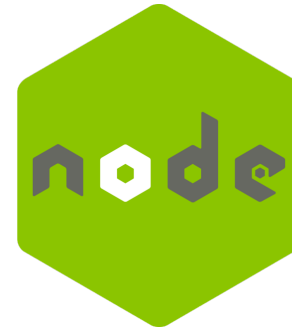
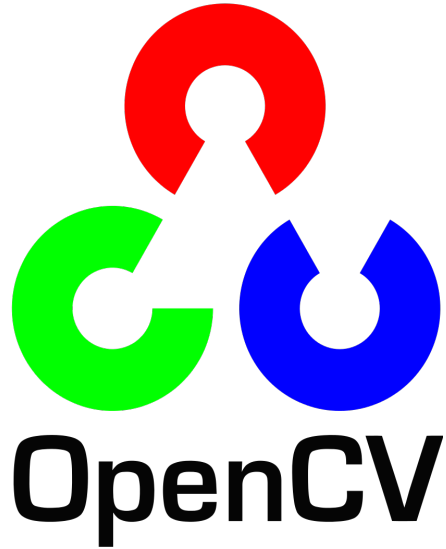




MediaPipe



Eyes  
direction  
recognition

# Team Work

---

- Mele Alessandro
- Traini Davide

Master's degree students in Computer Engineering  
at UNIVPM[[1](#)].

Repository link[[2](#)] 

Dataset link[[3](#)] 


# Workflow

---

- Dataset creation (60%)
- Classification model (30%)
- Regression model (10%)

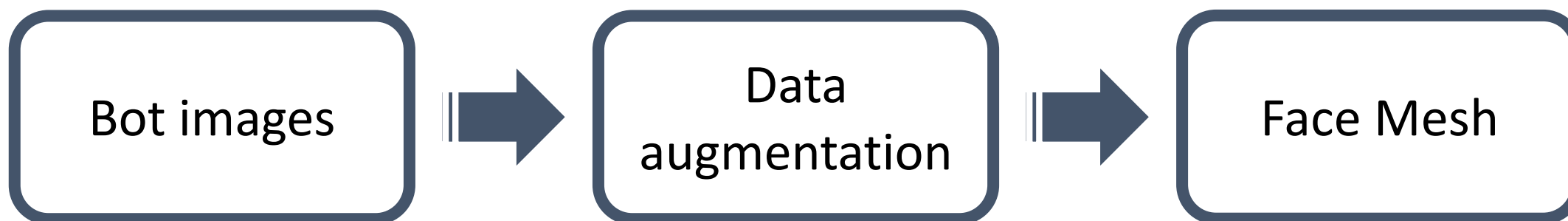
# Workflow

---

- 
- Dataset creation
    - Classification model
    - Regression model

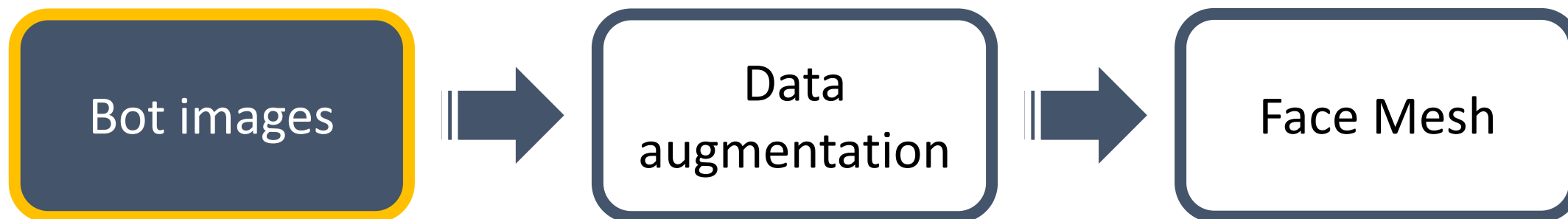
# Dataset creation

---



# Dataset creation

---

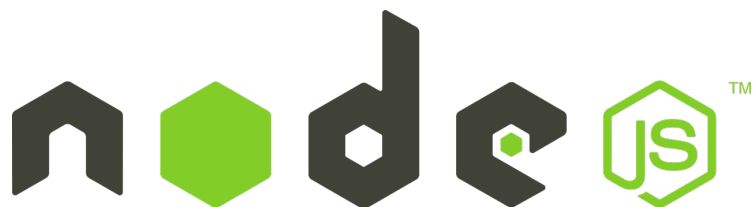


# Dataset creation

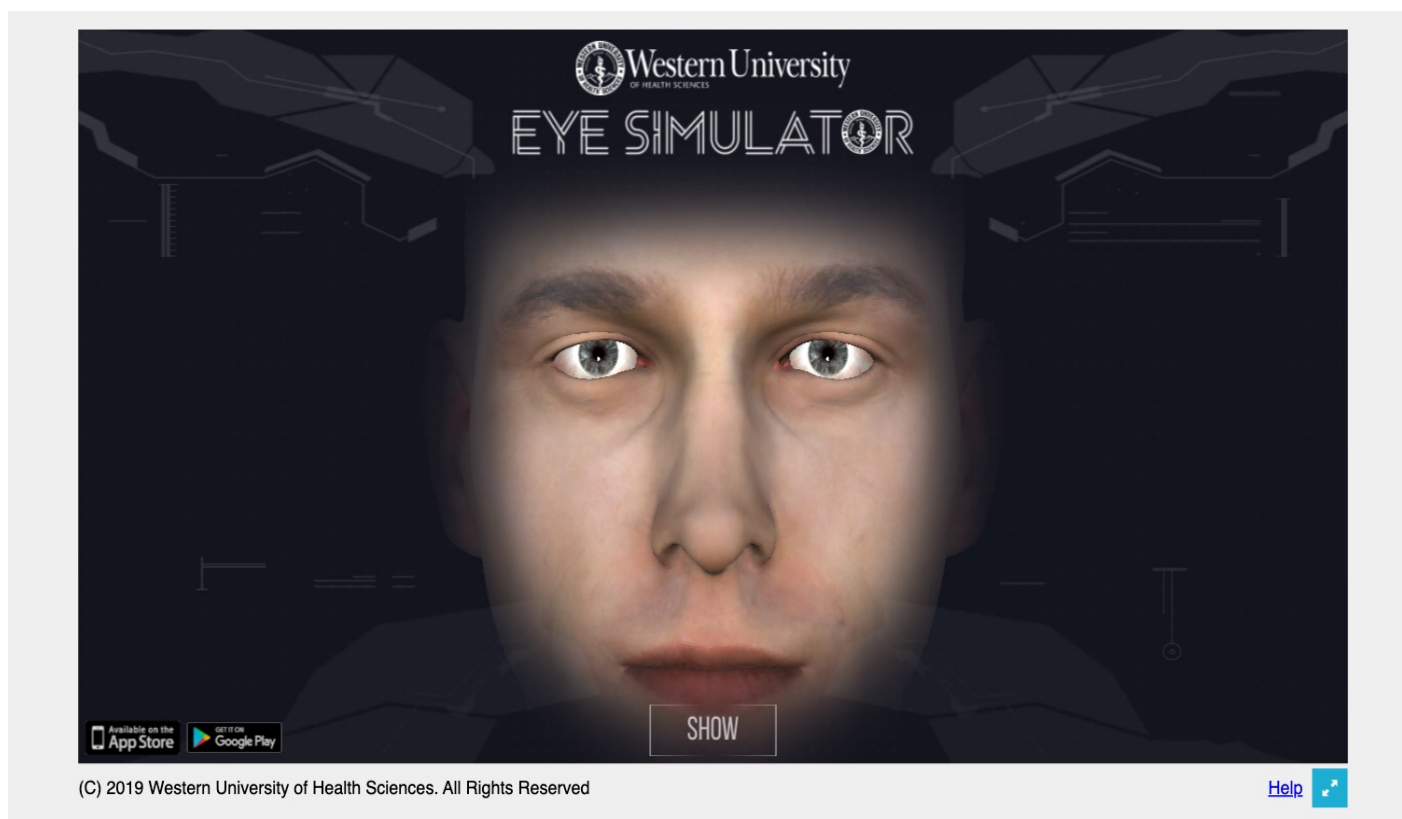
---

The dataset consists of images derived by an eye simulator of Wester University[\[4\]](#).

We developed a bot in Node.JS[\[5\]](#) that automatically takes screenshots about images moving mouse's pointer.

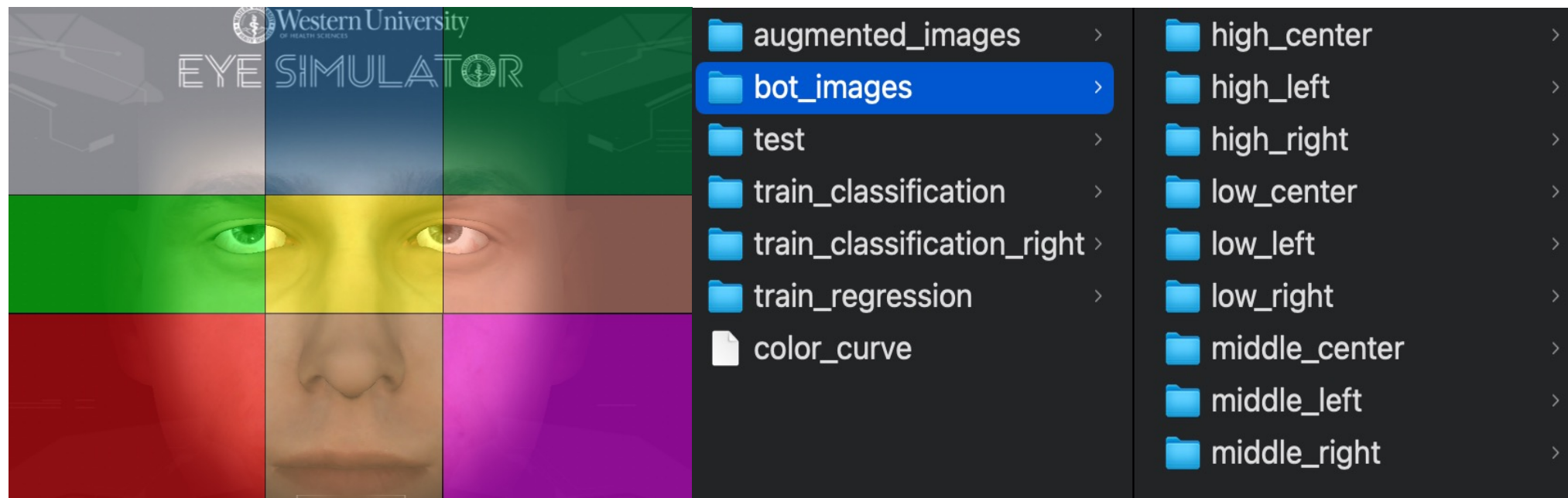


# Dataset creation



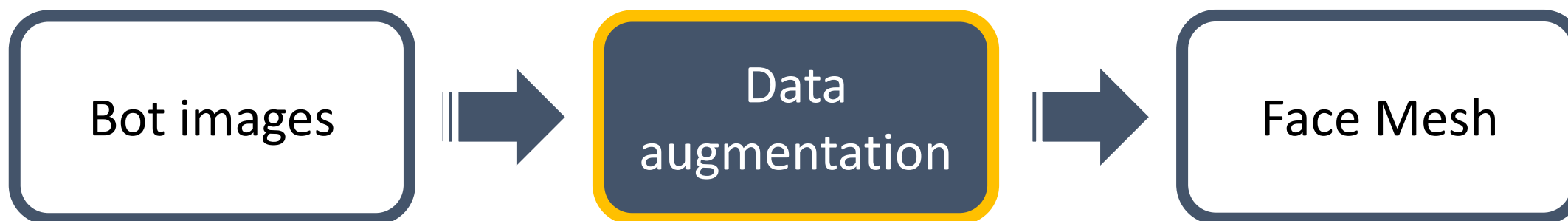


# Dataset creation



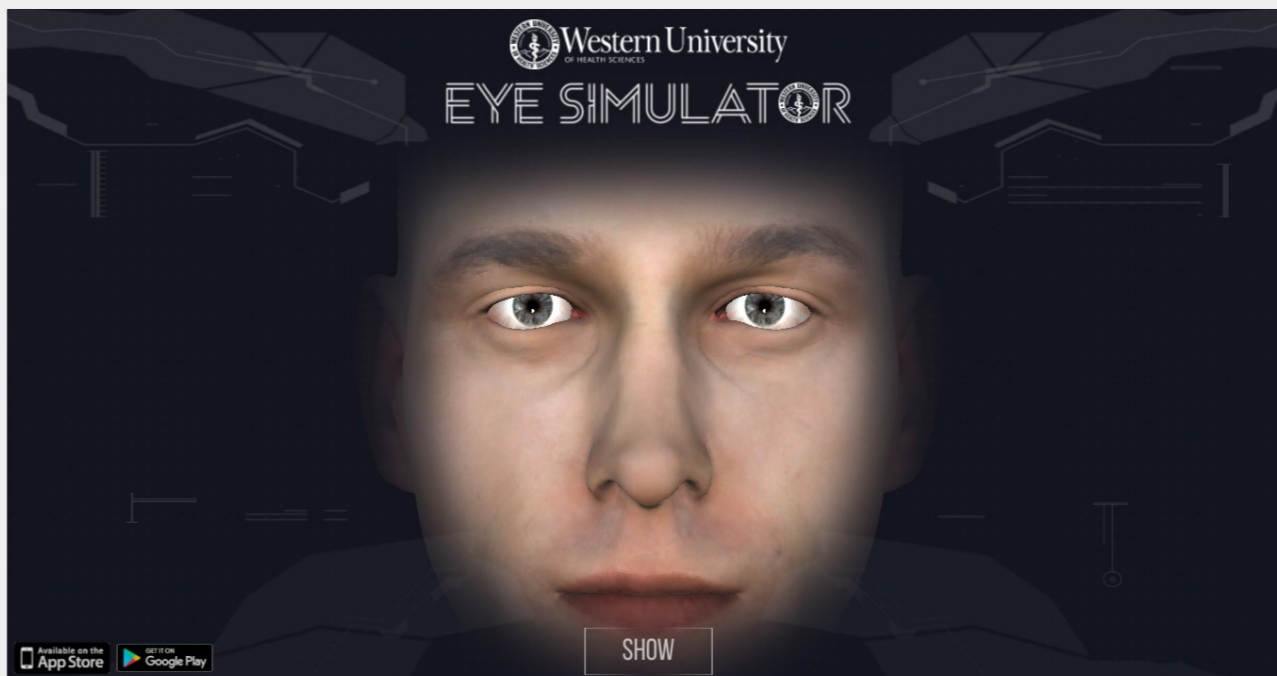
# Dataset creation

---



# Data augmentation

Starting here

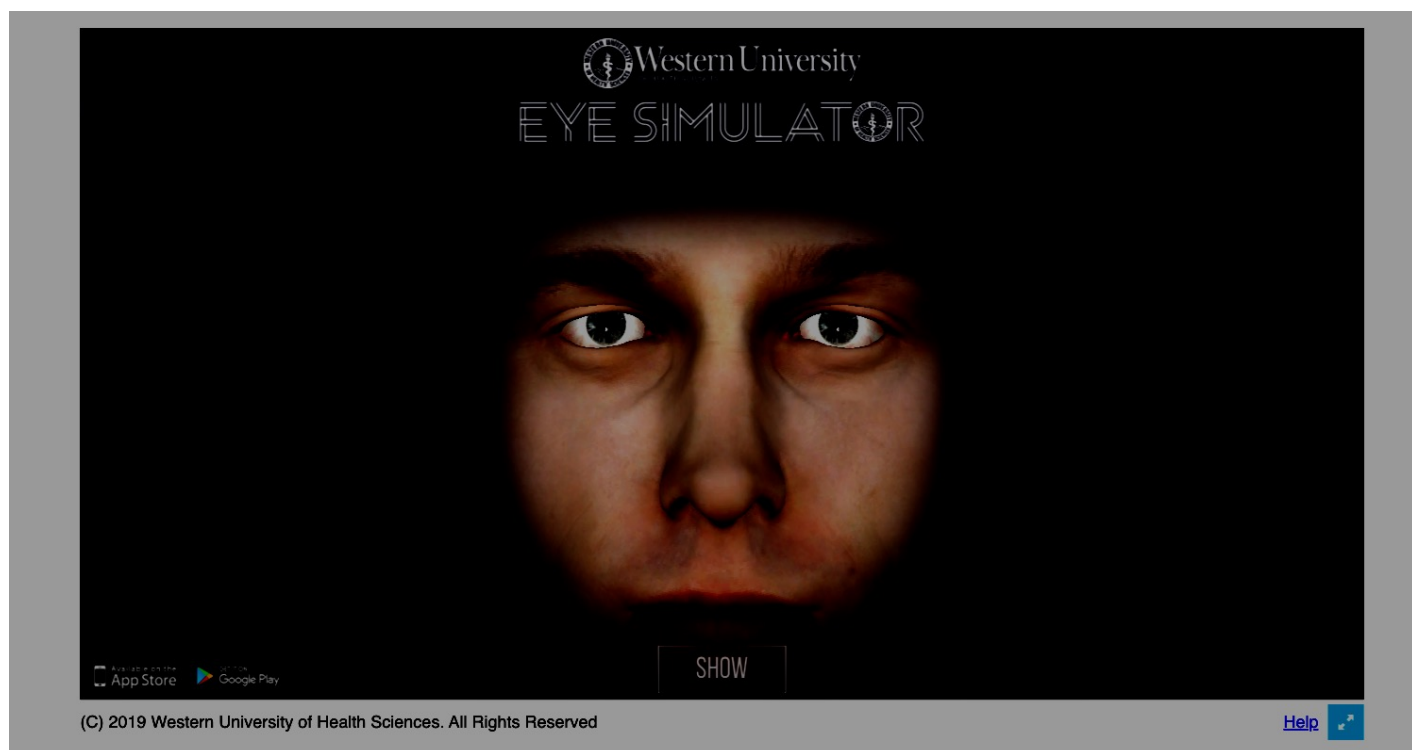
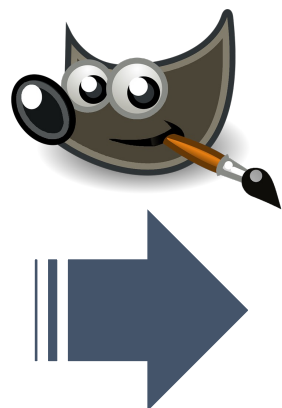


(C) 2019 Western University of Health Sciences. All Rights Reserved

[Help](#)

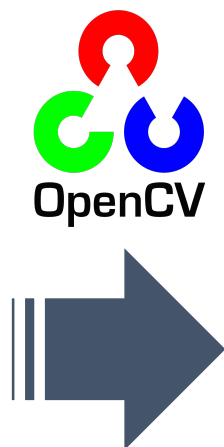
# Data augmentation

Modified colour curves, through BIMP[[6](#)], a GIMP[[7](#)] plugin



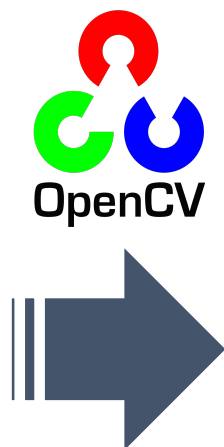
# Data augmentation

Rotation changes  $\pm 5^\circ$ , through OpenCV[[8](#)]



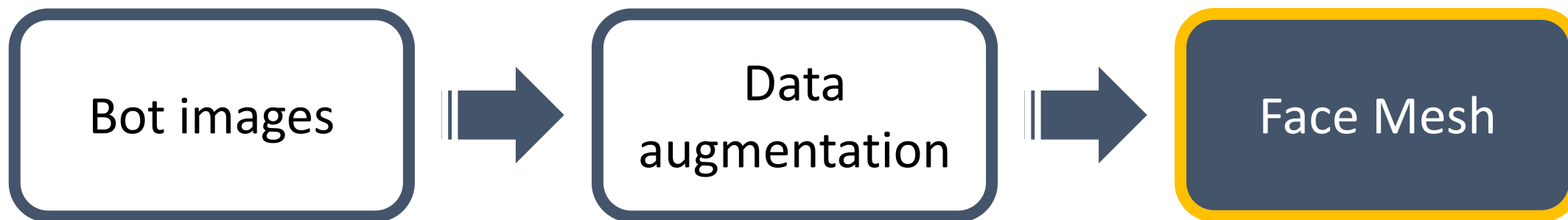
# Data augmentation

Perspective changes, through OpenCV



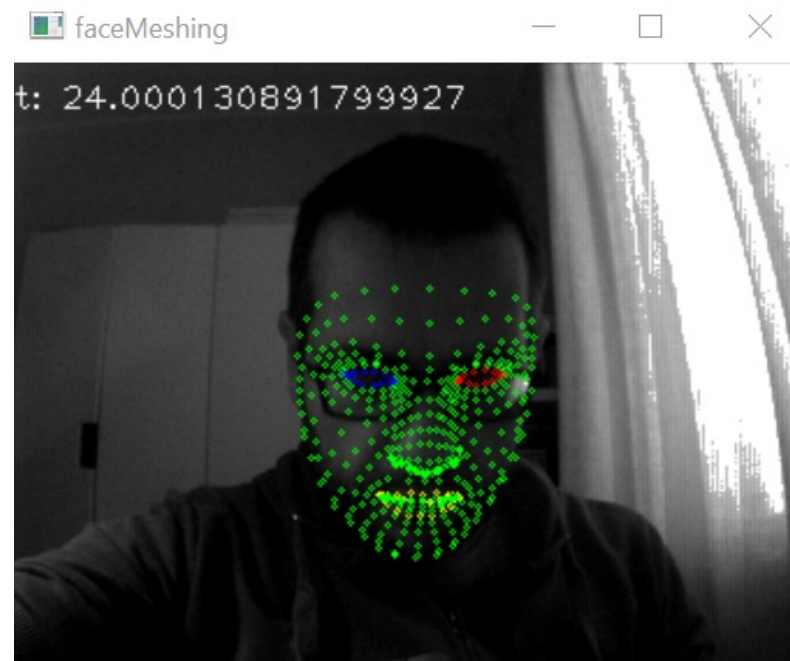
# Dataset creation

---



# Eyes extraction with Facemesh

MediaPipe Face Mesh[[9](#)] is a Machine Learning solution that estimates 468 3D face landmarks: it uses lightweight model architectures and delivers real-time performance critical for live experiences.

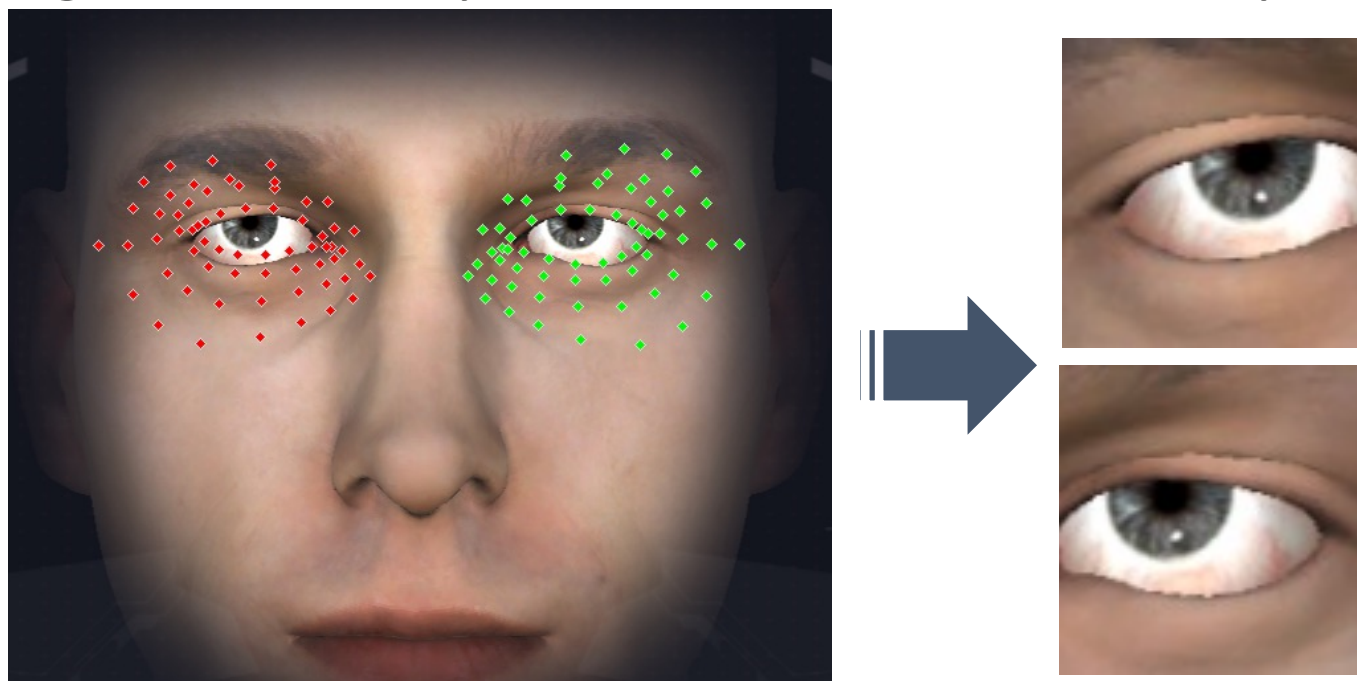


MediaPipe

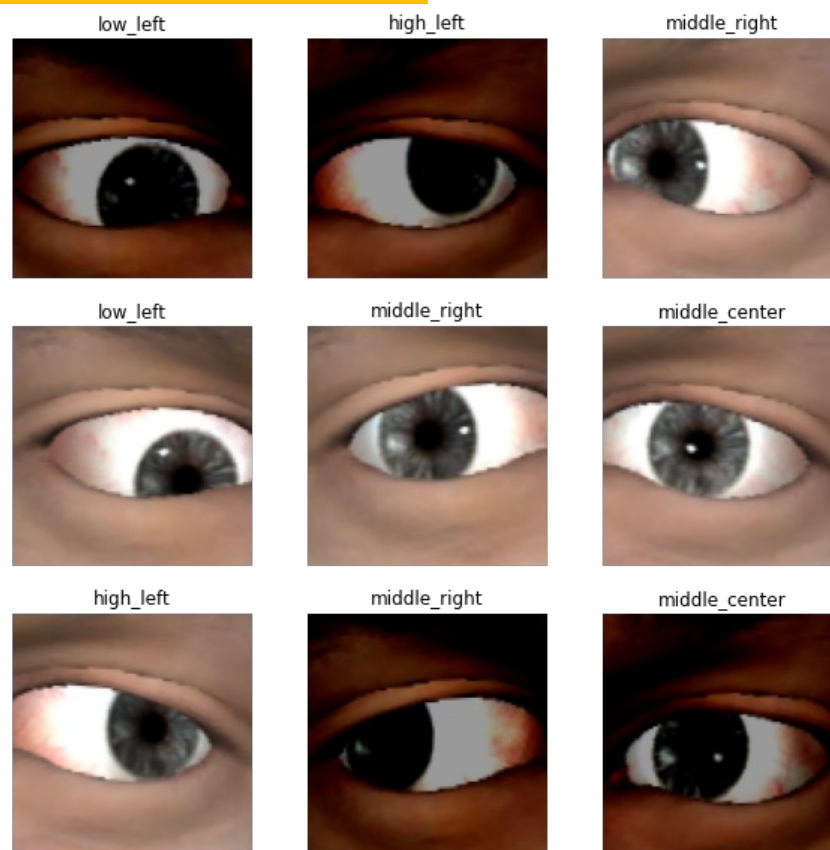


# Eyes extraction with Facemesh

Then images have been cropped in two ones which contained right and left eye, and resized at 100x100px.



# Dataset creation



# Workflow

---

- Dataset creation

 Classification model

- Regression model

# Classification model

The classifier was trained to recognize nine classes, identified by the quadrants visible in the image.

The chosen network is MobileNet v2.



# Classification model

---

Dataset: 5.376 images divided in:

- 80% Training set;
- 15% Validation set;
- 5% Test set;

Weights: Imagenet[[10](#)].

Every image has been rescaled, so pixels values are between 0 and 1.

# Classification model: Structure

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 100, 100, 3)]	0
tf.math.truediv (TF0pLambda)	(None, 100, 100, 3)	0
tf.math.subtract (TF0pLambda)	(None, 100, 100, 3)	0
mobilenetv2_1.00_224 (Functional)	(None, 4, 4, 1280)	2257984
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1280)	0
dropout (Dropout)	(None, 1280)	0
dense (Dense)	(None, 9)	11529
Total params: 2,269,513		
Trainable params: 2,050,313		
Non-trainable params: 219,200		

# Classification model: Train

---

```
Dropout = 0.3
Optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)
Loss = tf.keras.losses.SparseCategoricalCrossentropy(
    from_logits = False)
Metrics = ['accuracy']
```

```
BATCH_SIZE = 64
IMG_SIZE = (100, 100)
```

```
initial_epochs = 20
```

# Classification model: Fine Tuning

---

```
Dropout = 0.3  
Optimizer = tf.keras.optimizers.Adam(learning_rate=0.0001)  
Loss = tf.keras.losses.SparseCategoricalCrossentropy(  
    from_logits = False)  
Metrics = ['accuracy']
```

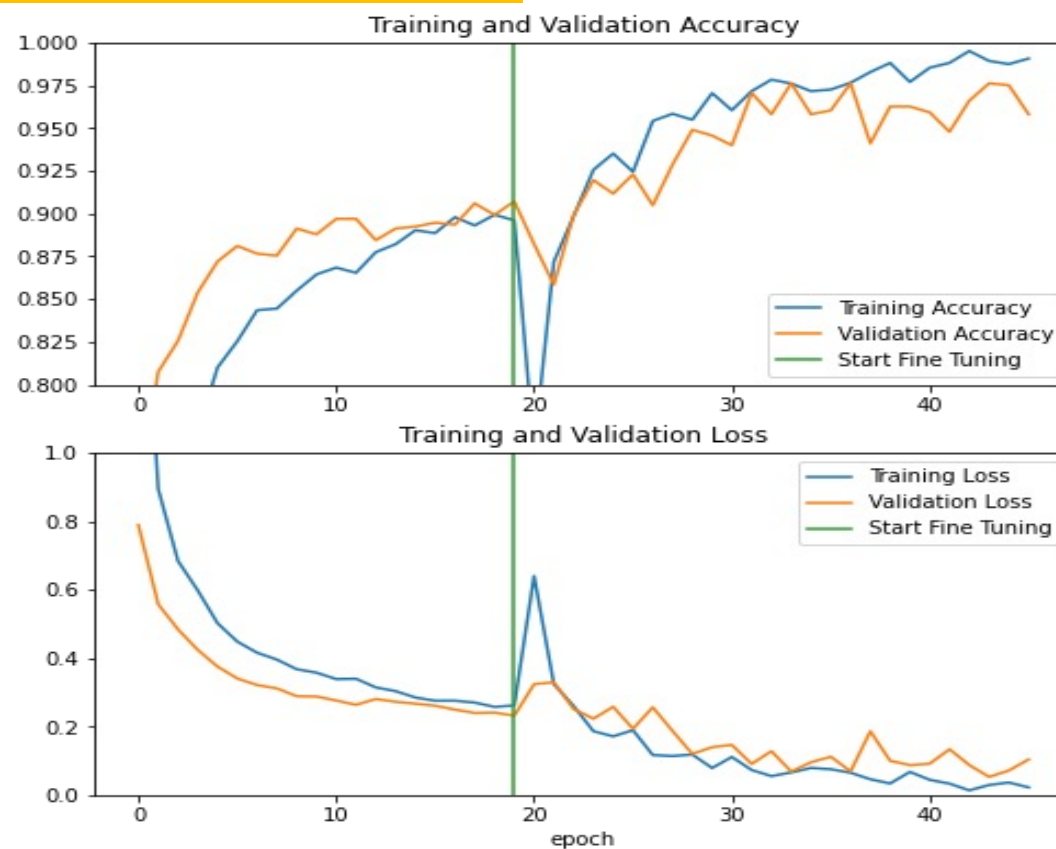
```
BATCH_SIZE = 64  
IMG_SIZE = (100, 100)
```

```
fit_epochs = 25
```

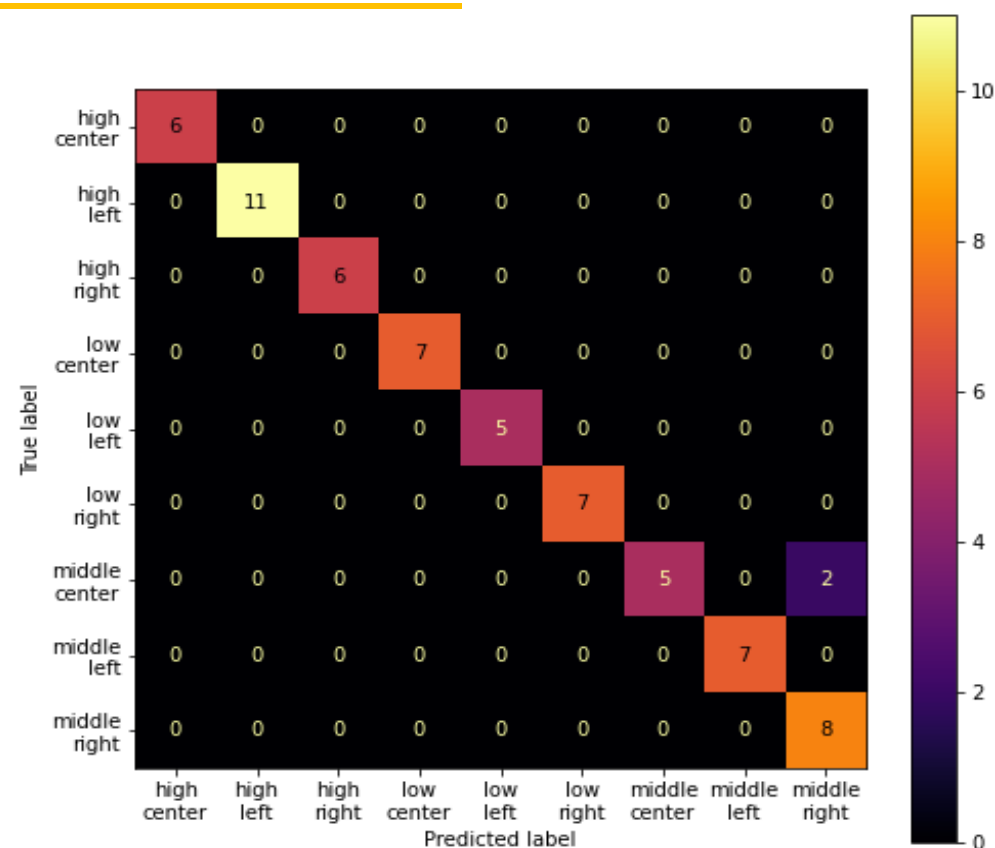
```
Fine_tune_at = 80
```



# Classification model: Performance



# Classification model: Confusion Matrix



# Classification model: Real images

---

Using real images the model was not able to generalize, so we tried to resolve with three methods:

- Train one model for left and another for right eye;
- Train the model with only middle\_left and middle\_right classes;
- Apply a cost matrix, to avoid unbalanced class problems.

The above listed methods were not sufficiently able to mitigate the generalization issue. A more complete data-set with synthetic and real images is a good candidate for that.

# Workflow

---

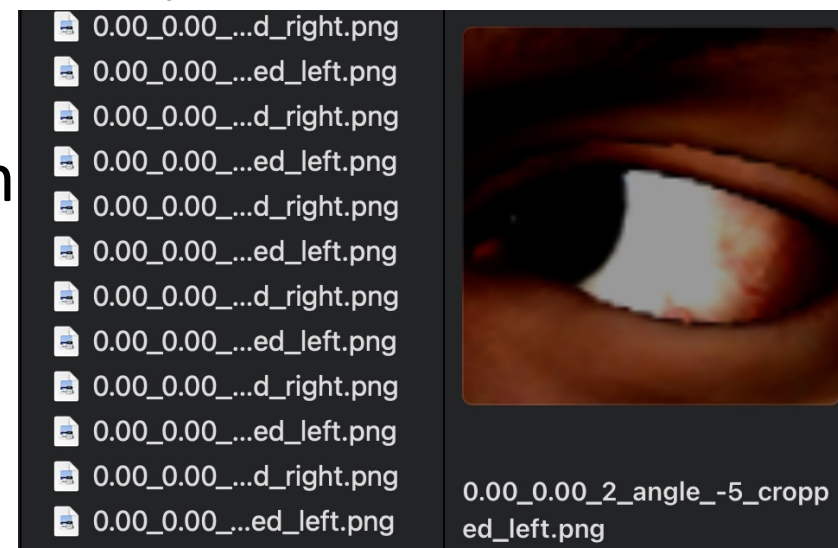
- Dataset creation
- Classification model

 Regression model

# Regression model: Dataset

Same as classification, but without folders (classes).

Images has been saved as *horPerc\_verPerc* where *Perc(s)* are normalized than maximum and minimum (x,y) cursor movement.



# Regression model: Structure

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 100, 100, 3)]	0
tf.math.truediv (TFOpLambda )	(None, 100, 100, 3)	0
tf.math.subtract (TFOpLambda )	(None, 100, 100, 3)	0
mobilenetv2_1.00_224 (Functional)	(None, 4, 4, 1280)	2257984
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1280)	0
dropout (Dropout)	(None, 1280)	0
dense (Dense)	(None, 2)	2562

=====  
 Total params: 2,260,546  
 Trainable params: 2,041,346  
 Non-trainable params: 219,200

# Regression model: Train

---

```
Dropout = 0.3  
Optimizer = tf.keras.optimizers.Adam(learning_rate=0.01)  
loss = 'mse'  
Metrics = ['mse', 'mae', 'mape']
```

```
BATCH_SIZE = 64  
IMG_SIZE = (100, 100)
```

```
initial_epochs = 20
```

# Regression model: Fine Tuning

---

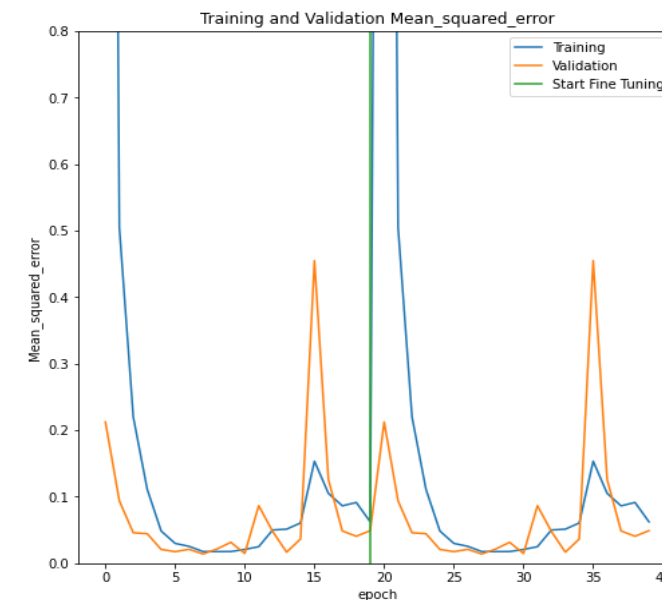
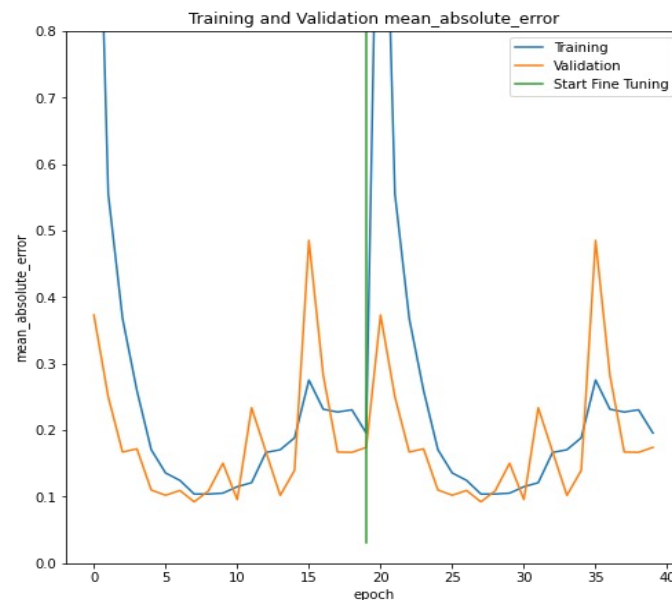
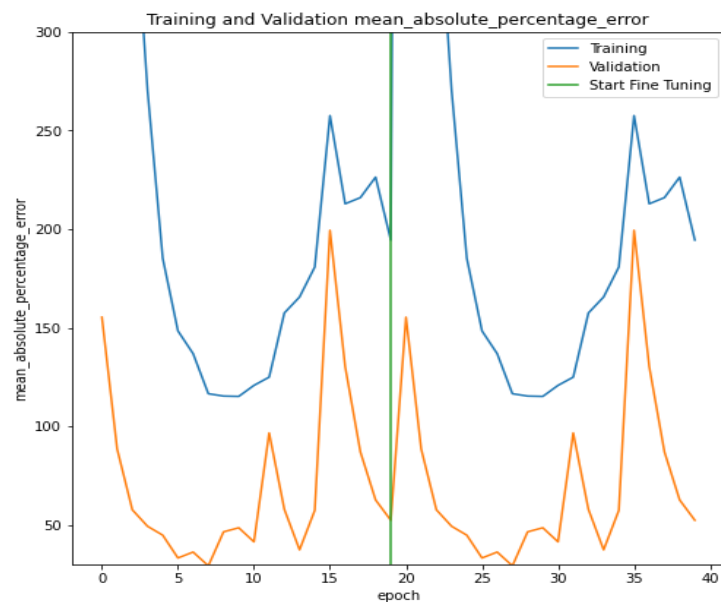
```
Dropout = 0.3  
Optimizer = tf.keras.optimizers.Adam(learning_rate=0.0001)  
loss = 'mse'  
Metrics = ['mse', 'mae', 'mape']
```

```
BATCH_SIZE = 64  
IMG_SIZE = (100, 100)
```

```
fit_epochs = 25  
Fine_tune_at = 80
```

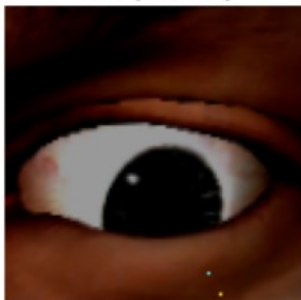


# Regression model: Performance

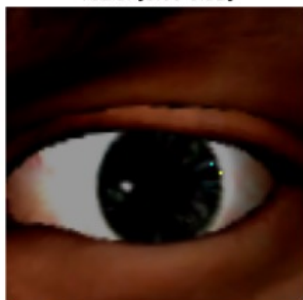


# Regression model: Apply model

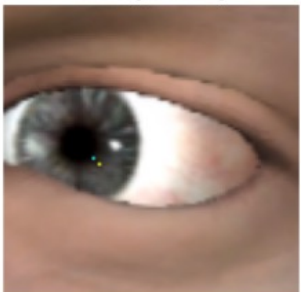
predetta: [0.72376174 0.9616422 ]  
reale: [0.68 0.89]



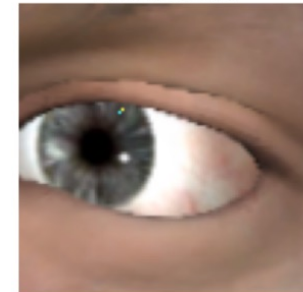
predetta: [0.7178555 0.5570349]  
reale: [0.68 0.52]



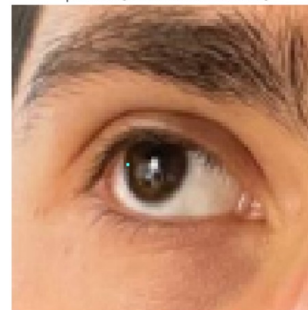
predetta: [0.32152328 0.5496877 ]  
reale: [0.3 0.52]



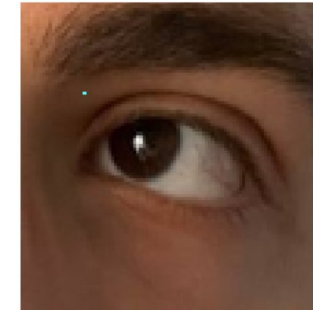
predetta: [0.3536686 0.36268732]  
reale: [0.34 0.37]



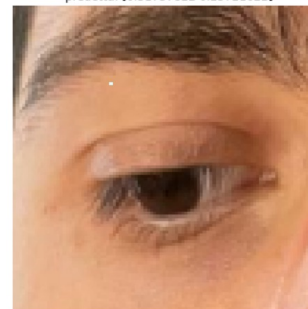
predetta: [0.37206239 0.5185051 ]



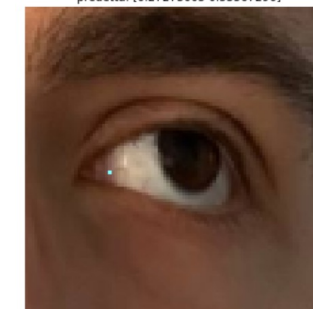
predetta: [0.20235385 0.2925929 ]



predetta: [0.31737822 0.25721622]



predetta: [0.27273005 0.53567296]



# Conclusions

---

Both classification and regression models are really accurate on synthetic dataset, but have poor performances on real world data.

A further approach would be to train the network on both synthetic and real data.

# References

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UNIVPM: <https://www.univpm.it/Entra/>

GitHub Repository: [https://github.com/AlessandroMele/eyes\\_direction\\_recognition](https://github.com/AlessandroMele/eyes_direction_recognition)

Drive folder for dataset: [https://drive.google.com/drive/folders/1CYh07UE\\_v58td-wKqa1jO1xbAOt65gS?usp=sharing](https://drive.google.com/drive/folders/1CYh07UE_v58td-wKqa1jO1xbAOt65gS?usp=sharing)

Western University eye simulator: <https://edtech.westernu.edu/3D-eye-movement-simulator/>

Node.JS: <https://nodejs.org/it/>

BIMP: <https://alessandrofrancesconi.it/projects/bimp/>

GIMP: <https://www.gimp.org>

OpenCV: <https://opencv.org>

Face Mesh: [https://google.github.io/mediapipe/solutions/face\\_mesh.html](https://google.github.io/mediapipe/solutions/face_mesh.html)

ImageNet: <https://www.image-net.org/>