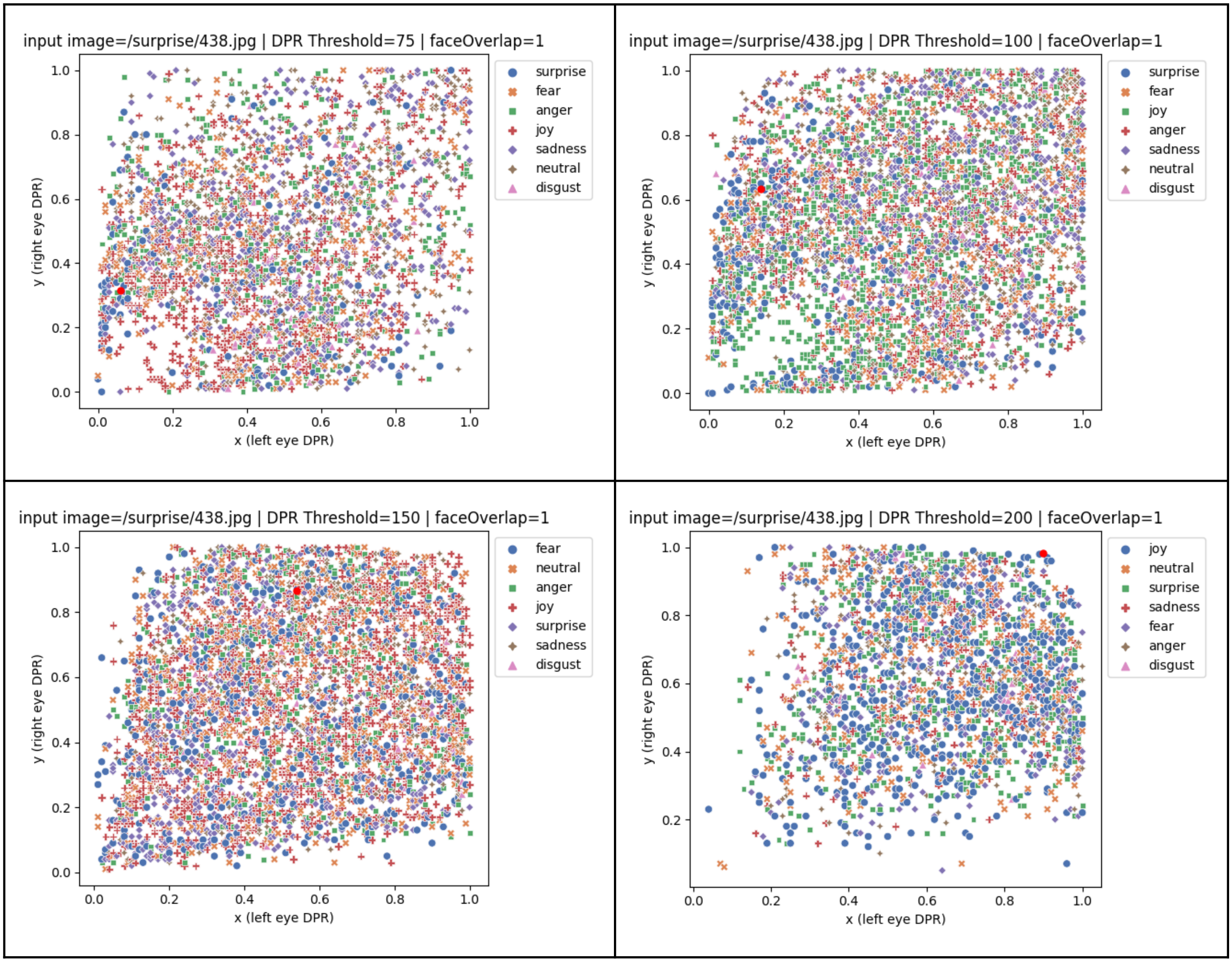
Name	**Value**
faceOverlap	Range: 1-5, From low to high, the size of the image processed. The first interaction the system has with the outside environment
dprThreshold	Range: 0-255, From low to high, the threshold for considering a pixel black or white. Second interaction with the outside environment which controls how to interpret one's memories and current context
knnDepth	Number of closest neighbor molecule aggregations to use as working memory, i.e., number of cases for case-based reasoning
feedback	{'faceOverlap': int, 'dprThreshold': int, 'knnDepth': int}
X	Left eye DPR
Y	Right eye DPR
mapOfTheWorld	Sorted by descending Euclidean distance from current outside image, i.e., image to predict for. { (x,y): [(label,molecule.object), ... (nth label, nth molecule.object)
Emotion Vector	Range 0-1: KNN label aggregation vote of two strongest feelings.
Lvl	Emotion Vector used for actioning feedback

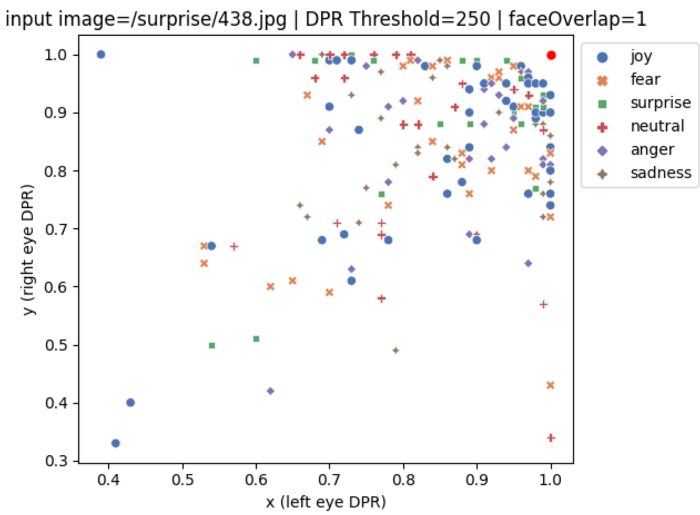
Name	**Input**	**function**	**Output**
Atom Initial State	**feedback**,imgPath, iteration,**faceOverlap**	Pre-processes image	Framework for Molecule
Molecule Aggregated Atoms based on dprThreshold	label,filepath,**dprThreshold,**iteration	Based on dprThreshold, re-processes memory and testing images.	Dictionary of aggregated x,y cords and their respective Molecule Objects, which contain labels, created for KNN map. A vote of aggregations of Molecules

Cell Network of Molecules form Cells	**x,y,mapOfTheWorld, knnDepth**	Collects K nearest neighbor aggregations to create **emotion vector**	**Emotion Vector**
Tissue Analysis of Cells	cellNetwork	Based on emotion vector, series of heuristics to increase emotion vector's label vote closest to 1	**feedback**

Appendix 2

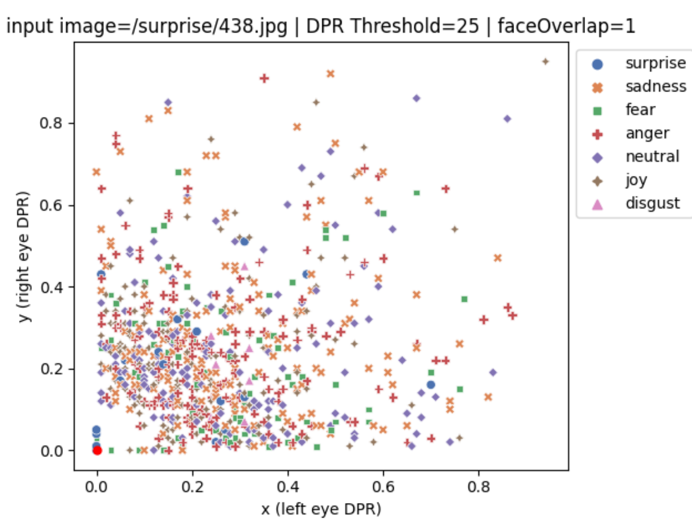


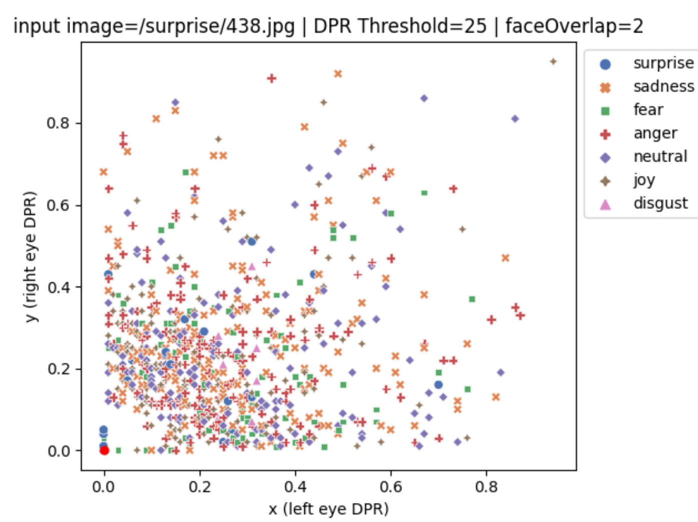

input image=/surprise/438.jpg | DPR Threshold=75 | faceOverlap=1
y (right eye DPR)
x (left eye DPR)
surprise
fear
anger
joy
sadness
neutral
disgust
input image=/surprise/438.jpg | DPR Threshold=100 | faceOverlap=1
y (right eye DPR)
x (left eye DPR)
surprise
fear
joy
anger
sadness
neutral
disgust
input image=/surprise/438.jpg | DPR Threshold=150 | faceOverlap=1
y (right eye DPR)
x (left eye DPR)
fear
neutral
anger
joy
surprise
sadness
disgust
input image=/surprise/438.jpg | DPR Threshold=200 | faceOverlap=1
y (right eye DPR)
x (left eye DPR)
joy
neutral
surprise
sadness
fear
anger
disgust

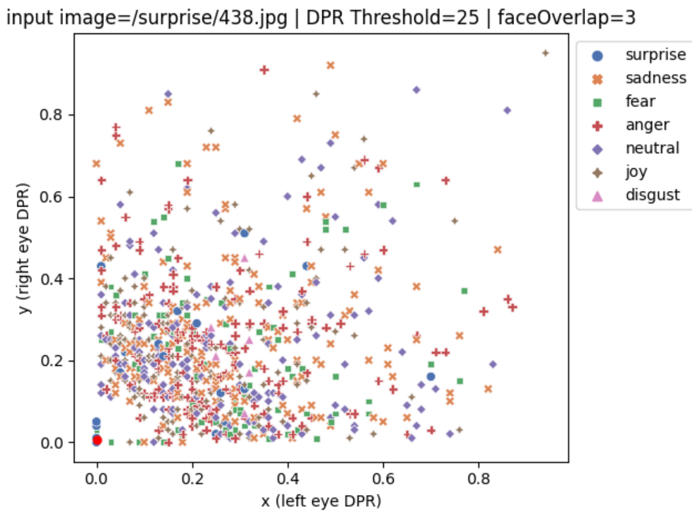


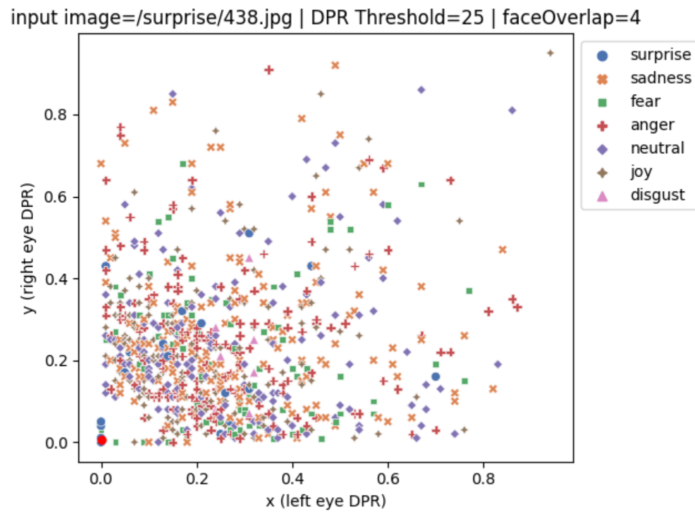
DPR Threshold	Left eye DPR (faceOverlap=1)	Right eye DPR (faceOverlap=1)
25	0.0	0.0
50	0.04	0.0667
75	0.06	0.3167
100	0.14	0.6333
150	0.54	0.8667
200	0.9	0.9833
250	1.0	1.0

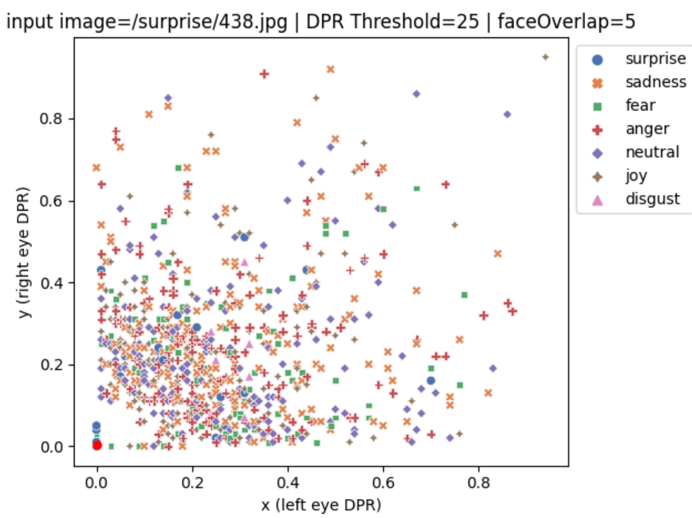
A2.1 Image /surprise/438.jpg for varying dprThreshold values and constant faceOverlap=1.





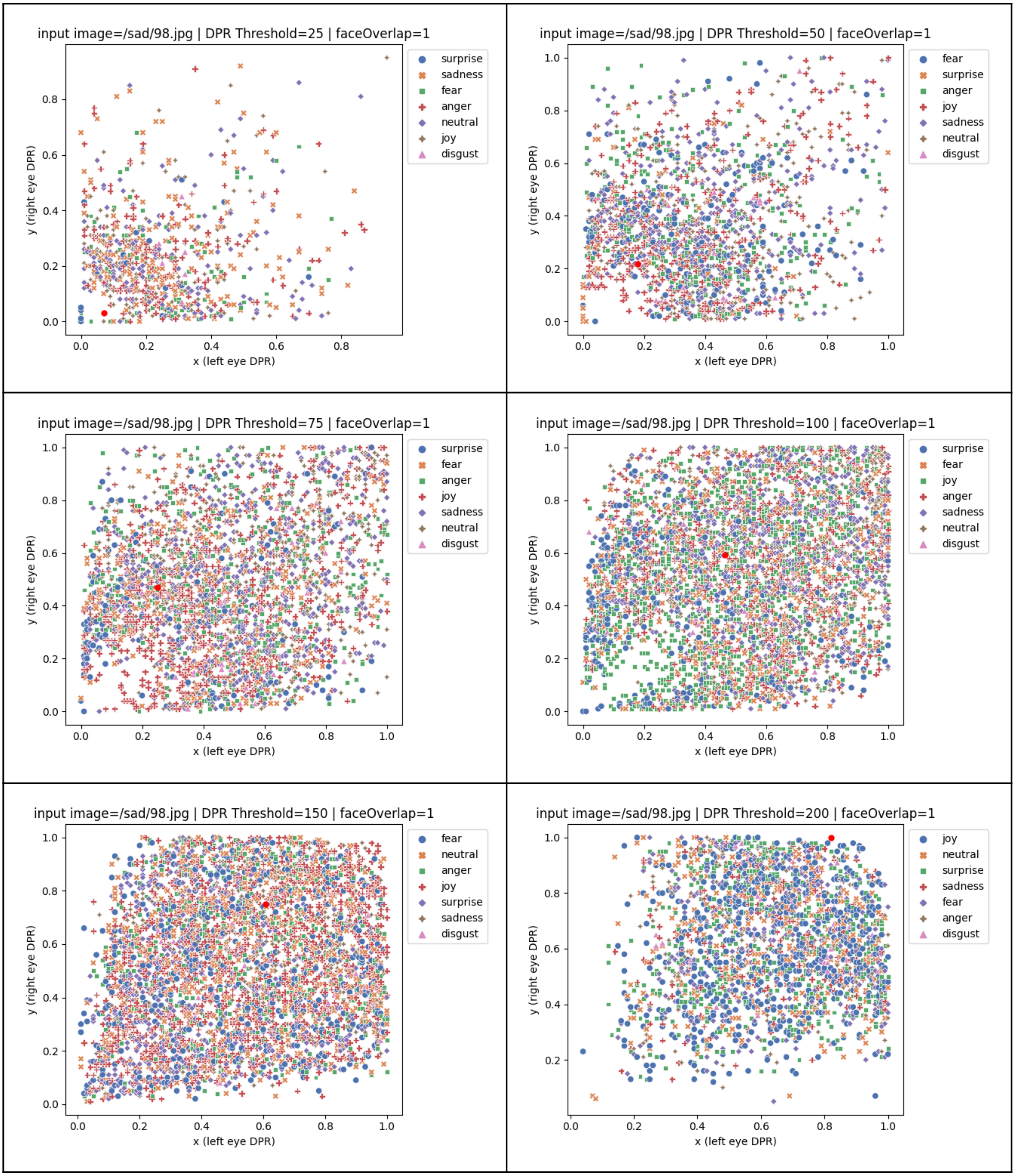


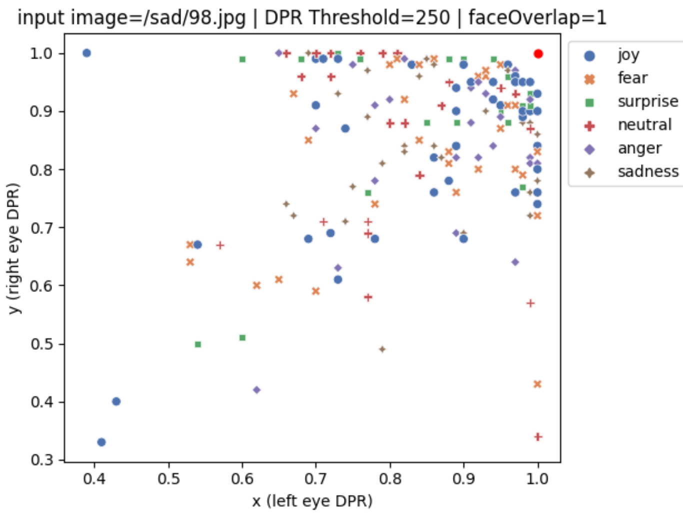




faceOverlap	Left eye	Right eye
1		
2		
3		
4		
5		

A2.2 Images /surprise/438.jpg for constant dprThreshold of 25 and varying faceOverlap values.

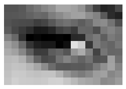
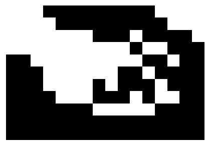
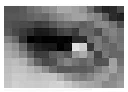
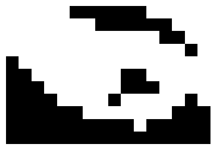

input image=/sad/98.jpg | DPR Threshold=25 | faceOverlap=1
surprise
sadness
fear
anger
neutral
joy
disgust
x (left eye DPR)
y (right eye DPR)
input image=/sad/98.jpg | DPR Threshold=50 | faceOverlap=1
fear
surprise
anger
joy
sadness
neutral
disgust
x (left eye DPR)
y (right eye DPR)
input image=/sad/98.jpg | DPR Threshold=75 | faceOverlap=1
surprise
fear
anger
joy
sadness
neutral
disgust
x (left eye DPR)
y (right eye DPR)
input image=/sad/98.jpg | DPR Threshold=100 | faceOverlap=1
surprise
fear
joy
anger
sadness
neutral
disgust
x (left eye DPR)
y (right eye DPR)
input image=/sad/98.jpg | DPR Threshold=150 | faceOverlap=1
fear
neutral
anger
joy
surprise
sadness
disgust
x (left eye DPR)
y (right eye DPR)
input image=/sad/98.jpg | DPR Threshold=200 | faceOverlap=1
joy
neutral
surprise
sadness
fear
anger
disgust
x (left eye DPR)
y (right eye DPR)



DPR Threshold	Left eye DPR (faceOverlap=1)	Right eye DPR (faceOverlap=1)
25	0.07143	0.03125
50	0.17857	0.21875
75	0.25	0.46875
100	0.46429	0.59375
150	0.60714	0.75
200	0.82143	1.0
250	1.0	1.0

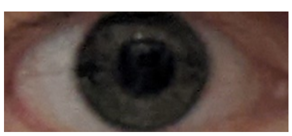
A2.3 Image /sad/98.jpg for varying dprThreshold values and constant faceOverlap=1.

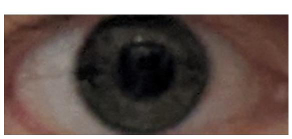
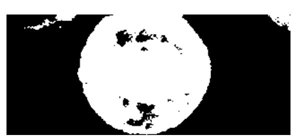
Appendix 3

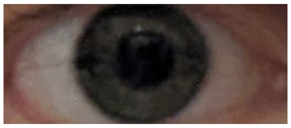
Iteration	Left Eye	Left Eye DPR	Feed Back
1			feedback: {'faceOverlap': 4, 'dprThreshold': 100, 'knnDepth': 7} x: 0.65 y: 0.466 “ joy and sadness makeup 0.71 lvl: 0.71
2			feedback: {'faceOverlap': 4, 'dprThreshold': 125, 'knnDepth': 5} x: 0.92 y: 0.68 “joy and sadness makeup 0.8” lvl: 0.8

A3.1 Image Label: Joy

Iteration	Left Eye	Left Eye DPR	Feedback

0			feedback: {
			'faceOverlap': 4,
			'dprThreshold': 25,
			'knnDepth': 7
			}
			
			x: 0.13
			y: 0.11
			anger and joy makeup 0.71
			lvl: 0.71

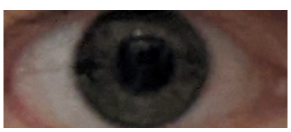
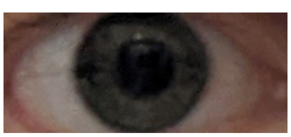
1			feedback: {'faceOverlap': 4, 'dprThreshold': 50, 'knnDepth': 5} x: 0.36 y: 0.34 disgust and sadness makeup 0.4 lvl: 0.4

3			feedback: {'faceOverlap': 4, 'dprThreshold': 75, 'knnDepth': 3} x: 0.59 y: 0.58 neutral and anger make up 1.0 lvl: 1.0

A3.2 Non-labeled Self Image after riding the NYC Subway

Iteration	Left eye	Left eye DPR	Feedback

0			feedback: {
			'faceOverlap': 2,
			'dprThreshold': 25,
			'knnDepth': 7
			}
			
			X:0.13
			y: 0.11
			anger and joy
			makeup 0.71
			lvl: 0.71

1			feedback: {'faceOverlap': 2, 'dprThreshold': 50, 'knnDepth': 5} x: 0.37 y: 0.34 anger and sadness makeup 0.6 lvl: 0.6
2			feedback: {'faceOverlap': 3, 'dprThreshold': 50, 'knnDepth': 5} x: 0.36 y:0.34 anger and sadness makeup 0.6 lvl: 0.6

3			feedback: {'faceOverlap': 4, 'dprThreshold': 50, 'knnDepth': 5} x: 0.36 y: 0.34 disgust and sadness makeup 0.4 lvl: 0.4
4			feedback: {'faceOverlap': 4, 'dprThreshold': 75, 'knnDepth': 3} x: 0.59 y: 0.58 neutral and anger make up 1.0 lvl: 1.0

A3.3 Non-labeled Self Image after riding the subway. Different initialized values