AI Solution for non-invasive monitoring of essential bio-signal marker (Breathing Rate)

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Introduction and Motivation

Acute shortage of healthcare workers

- Healthcare workers are overworked and burnt out during Covid-19 [1]
- A non-invasive solution for monitoring biosignals from a distance is the need of the hour

Need of the hour: An improved solution for real-time nonintrusive monitoring of human bio-signals

- Monitor critically ill contagious patients such as residents of nursing and seniors homes.
- Reduce the burden on healthcare workers to a large extent, especially in pandemics similar to Covid-19

But How? Using thermal images to identify and monitor bio signals

- Here we detect the radiation naturally emitted from an object, no external source of radiation required. [2]
- Certain biomarker information can be identified only in thermal data eg. body temperature, inspiration/expiration temperature, etc
- This technique could be applicable to anyone

Proposed Solution: Predecessor

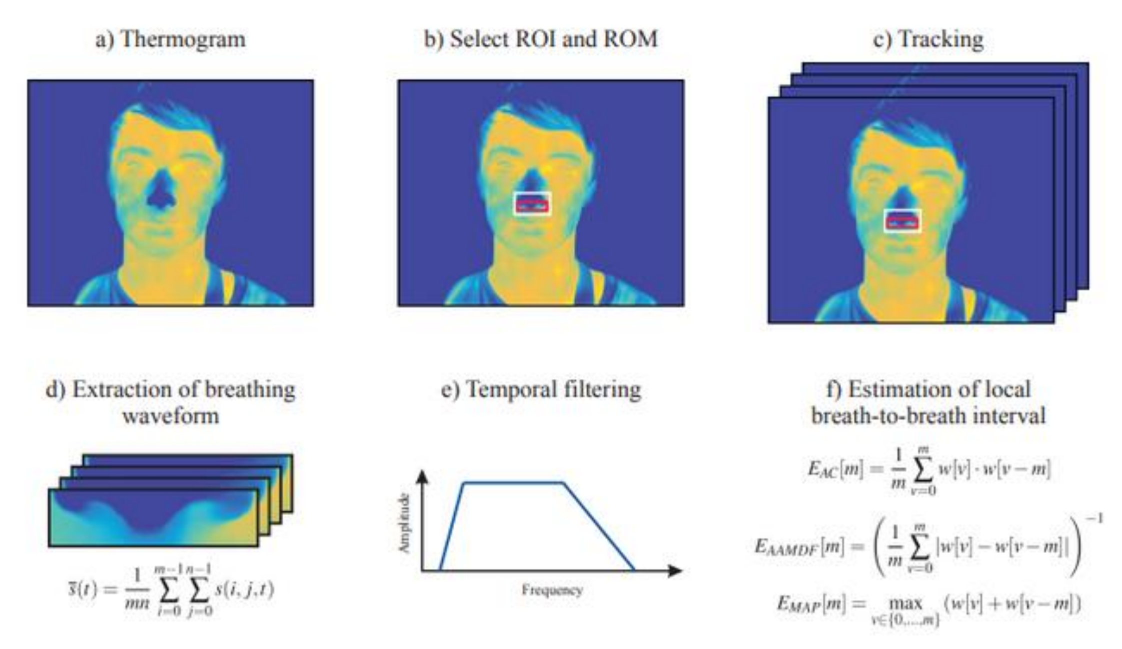
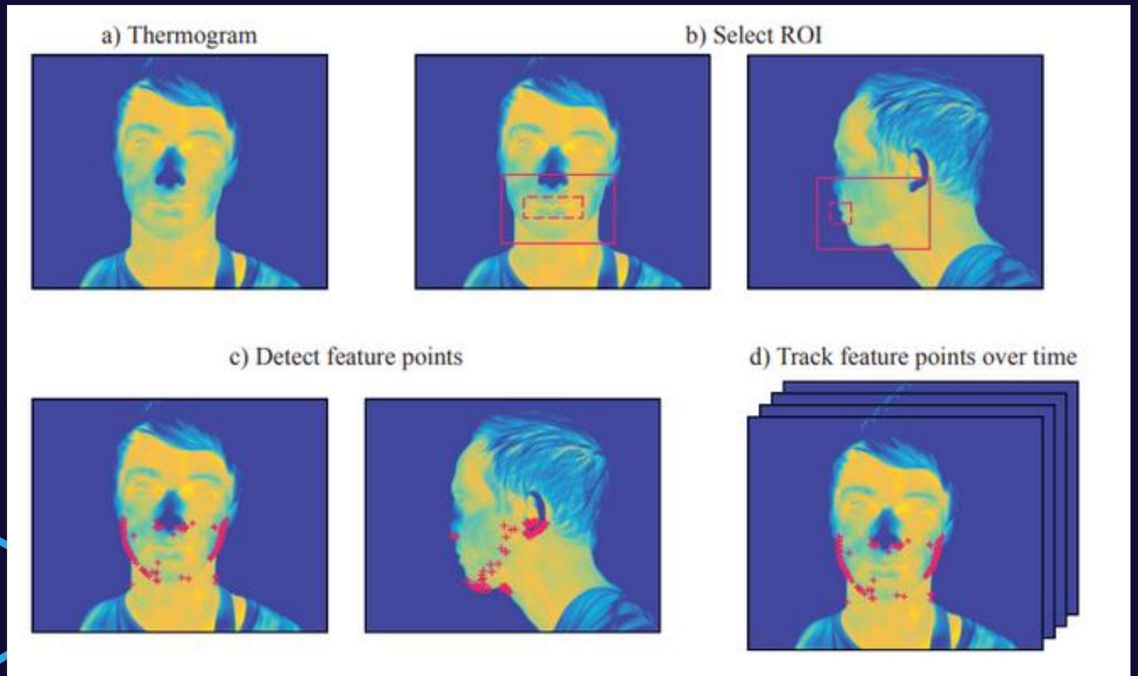


Fig 1 (above) describes the steps to find the respiratory rates and Fig 2 (below) for heart rates



Monitoring of Cardiorespiratory Signals Using Thermal Imaging: A Pilot Study on Healthy Human Subjects by Pereira et al. [4]

- 20 candidates were chosen for participation.
- Frontal and side profile thermal videos.
- Breathing rate estimated using temperature fluctuations under the nose during the respiratory cycle.
- Periodic vertical movement of the head due to cyclical ejection of blood flow from the heart to the head used to assess HR.

A good starting point to further explore the idea and extend it to diverse population by implementing our own AI models, python utilities and strategies.

Proposed Solution

1. Export required data from the thermal camera

Extract the temperature data from captured thermal recordings to create thermal image frames

2. Train the model using the exported data

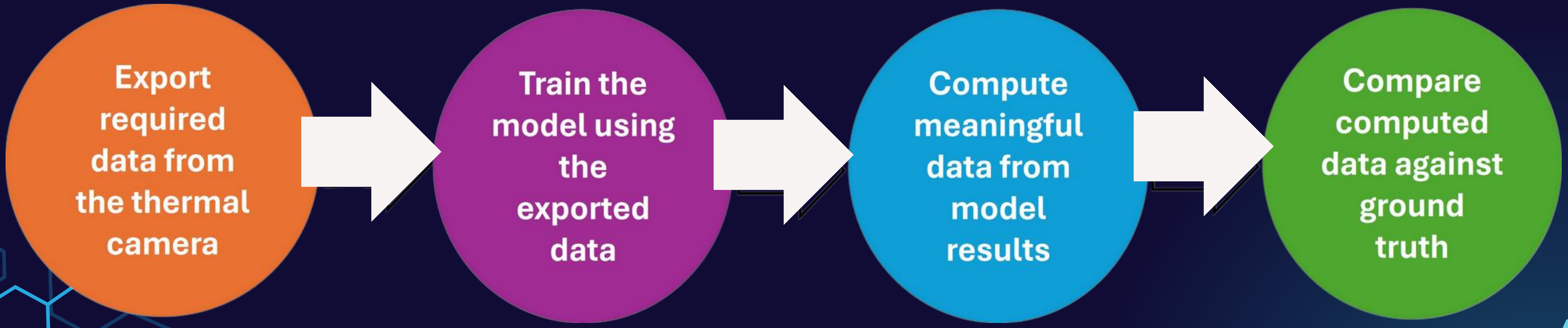
Utilize a Computer vision model, either pre-trained or transfer-trained, to identify and track the region of interest on each image frame.

3. Compute meaningful data from model results

Compute the maximum temperature identified for each image frame

4. Compare computed data against ground truth

Verify the accuracy of the captured and computed data by comparing it with the data from the "ground truth" system



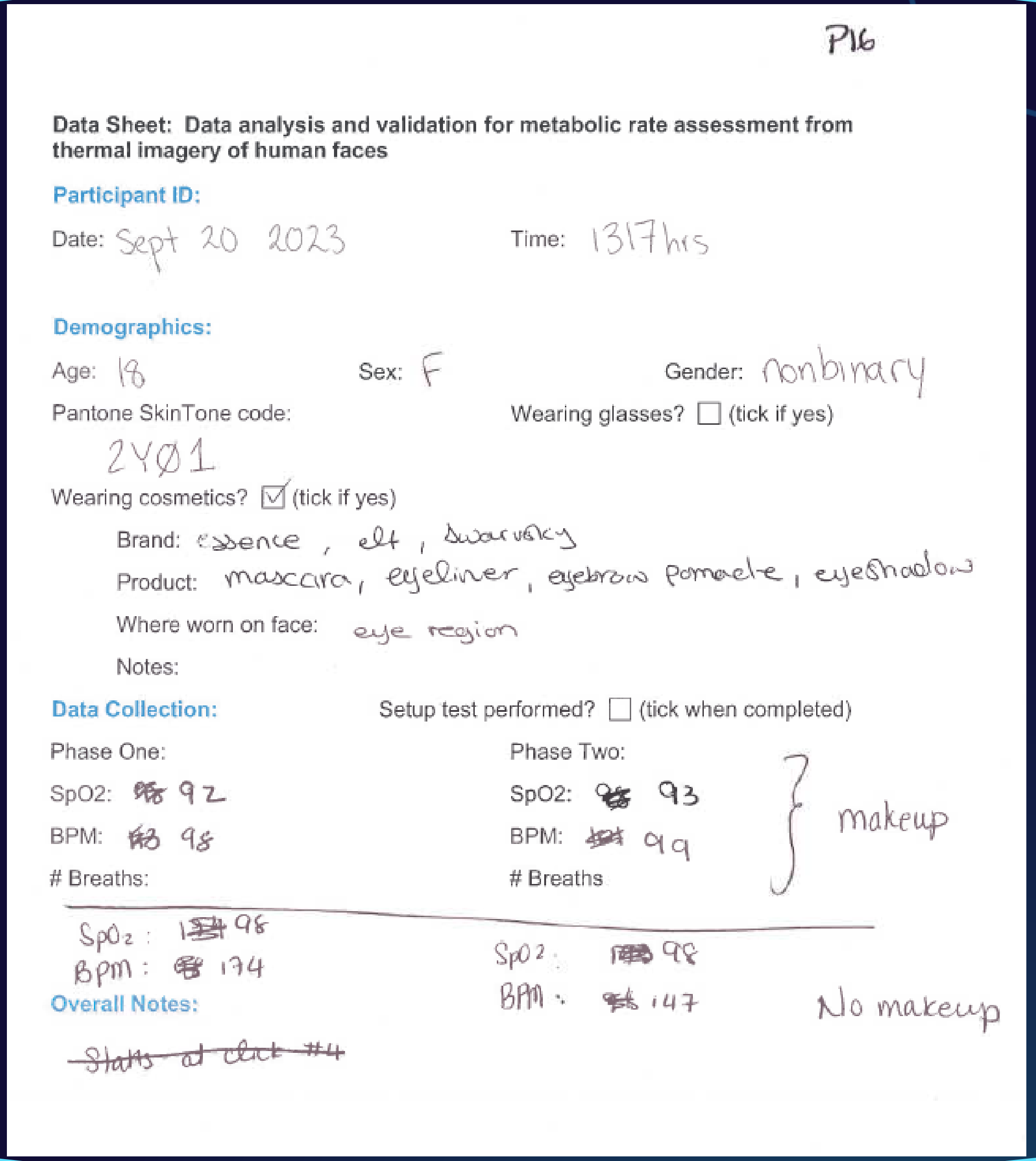
Thesis in detail: Data Collection

1. Data Collection

Due to lack of readily available and viable data for thesis, we gathered data from 15 diverse participants, covering various ethnicities, genders, and age groups after obtaining approval from the Research Ethics Board (REB) of the University of Guelph.

A participant data sheet was used to record the date, time, age of the participant, gender, skin color (obtained from matching Pantone colour swatch to the skin at the back of the participant's nec), along with details of cosmetic worn and use of spectacles.

After the individual participant information was collected, "ground-truth" instruments (pulse oximeter, tensionometer, portable ECG) were attached to the participants which measured their breathing rate, heart rate, and blood oxygenation level. These were recorded in data sheet as well.


P16

Data Sheet: Data analysis and validation for metabolic rate assessment from thermal imagery of human faces

Participant ID:

Date: Sept 20 2023 Time: 1317hrs

Demographics:

Age: 18 Sex: F Gender: nonbinary

Pantone SkinTone code: 2YØ1

Wearing glasses? ☐ (tick if yes)

Wearing cosmetics? ☑ (tick if yes)

Brand: essence, elf, Swarovsky

Product: mascara, eyeliner, eyebrow pomade, eyeshadow

Where worn on face: eye region

Notes:

Data Collection: Setup test performed? ☐ (tick when completed)

Phase One:

SpO2: ~~98~~ 92

BPM: ~~83~~ 98

Breaths:

Phase Two:

SpO2: ~~95~~ 93

BPM: ~~104~~ 99

Breaths

makeup

SpO2: 98

Bpm: 174

SpO2: 98

BPM: 147

No makeup

Overall Notes:

~~Starts at click #4~~

Thesis in detail: Data Collection

1. **Data Collection**

The data of each participant was recorded in two phases.
Phase 1: The ground truth instruments were secured to participants' bodies, and they were asked to breathe through their noses.
Phase 2: Participants were to move their arms up and down twelve times vigorously. Then Phase 1 process was repeated.

2. **Thermal camera**

FLUKE TiS75+ Thermal Camera: chosen due to its ability to capture and produce simultaneous recordings in both thermal and visible light.
FLUKE's proprietary software SMARTVIEW Classic 4.4: to process the IS3 thermal recordings into CSV temperature files.

3. **Lab set up**

The lab was set up in a closed room with fluorescent lights and contained a tripod with the FLUKE thermal camera and a visible light camera placed 1m away from the face of the participant

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Thesis in detail: Initial Groundwork

Identify a computer vision model to implement the proposed solution

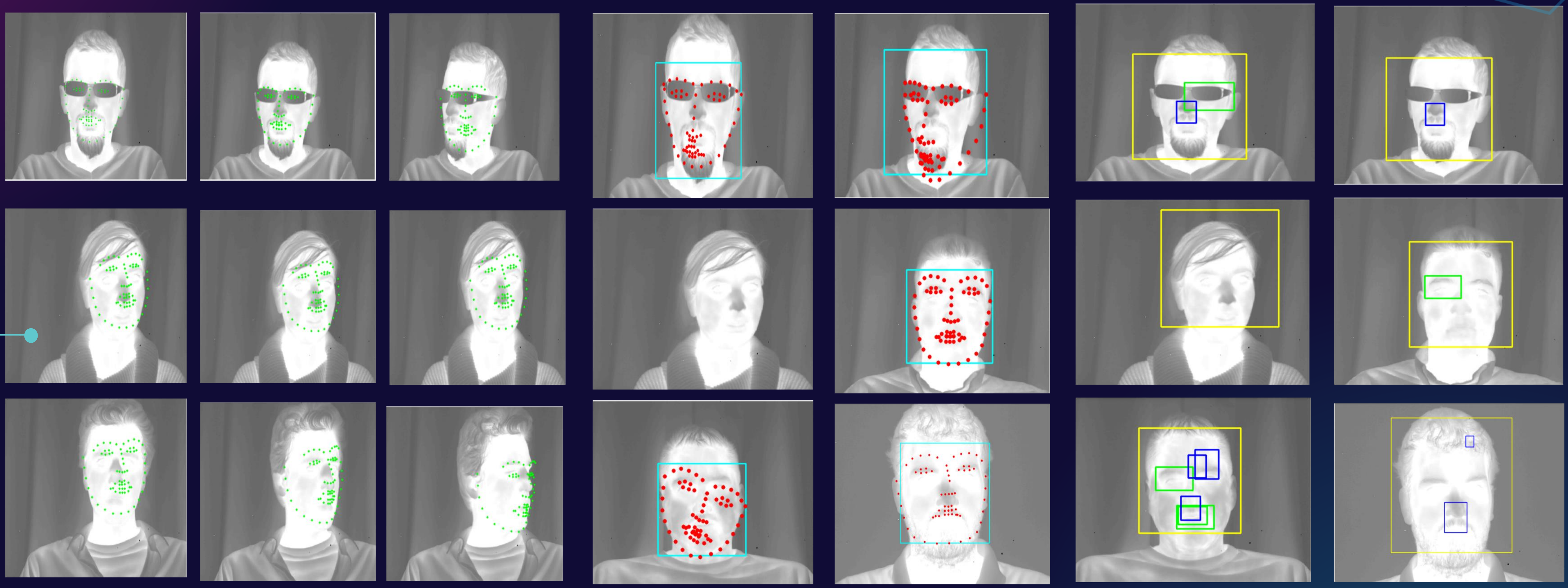
- "Initial set of thermal images from **Universite Laval Face Motion and Time-Lapse Video Database** (UL-FMTV) [6] which consisted of the frontal and side profile views (left and right) of about 140 diverse participants, including those who had facial hair or wore spectacles.
- Unfortunately, the database predominantly consisted of static images with very few motion videos that could not be repurposed for thesis requirement. However, we were able to utilize this data to evaluate common computer vision models.
- Test image set consisting of 26 randomly chosen participants was created to compare the performance of popular computer vision models in identifying facial features.
- Three popular computer vison models chosen for this task: Caffe[7], dlib[8], Haar-Cascade[9].

Thesis in detail: Groundwork results

Caffe Model

dlib Model

Haar-Cascade Model



Thesis in detail: Groundwork results

Caffe Model

Total no. of images	26
No. of frontal images in which the facial landmarks were identified accurately	9 (35% of images)
No. of side profile images in which the facial landmarks were identified accurately	7 (27% of images)
No. of side profile images in which the facial landmarks were identified inaccurately	10 (38% of images)

dlib Model

Total no. of images	26
No. of frontal images in which the facial landmarks were identified accurately	5 (19% of images)
No. of side profile images in which the facial landmarks were identified accurately	0
No. of side profile images in which the facial landmarks were identified inaccurately	3 (12% of images)

Haar-Cascade Model

Total no. of images	26
No. of images in which the face was identified accurately	21 (80% of images)
No. of images in which the at least one eye was identified accurately	9 (35% of images)
No. of images in which the mouth was identified accurately	5 (19% of images)
No. of images in which the nose was identified accurately	7 (27% of images)

None of the evaluated common Computer Vision models could accurately anchor the facial landmarks on the thermal images.

These models cannot identify facial features on thermal images as they were trained on visible light images.

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Thesis in detail: Facial data processing

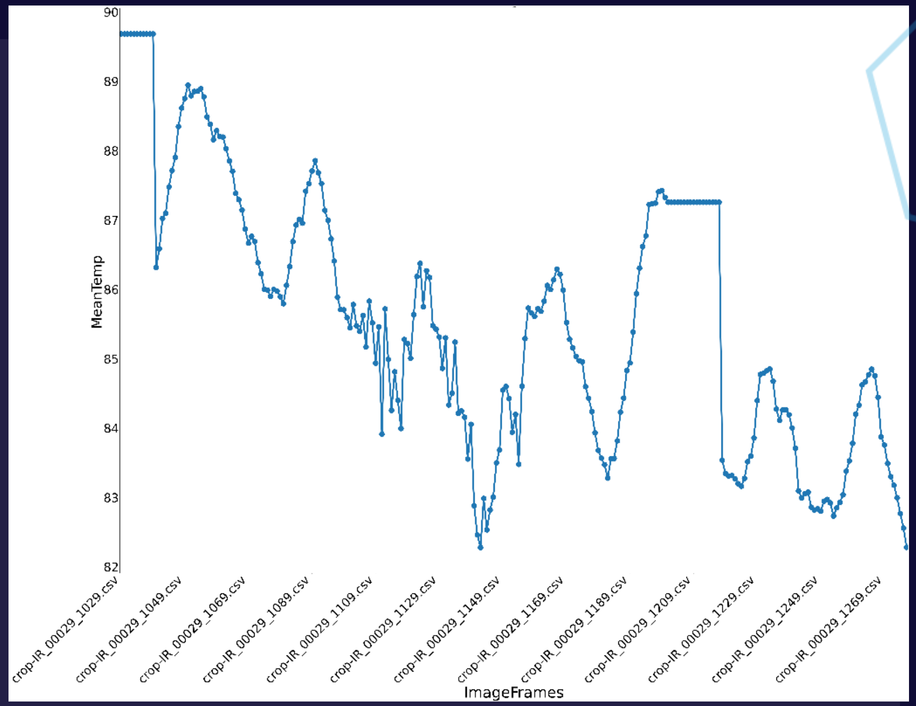
tempCSVtoGrayscale.py

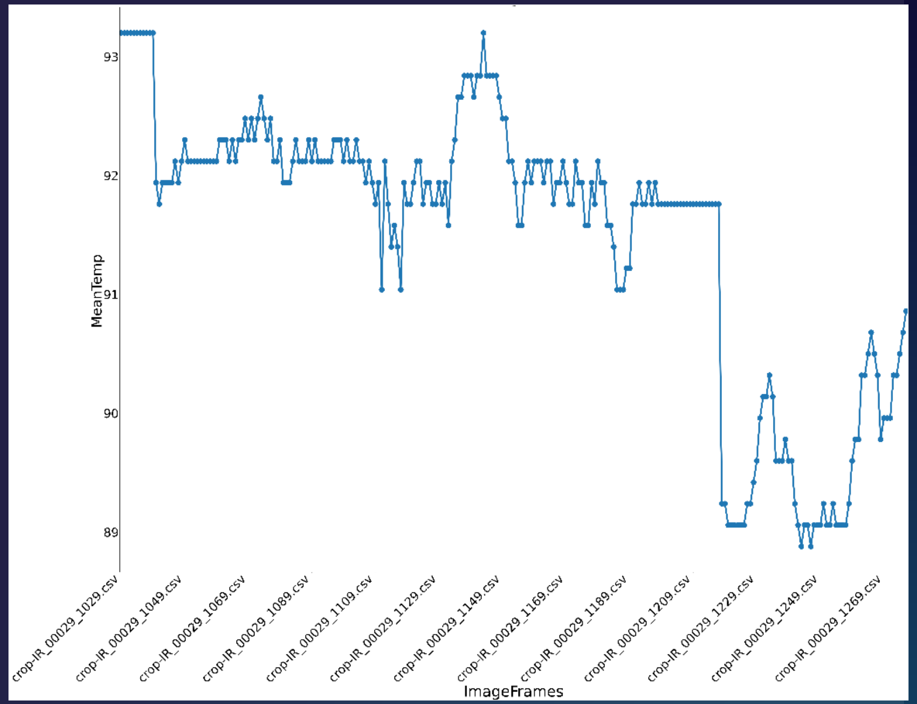
The conversion of CSV Data to Thermal image

- "tempCSVtoGrayscale.py" Python utility is applied to data obtained during data collection process to create image files and ROI crop files
- Minimum defined temperature set to 16◦C and Maximum defined temperature was set to 40◦C
- Initial thought process: obtain thermal and visible light images -> apply existing computer vision models to visible light images and the obtained bounding box of facial features -> map the bounding box to thermal images.

Thesis in detail: Facial data processing

identify changing cell values-<MAX/Mean> values-numpy.ipynb



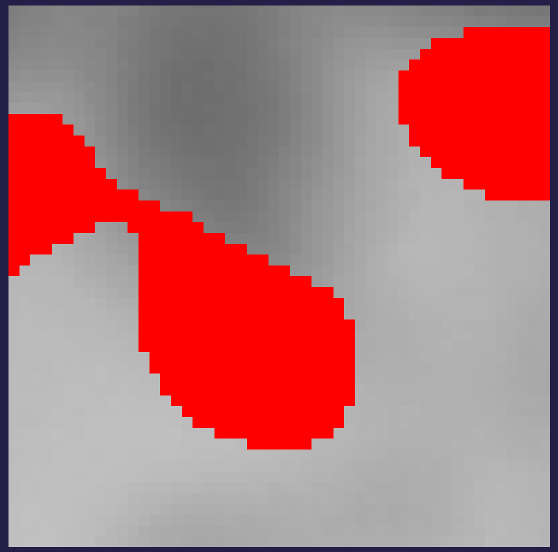


- Thermal camera was unable to generate visible light images, hence a fixed 50x50 bounding box (computed manually) approximating the nose mouth region was chosen for each participant.

Identifying the areas of temperature fluctuations in the nose/mouth region

- Next, “identify changing cell values-MAX values-numpy.ipynb" and "identify changing cell values-Mean values-numpy.ipynb“ python utilities were created to generate mean and max temperature graphs from the cropped nose_mouth ROI.

Thesis in detail: Facial data processing



identify changing cell values-<MAX/Mean> values-numpy.ipynb

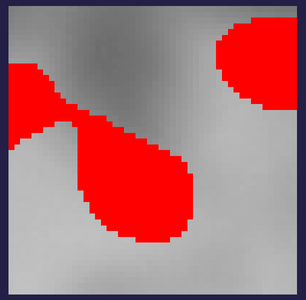
Identifying the areas of temperature fluctuations in the nose/mouth region

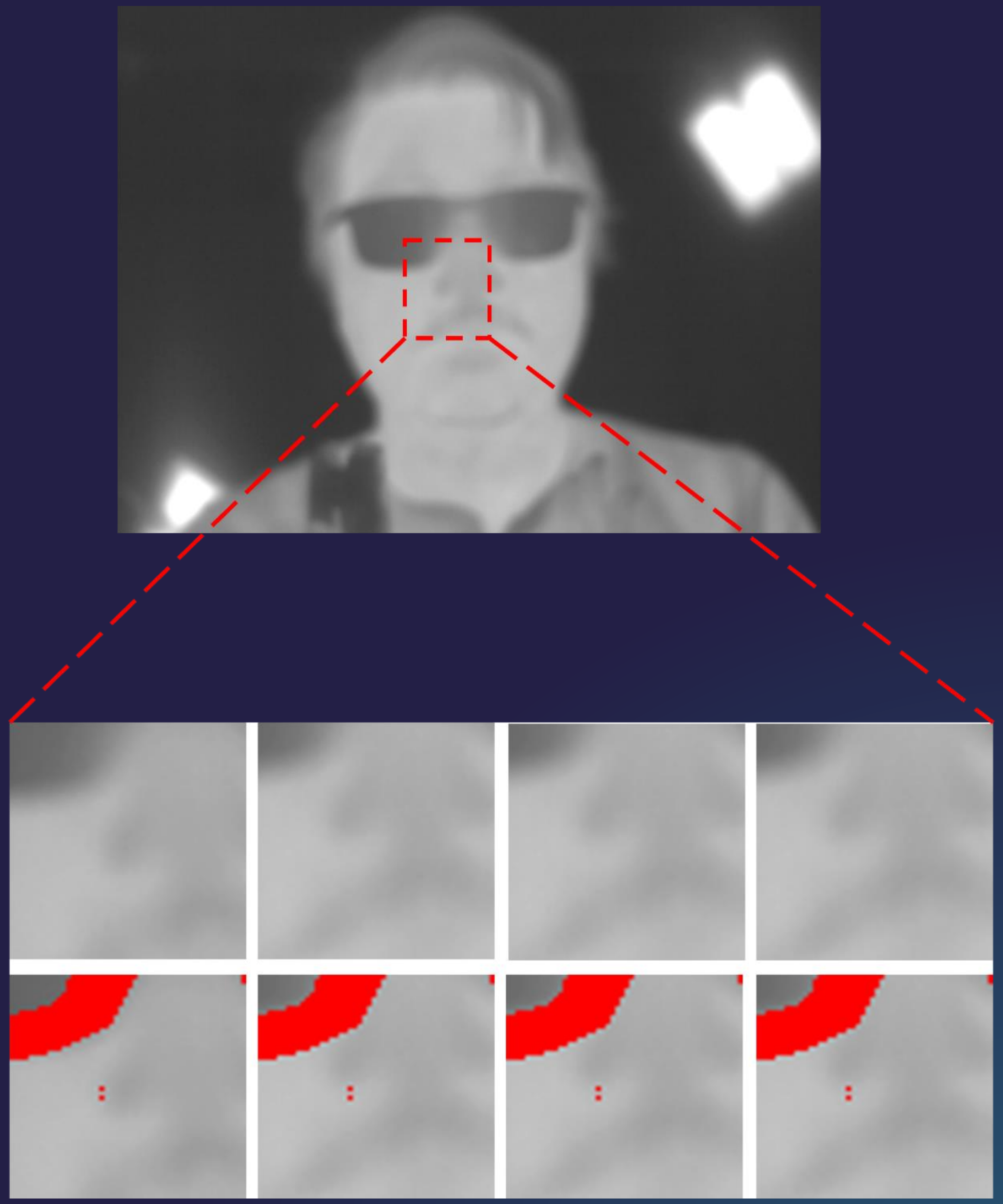
- Calculating the differential NumPy array between maximum and minimum temperature recorded at each cell of the series of 50x50 NumPy array,
- Calculating the normalized temperature at each pixel in NumPy array and identifying the unique temperature values within the NumPy array.
- Apply knee analysis to identify threshold on the monotonic list of cumulative sum of the unique values
- Identifying the index position where the normalized temperature is greater than the calculated threshold value
- Map the mean and maximum temperature from the identified fluctuating pixels to that particular frame and plot the corresponding values of image frames to a mean and max temperature graph.

Thesis in detail: Facial data processing

Issue seen

- As static bounding boxes, not dynamic, were used to identify the nose/mouth region in the image frames of each participant, these fixed bounding boxes were unable to automatically map to any change in the positioning of the nose/mouth region across the image frames.
- During recording, even the slightest movement could alter the actual position of the nose/mouth region, and a fixed bounding box could not correctly track the region of interest
- One instance where the issue is highlightened is shown In the image here.





Thesis in detail: Facial data processing

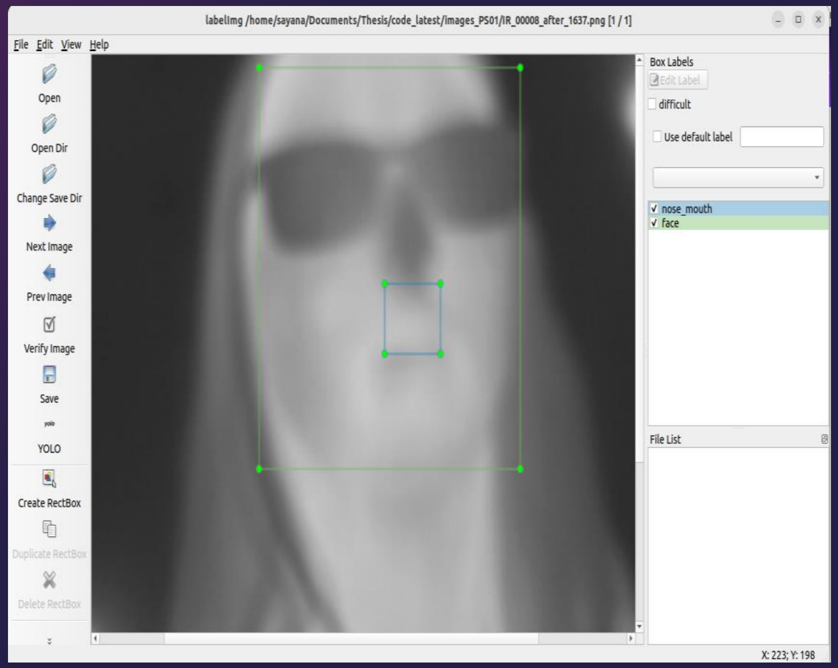
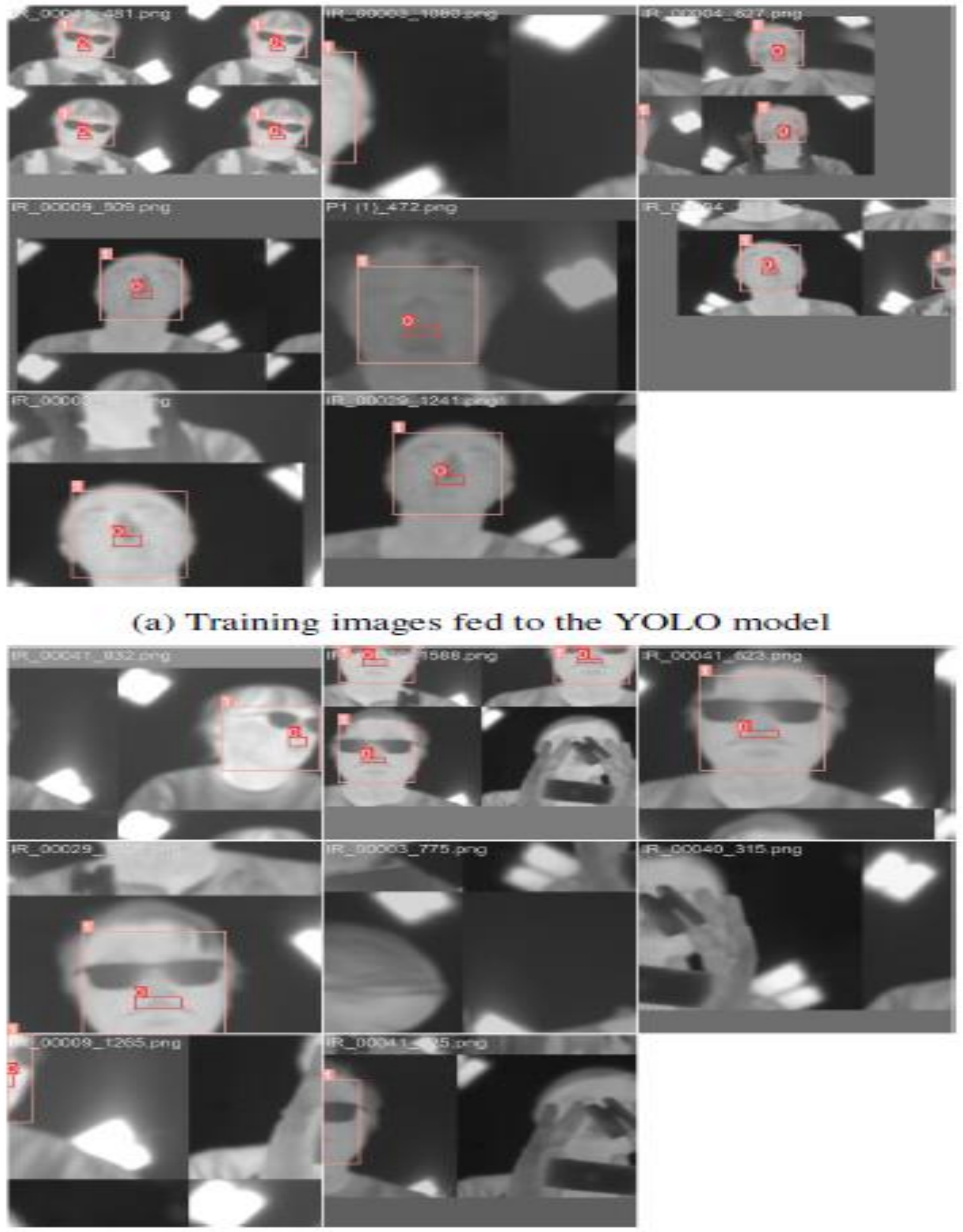


Image annotation using LabelImg



(a) Training images fed to the YOLO model

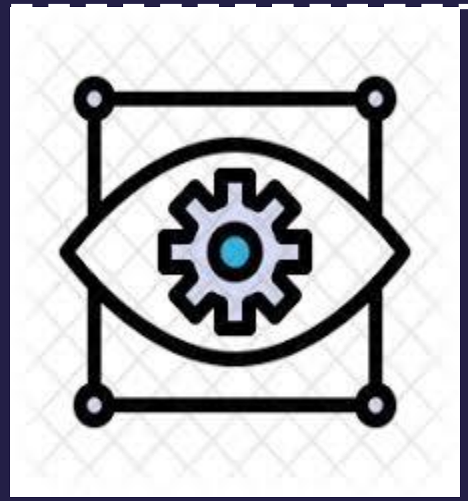
(b) Training images with images not having annotations

Better Solution: YOLO via Transfer training

- Transfer training: leveraging a pre-trained model on a large dataset and fine-tuning it on a smaller, task-specific dataset
- LabelImg was used to create annotations for our training images.
- These annotations and training images would then be used to fine-tune the YOLOv8 model.

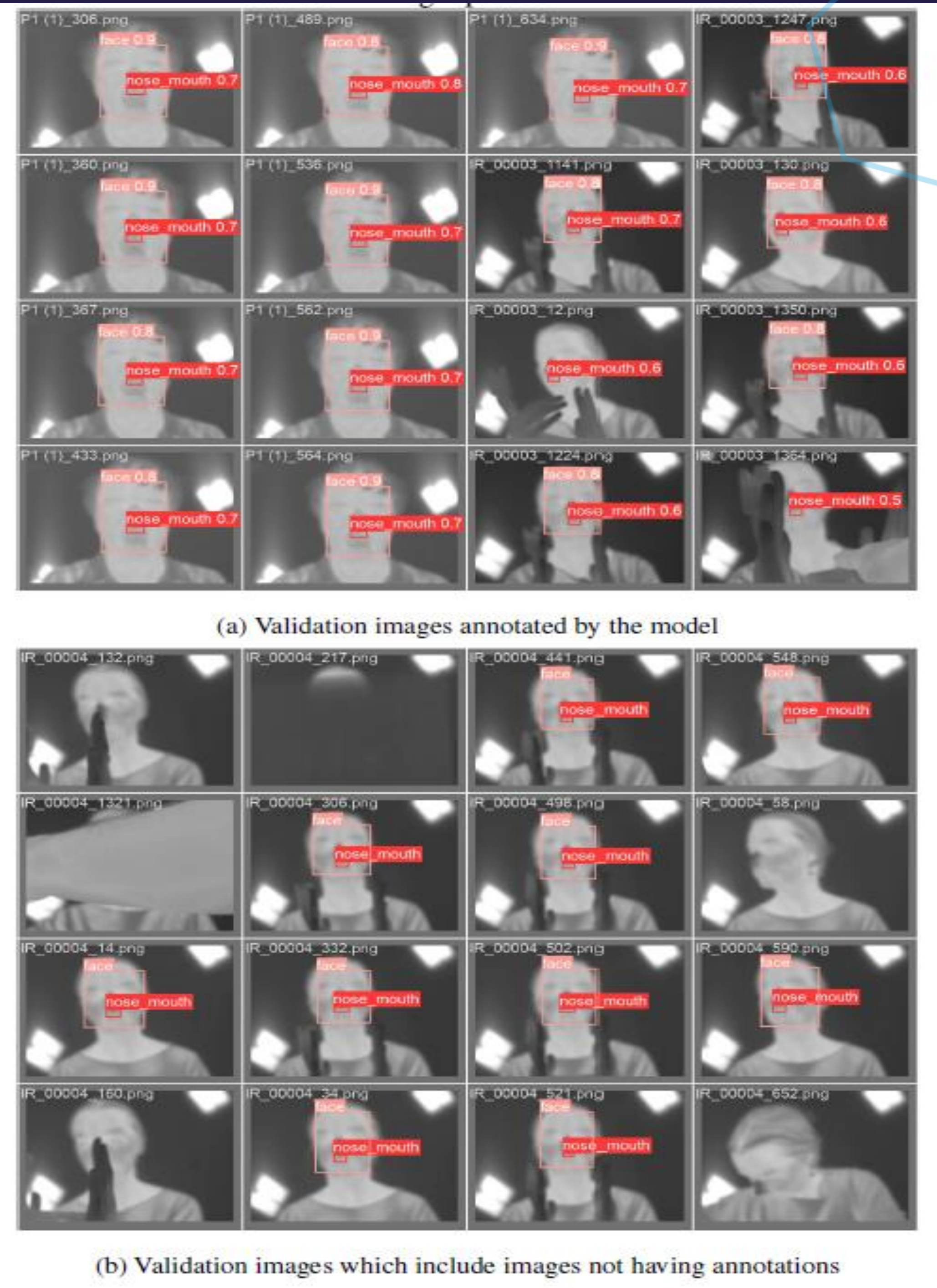
Thesis in detail: Facial data processing

Annotated training and validation images



YOLOv8

thesis_yolo.ipynb



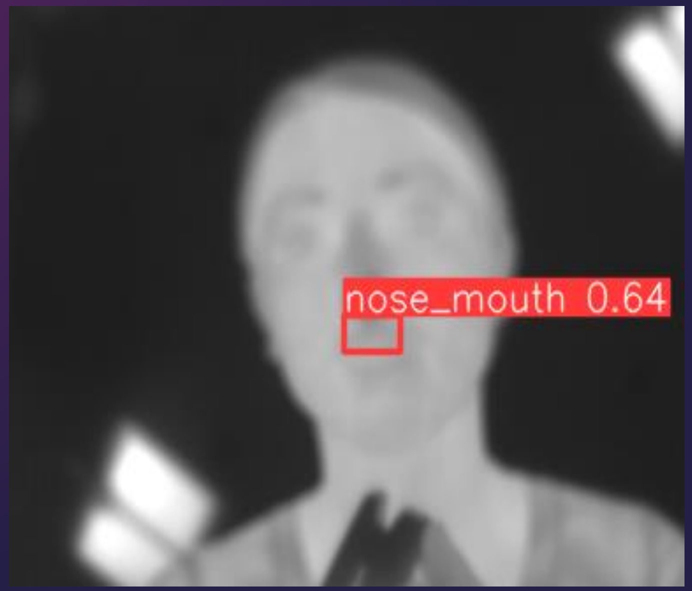
(a) Validation images annotated by the model

(b) Validation images which include images not having annotations

Better Solution: YOLO via Transfer training

- A total of 907 images were manually annotated to finetune the model.
- The "thesis_yolo.ipynb" Python utility was created to fine-tune the YOLOv8 model.
- The YOLO commands with modes such as Train and Predict were used to train the initial model and evaluate the generated model, respectively.

Thesis in detail: Facial data processing

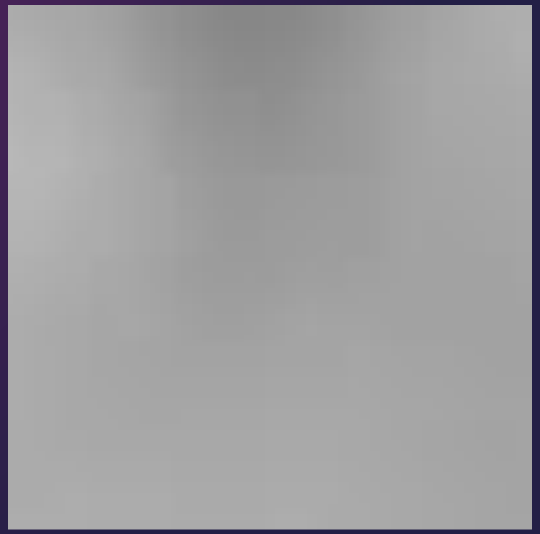


imageBBresampling.py

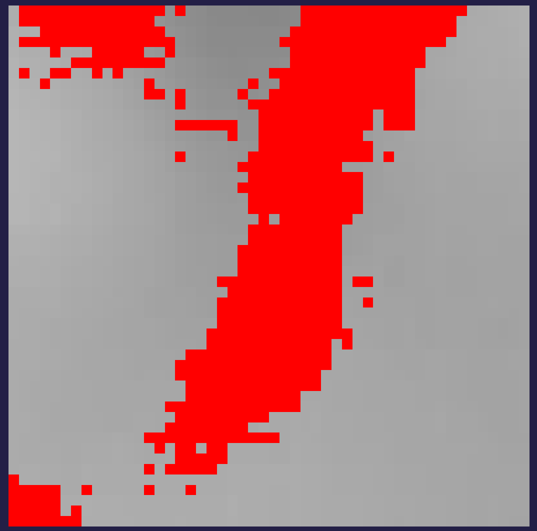
The conversion of the temperature/image bounding box into a 50x50 grid

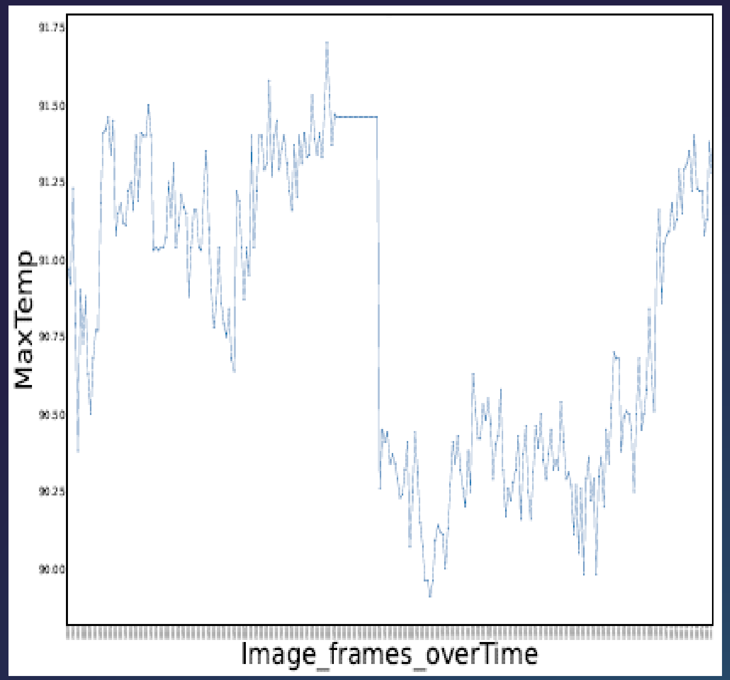
- Although the YOLOv8 was able to detect the nose/mouth region on the images of each participant, there was no uniformity in the dimensions of the bounding box of the detected nose/mouth region.
- For this, imageBBresampling.py utility was created to convert the obtained bounding box specific image pixels and temperature values of an image file to a fixed 50x50 grid crop of the image file and temperature csv file.
- The output of this utility, a more accurate 50x50 cropped nose/mouth region, and the associated cropped 50x50 temperature value pixel data was then fed to "identify changing cell values-MAX values-numpy.ipynb" utility.

Thesis in detail: Facial data processing



identify changing cell values-MAX values-numpy.ipynb





Obtaining and evaluating a temperature measure

- As a more accurate nose/mouth region was identified and resized to 50x50 grid, the results obtained from "identify changing cell values-MAX values-numpy.ipynb" utility were also much better when compared with the first version.
- Additionally, we could also observe the expected temperature fluctuation pixels were being highlighted.

Thesis in detail: Tensionometer data processing

Processing Tensionometer data to create Timestamp column

- It is necessary to identify the exact timestamp, up to the millisecond, of each tick on the tensionometer.
- This would help during the alignment phase of the thesis where we align the computed max temperature with ground truth data.

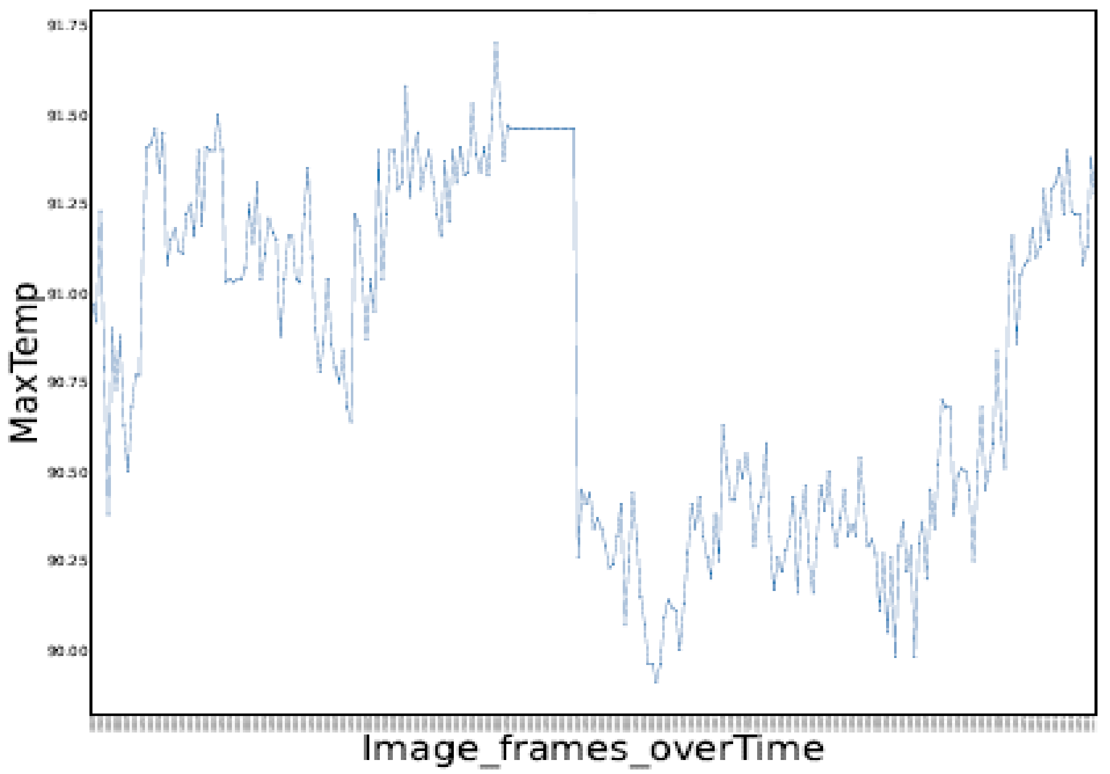
```
millis,stamp,tickTime,delay,datetime,raw,adj
1940,1678457445,0,249,"2023/03/10 14:13:45",505.00,9749.04
2190,1678457445,12,237,"2023/03/10 14:13:45",505.00,9749.04
2440,1678457446,7,242,"2023/03/10 14:13:46",507.00,9825.58
2690,1678457446,4,245,"2023/03/10 14:13:46",506.00,9787.23
```

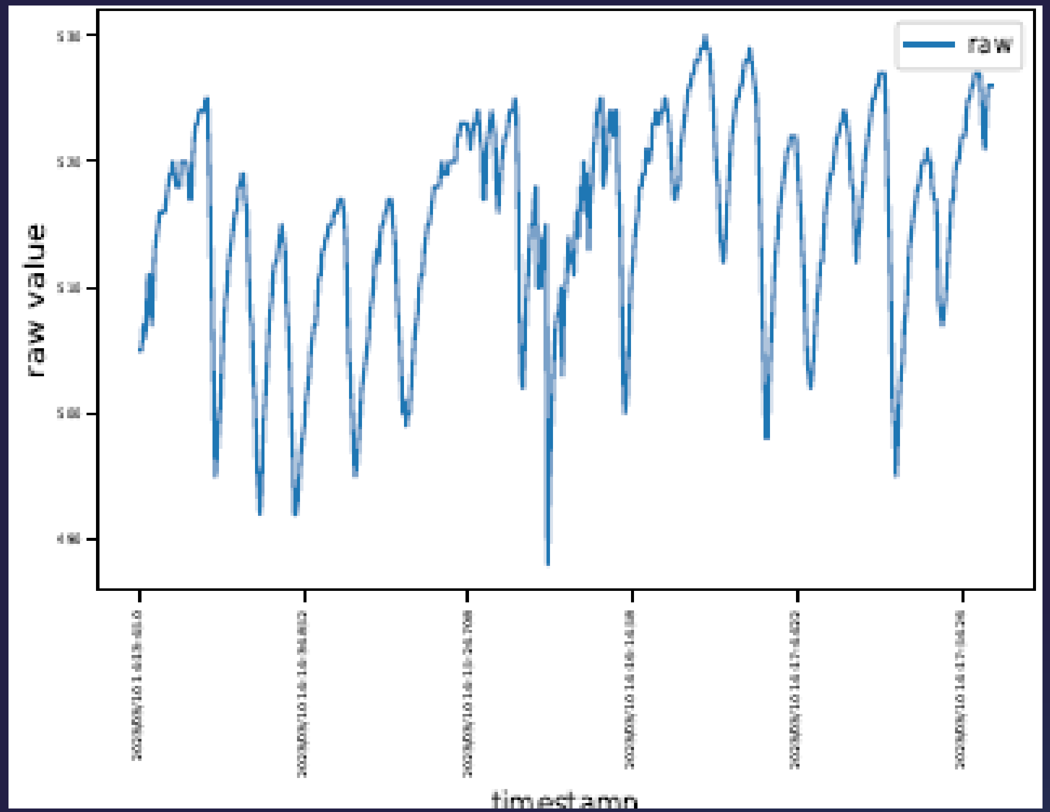
Original tensionometer log data

```
millis,Diff in time of Millis,millis_new,stamp,datetime,raw,adj,istimeChanged,time_stamp
1940,,0,1678457445,2023/03/10 14:13:45,505.0,9749.04,False,2023/03/10 14:13:45.0
2190,250.0,250,1678457445,2023/03/10 14:13:45,505.0,9749.04,False,2023/03/10 14:13:45.5
2440,250.0,500,1678457446,2023/03/10 14:13:46,507.0,9825.58,True,2023/03/10 14:13:46.0
2690,250.0,750,1678457446,2023/03/10 14:13:46,506.0,9787.23,False,2023/03/10 14:13:46.5
```

Processed tensionometer log data

Thesis in detail: Determining the correlation between the two data

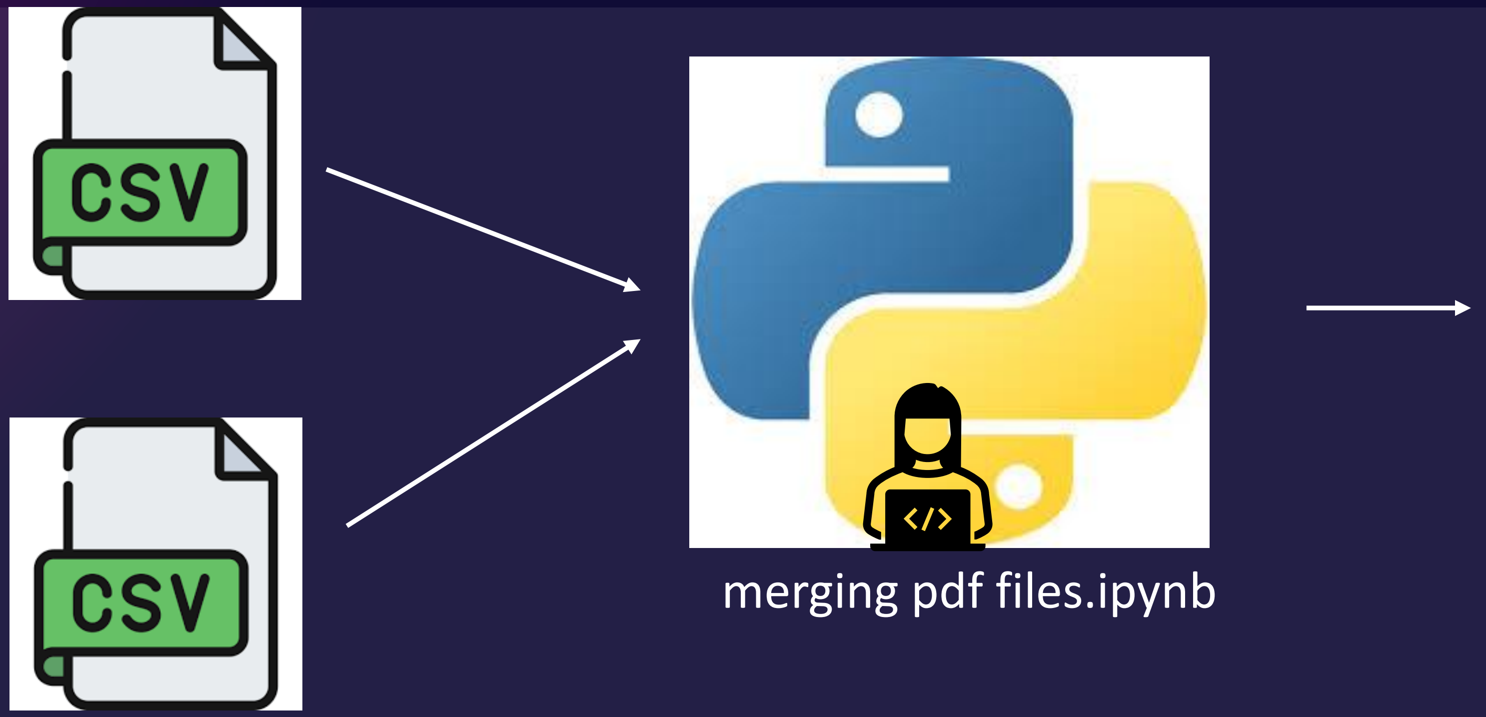




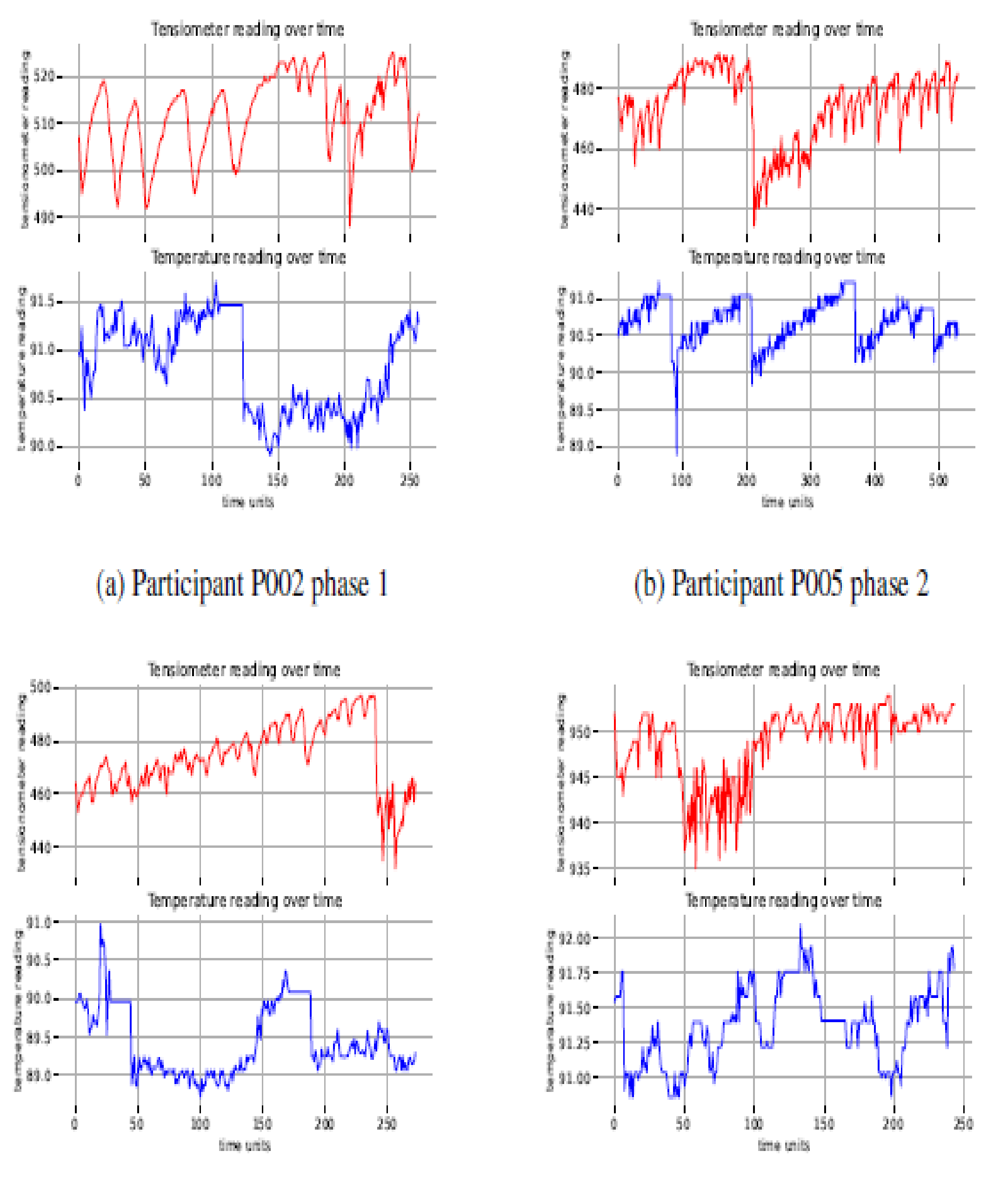
Aligning and matching the two signals

- The common factor to align these two data would be the timestamp, calculated up to the millisecond.
- Unfortunately, the timeline captured for tensionometer data was not lining up or in sync with the image frame time stamp.
- Hence, we could not directly compare these two data files, as the timestamps for the computed data were different from the timestamp recorded by the tensionometer for the same participant.

Thesis in detail: Determining the correlation between the two data



merging pdf files.ipynb



(a) Participant P002 phase 1

(b) Participant P005 phase 2

(c) Participant P007 phase 1

(d) Participant P011 phase 1

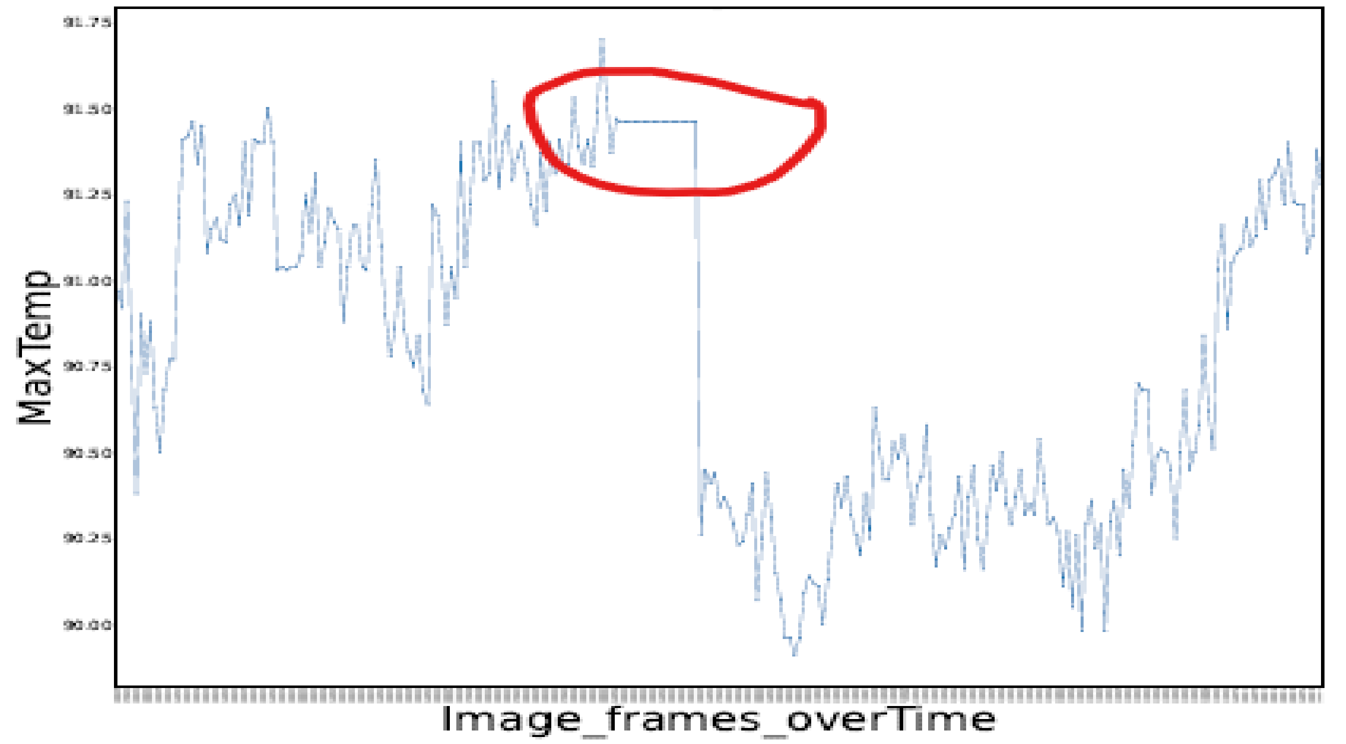
Measuring correlation between the tensionometer and computed temperature signal via RMSE method

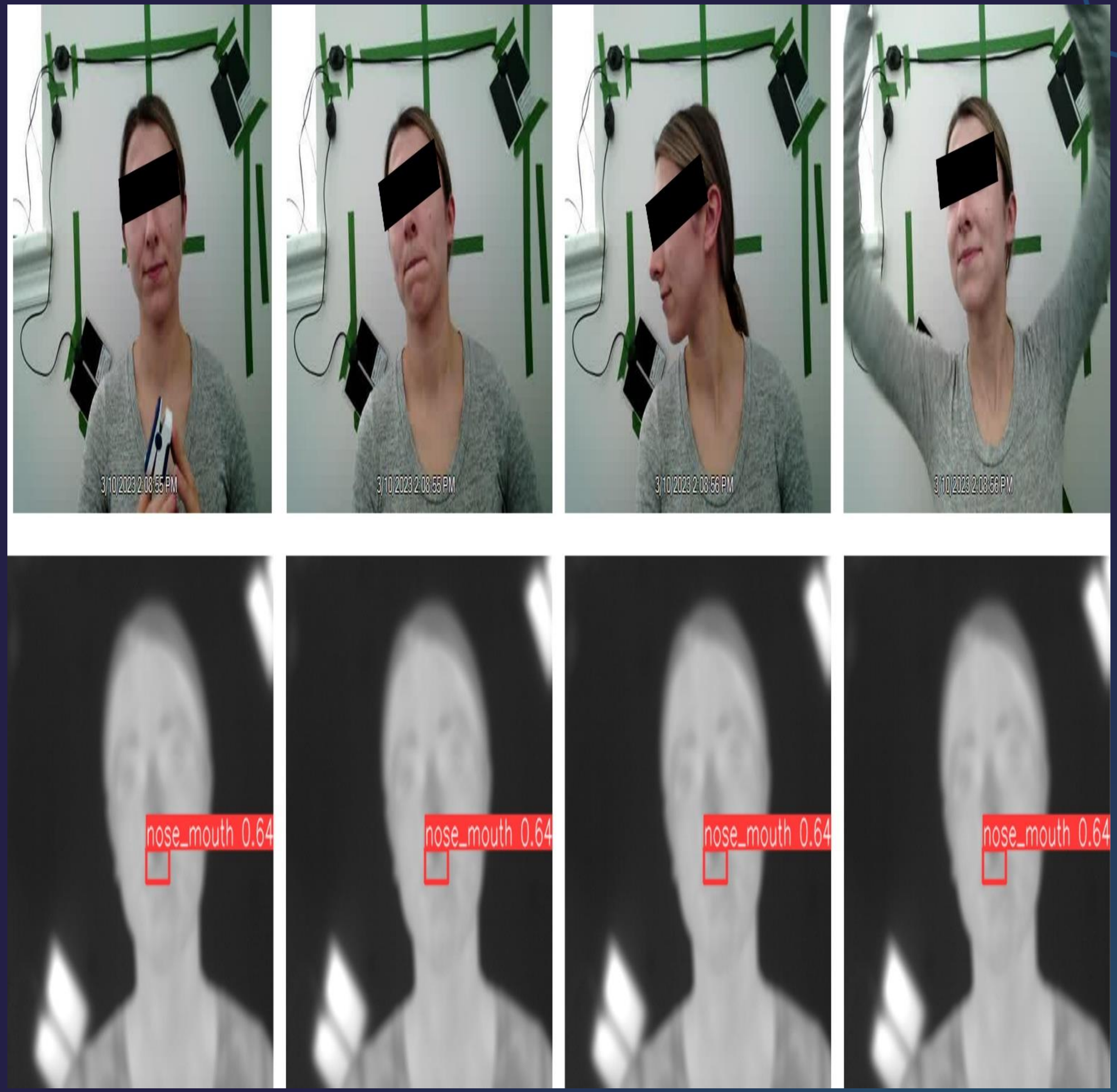
- In this utility, we import the calculated Max temp CSV file and the modified tensionometer CSV file and use the RMSE (Root Mean Square Error) method to identify portions of data that have the least RMSE least difference.
- The idea is to capture the time sequence where the two data are mostly in sync

Thesis in detail: Determining the correlation between the two data

Issue: Freezing of image frames

- The temperature computed over certain sections of the image frames seem to be of the same value.
- Comparison of the thermal images recorded with the timestamp-based visible light screenshots led to the conclusion that the thermal camera was freezing during the recording.

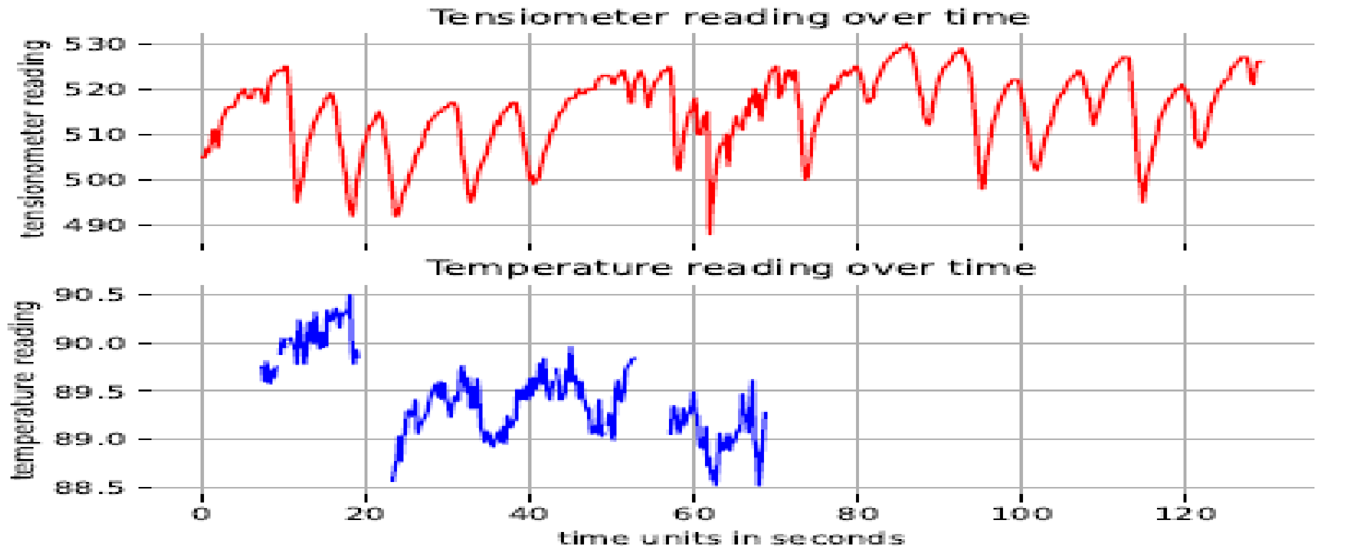




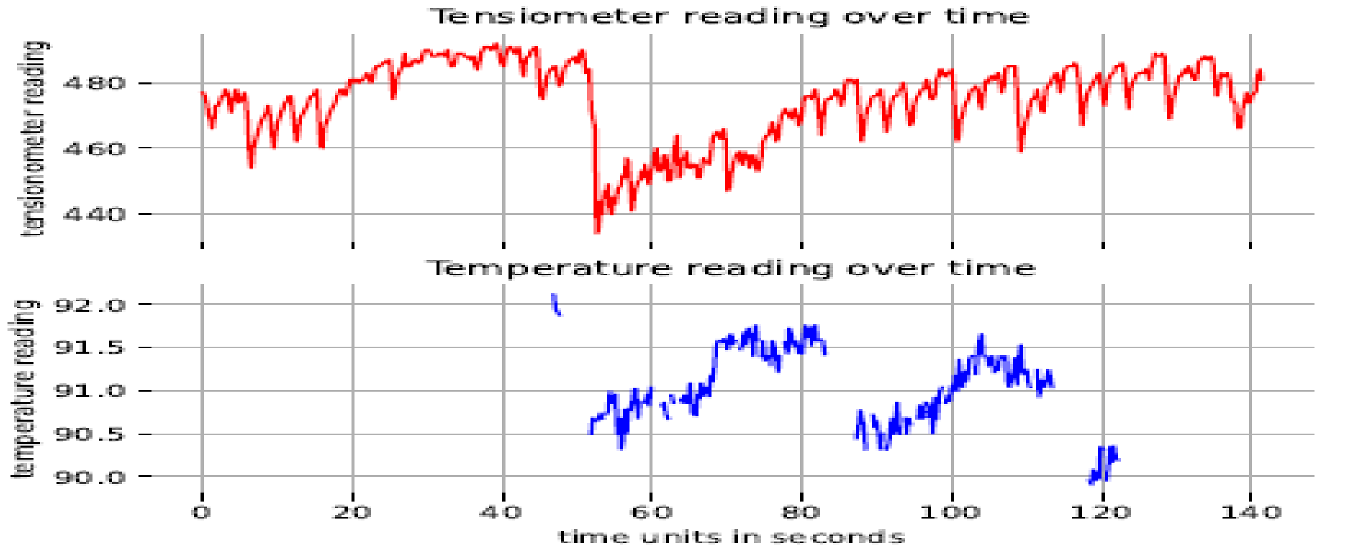
Thesis in detail: Determining the correlation between the two data

Measuring correlation between the tensionometer and updated temperature signal via RMSE method

- Probable solution: Mark repeating temperature values in the computed maximum temperature CSV as NAN (NAN or Not a Number represents missing or undefined data)
- Next, modify the "merging pdf files.ipynb" Python utility to align the two datasets while ignoring the NAN values.
- Finally, the RSME was applied, and correlation was graphed between the new computed temperature data and the tensionometer data.
- Unfortunately, due to large swathes of missing temperature data, the RMSE method could not be utilized to correlate it with tensionometer data, and this was true for every participant.



(a) Tensionometer data and maximum temperature data over time for one of the participants

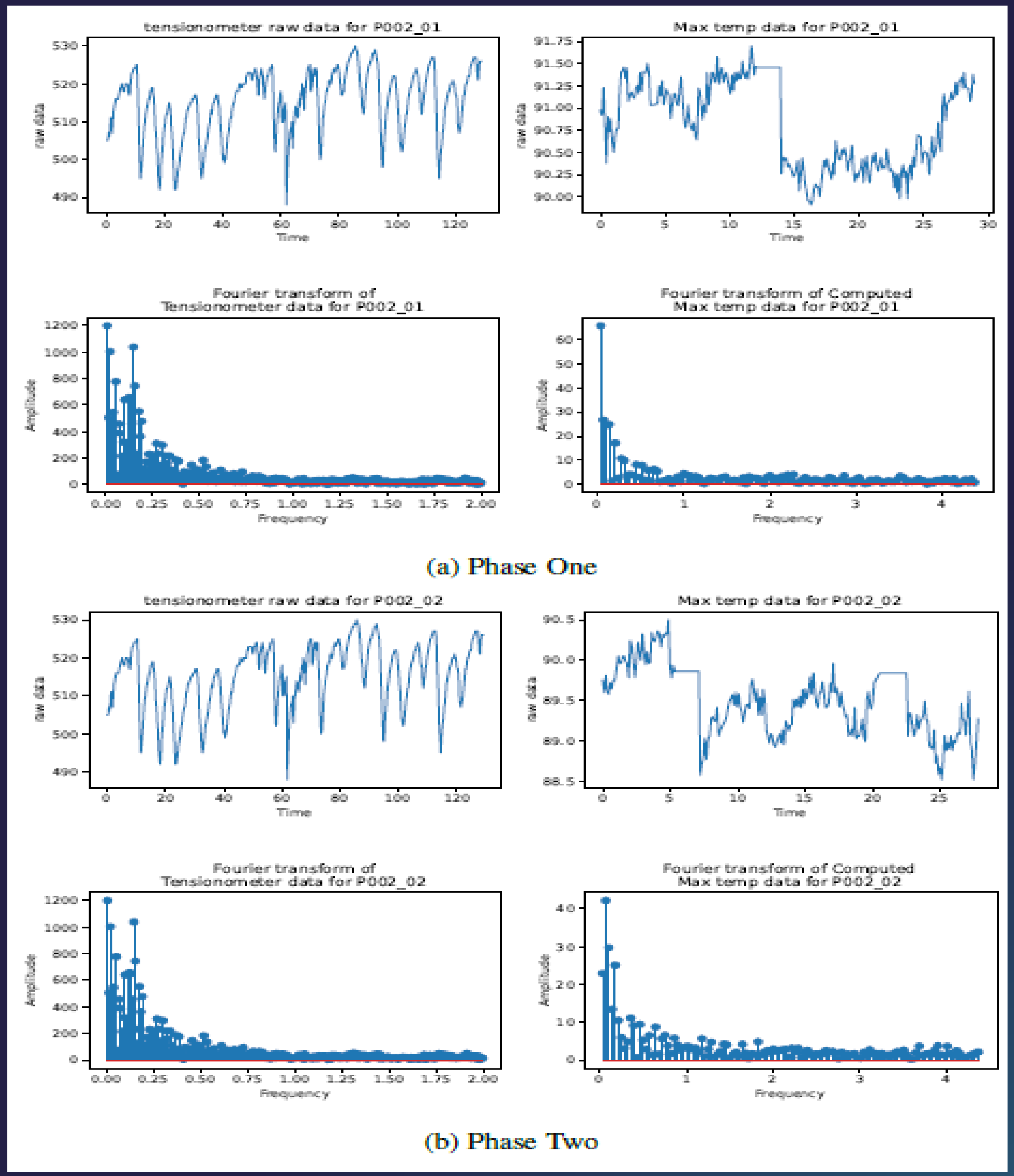


(b) Tensionometer data and maximum temperature data over time for another participant

Thesis in detail: Determining the correlation between the two data

Alternate method: Comparing the Fourier transformations of both signals

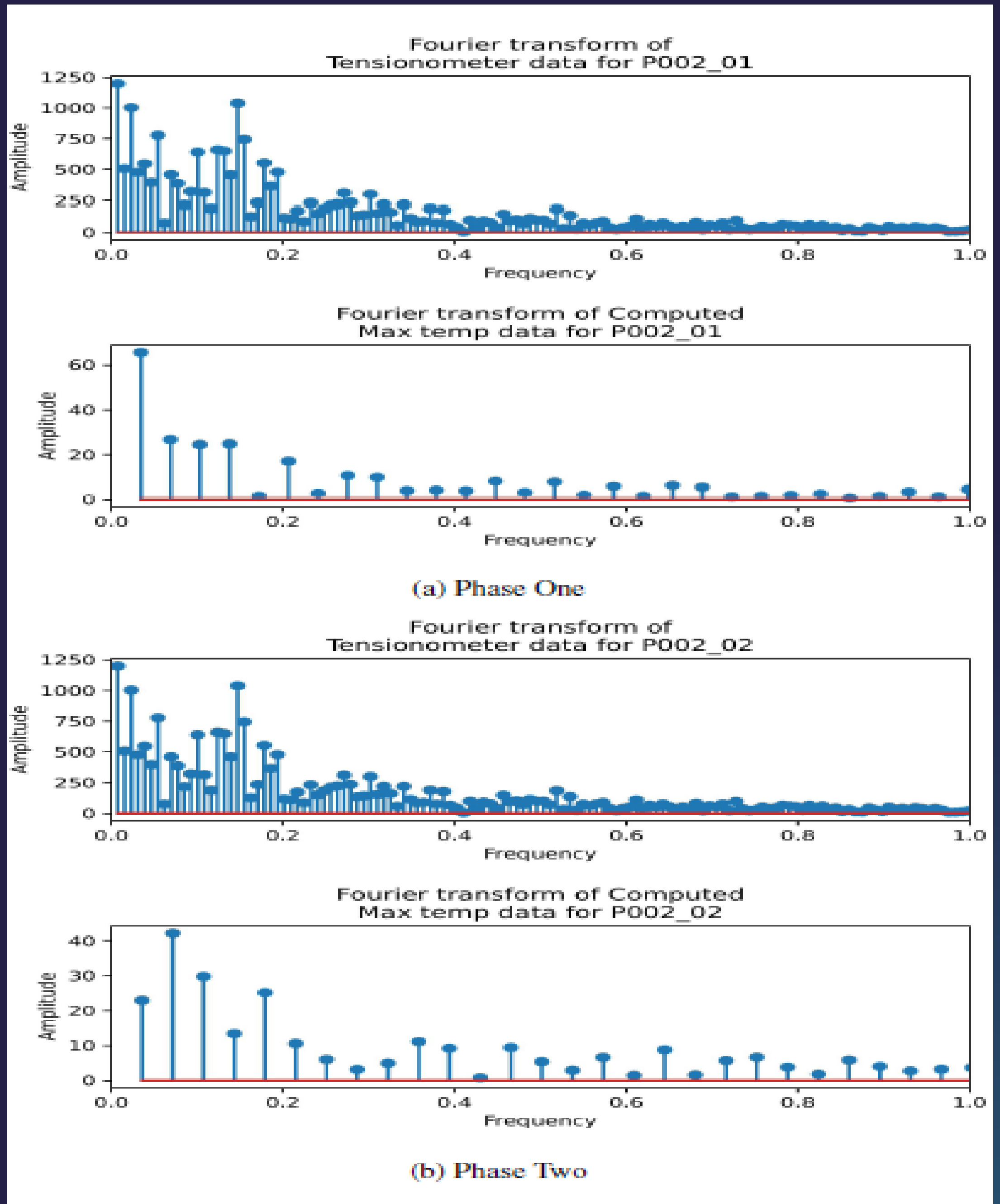
- Python utility, "FFT.ipynb" was created which produced side-by-side FFT graph comparisons for the two data of each participant.
- To gain more insight, the FFTs of tensionometer data and computed max temperature data specific to frequencies between 0 and 1.0 were compared to identify correlation
- Few conclusions could be drawn:
  - The camera freeze issues meant incorrect values were introduced into the temperature reading over image frames. Hence, correct temperature data readings were missing for quite a lot of image frames.



Thesis in detail: Determining the correlation between the two data

Alternate method: Comparing the Fourier transformations of both signals

- The human metabolic activities essentially correspond to the lower frequencies which is where most of the activity peaks in FFT graphs are seen.
- Additionally, lack of large activity peaks in the high frequency ranges for both set of data means the FFT is not hallucinating or introducing any nonsensical data.
- The most prominent frequencies in the pairs of FFT plots are not in the same place where it was expected due incorrect placement of the ground truth measurement tool, the freezing issue of the thermal camera, changes in the baseline offset, etc. This would make the signals "non-stationary"



Keys Highlights of the thesis : Using YOLO

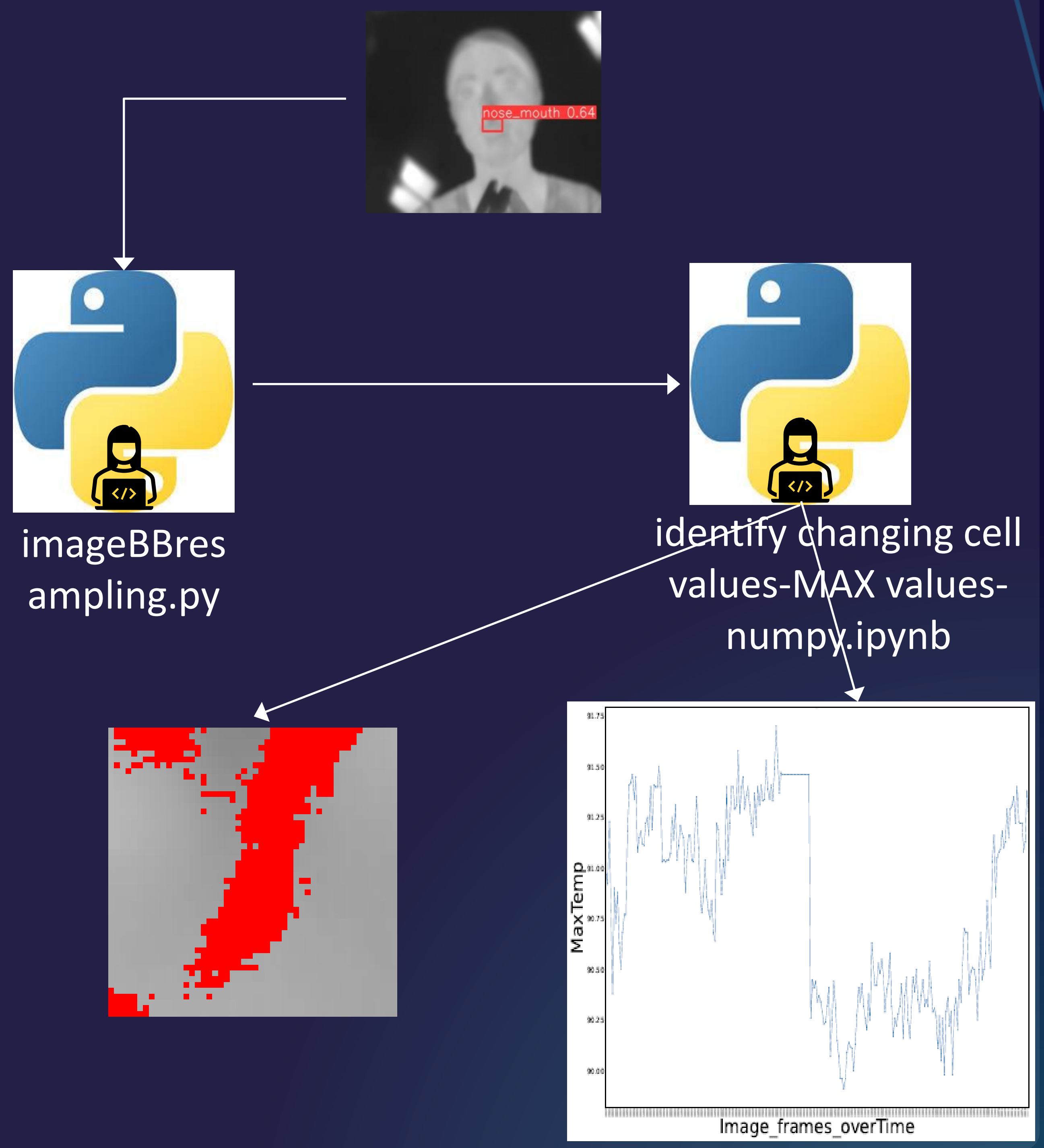
YOLO as an appropriate AI model for this thesis

- A solution that would accurately (>95% of success in identifying nose_mouth region in ROI expected image frames of the participants) track the nose_mouth region in any image frame and provide the bounding box for the identified region of interest.
- YOLOv8 is particularly good at the detection of objects which was the requirement for this task (of detecting a nose_mouth region) with very few overheads.
- Ease in adopting the model when compared to the previous methods of utilizing Photo-plethysmography or complicated wavelength computation.
- YOLOv8 worked perfectly well in identifying the region of interest with more than 95% accuracy
- Only 907 (30% of total images) manually annotated images were required to train the YOLOv8 model for all the 15-participant data samples.

Keys Highlights of the thesis : Thermal extraction

Thermal extraction for temperature computation

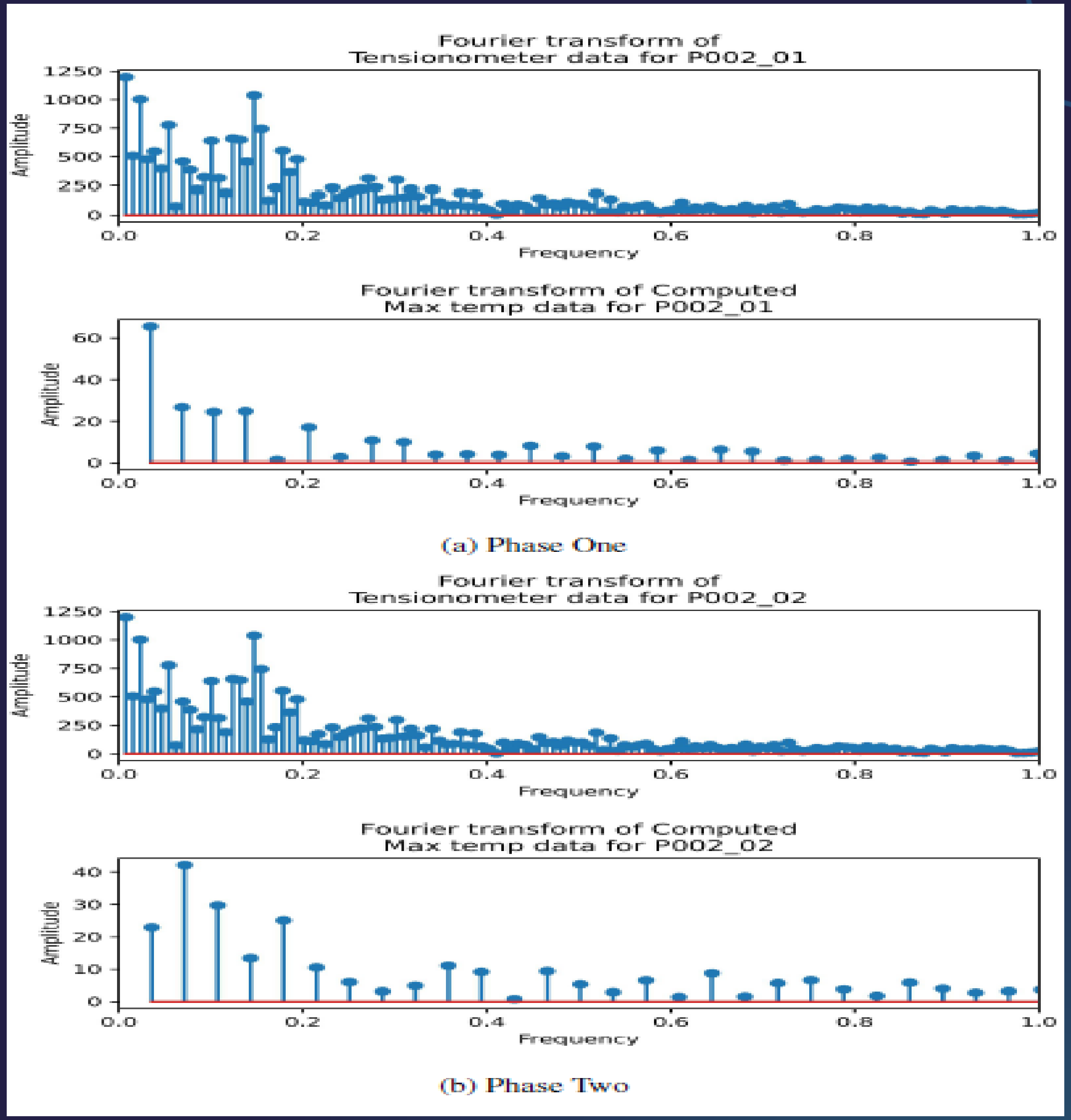
- Once the bounding box of the nose_mouth region was identified in the image frames, the next step was to extract the temperature data.
- Python utilities, namely imageBBresampling.py and identify changing cell values-MAX values-numpy.ipynb were used for this.
- imageBBresampling.py was required as the image frames had nose_mouth regions of similar aspect ratios but different bounding box values.
- identify changing cell values-MAX values-numpy.ipynb was required only to compute the maximum temperature for each image frame based on the fixed 50x50 region of interest grid obtained from imageBBresampling.py.



Keys Highlights of the thesis : Tensionometer and Thermal data alignment

Tensionometer and Thermal data alignment

- Successful in identifying a plausible way of interpreting the breathing rate from a given facial temperature file.
- The results from Fourier Transformation prove correlation or similarity between the captured ground truth data and the computed breathing oscillations.
- Most of the activity peaks are seen in the lower frequencies of FFT graph for tensionometer data and computed temperature data which corresponds to the low frequency metabolic activity (breathing rate)
- The peaks are not aligned at the exact frequencies in the FFT graphs due to noise in data. Applying **wavelet transform** instead of Fourier Transform on the data sets might provide a better insight.



Questions


THANK YOU

References

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Future works

1. B Spline interpolation

Development of an alignment solution like a B spline interpolation implementation that could approximate the missing temperature values and the result could then be successfully aligned to tensionometer data.

2. Wavelet transform

Wavelet transform helps analyze signals by breaking them down into basic components. But unlike the Fourier transform, which looks at only frequencies evenly, the wavelet transform allows for both time and frequency localization.

3. Monitoring other vital bio-signals

The data captured during the data collection method could be extended to compute heart rate and other vital bio signals as well.

Appendix

Thesis in detail: Facial data processing

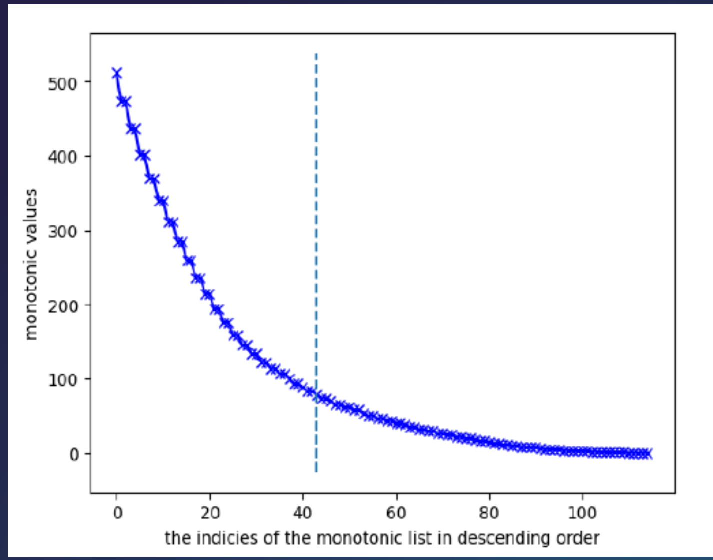
Issues seen due to static bounding box

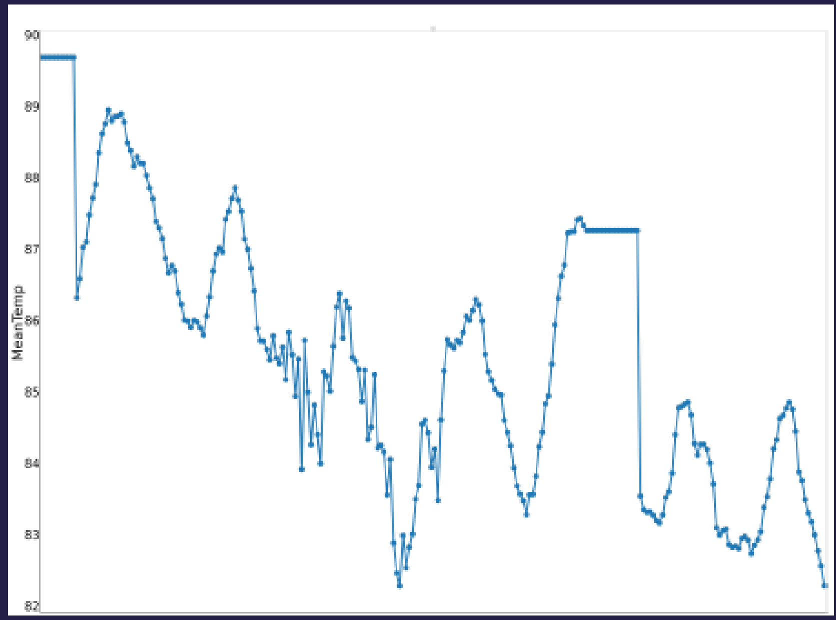
Thesis in detail: Facial data processing

Identifying the areas of temperature fluctuations in the nose/mouth region

$$norm\_diff\_arr = \frac{(diff\_arr - np.min(diff\_arr))}{(np.max(diff\_arr) - np.min(diff\_arr))}$$

$$uni\_diff\_arr = np.unique(norm\_diff\_arr)$$





Thesis in detail: Facial data processing

Better Solution: YOLO via Transfer training

```
image 250/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_867.png: 288x384 1 nose_mouth, 8.1ms
image 251/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_868.png: 288x384 1 nose_mouth, 8.2ms
image 252/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_869.png: 288x384 1 nose_mouth, 8.1ms
image 253/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_870.png: 288x384 1 nose_mouth, 9.1ms
image 254/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_871.png: 288x384 1 nose_mouth, 8.1ms
image 255/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_872.png: 288x384 1 nose_mouth, 8.2ms
image 256/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_873.png: 288x384 1 nose_mouth, 8.1ms
image 257/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_874.png: 288x384 1 nose_mouth, 8.2ms
image 258/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_875.png: 288x384 1 nose_mouth, 8.1ms
image 259/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_876.png: 288x384 1 nose_mouth, 9.7ms
image 260/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_877.png: 288x384 1 nose_mouth, 8.1ms
image 261/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_878.png: 288x384 1 nose_mouth, 8.2ms
image 262/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_879.png: 288x384 1 nose_mouth, 8.1ms
image 263/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_880.png: 288x384 1 nose_mouth, 8.2ms
image 264/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_881.png: 288x384 1 nose_mouth, 8.1ms
image 265/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_882.png: 288x384 1 nose_mouth, 8.1ms
image 266/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_883.png: 288x384 1 nose_mouth, 8.1ms
image 267/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_884.png: 288x384 1 nose_mouth, 8.1ms
image 268/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_885.png: 288x384 1 nose_mouth, 9.4ms
image 269/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_886.png: 288x384 1 nose_mouth, 8.2ms
image 270/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_887.png: 288x384 1 nose_mouth, 8.2ms
image 271/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_888.png: 288x384 1 nose_mouth, 8.2ms
image 272/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_889.png: 288x384 1 nose_mouth, 8.4ms
image 273/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_890.png: 288x384 1 nose_mouth, 8.1ms
image 274/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_891.png: 288x384 1 nose_mouth, 8.1ms
image 275/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_892.png: 288x384 1 nose_mouth, 8.2ms
image 276/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_893.png: 288x384 1 nose_mouth, 9.9ms
image 277/277 /content/drive/MyDrive/yolov8/test/P002_01/IR_00009_894.png: 288x384 1 nose_mouth, 8.1ms
Speed: 0.7ms preprocess, 9.9ms inference, 4.1ms postprocess per image at shape (1, 3, 288, 384)
Results saved to runs/detect/predict3
257 labels saved to runs/detect/predict3/labels
```

(a) YOLO did not detect nose/mouth region in this image frame as the hands were obstructing part of the face

(b) YOLO did not detect nose/mouth region in this image frame as the clapperboard was obstructing part of the face

Thesis in detail: Determining the correlation between the two data

Measuring correlation between the tensionometer and computed temperature signal via RMSE method

$$RMSE = \sqrt{\frac{\sum_{i=0}^{N-1}(y_i - \hat{y}_i)^2}{N}}$$

where,
RMSE = root-mean-square error
i = the variable i
N = the number of non-missing data points
y = the tensionometer value, and
ˆy = Maximum temperature value