Maastricht University

Investigating the Explainability Power of Transformers in the Video Domain.

Research Internship

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Introduction

Introduction

- Explainable AI (XAI) is very important.
- Transformers new in CV.
- First time emotion detection is done.
- Adapt visual techniques from images to videos.
- Quantitatively compare visual techniques.
- Emotion trends inline with affective computing?

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- Methodology
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- Discussion and further research
- Conclusion

Methodology

Problem Statement

How does the self-attention mechanism identify emotions?

Research Questions

1. What is the performance of the TimeSformer model on detecting emotions when trained and tested on the CREMA-D [3] dataset?
2. How can visual techniques such as Grad-CAM be extended to the video domain?
3. Can the reasoning behind the prediction outputs of the TimeSformer model be visualized using the extended visual techniques?
4. Can occlusion testing be used to quantitatively evaluate the visual technique performances?
5. Based on the performed analysis, can we obtain a set of visual patterns for each emotion?

TimeSformer

- Multi-Head Self-Attention (MHSP) mechanism success in NLP (BERT) [7].
- Extended version of the vision transformer (ViT) [8].
- Pure transformer model for videos [2], [14], [15].

TimeSformer

Patches = N
Frames = F

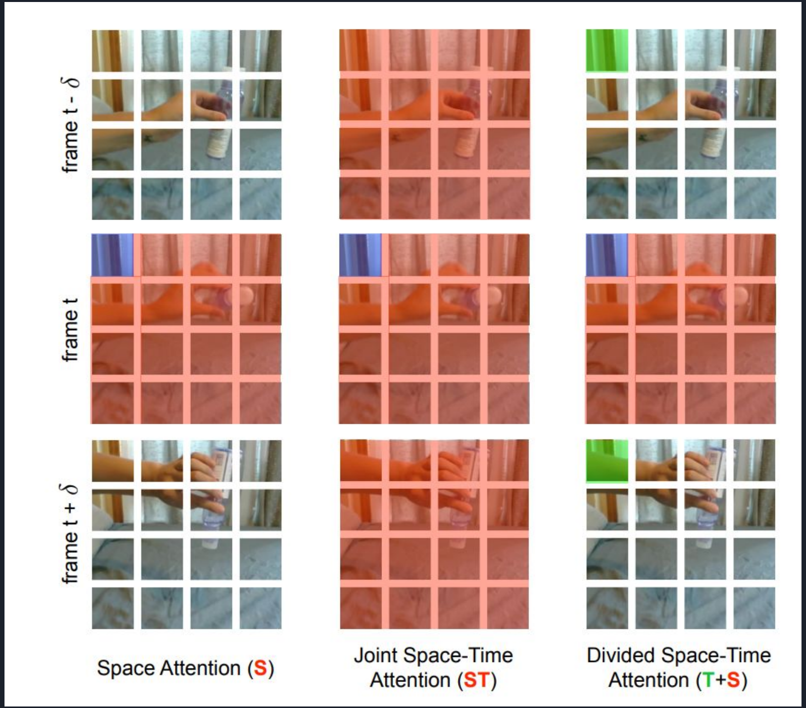
frame t - δ
frame t
frame t + δ
Space Attention (S)
Joint Space-Time Attention (ST)
Divided Space-Time Attention (T+S)

Image from [2].

N NF N + F

TimeSformer

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TimeSformer

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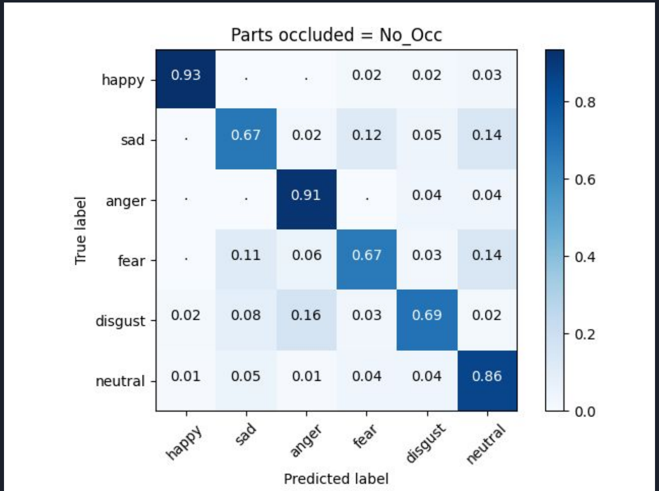
- Extended version of the vision transformer (ViT) [8].
- Pure transformer model for videos [2], [14], [15].
- Divided Space-Time attention.
- In practice: temporal attention then spacial attention.
- Transformers are ideal for transfer learning.

CREMA-D

- 6 emotions: Happy, Anger, Sad, Disgust, Fear and Neutral.
- 7442 videos.
- 91 actors.
- Crowd-sourced labelling.
- ‘Non-spontaneous’ emotions.
- Facial expressions.

Model training and performance

- 8 evenly spaced out frames.
- Cropping with FaceNet.
- Dataset split 90% training, 5% validation, 5% testing.
- 81% accuracy produced.
- Additional data augmentation not needed.



Visual Techniques

- Grad-CAM
- Rollout
- Transformer Interpretability Beyond Attention Visualization (TIBAV)

Grad-CAM

- Grad-CAM [13]:
  - Uses gradients of last layer.
  - Class-specific.
- Grad-CAM++ [4]:
  - Second order gradients of last layer.
  - Class specific.
- Eigen-CAM [9]:
  - First principle component of the 2D activations.
  - Not class specific.

Rollout

- Rollout [1]:
  - Designed for NLP.
  - Recursively multiples attention maps together from each block.
  - $A_L = \min_h(A_L)$
  - $R = (I + A_L)R$
- Rollout-Grad:
  - Inspired by TIBAV.
  - $A_L = \mathbb{E}_h(A_L * \Delta A)$
  - $R = (I + A_L)R$
  - Class-specific

TIBAV

- Class-specific [5], [6].
- Similar to Rollout-Grad.
- Takes positive attention.
- $A_L = \mathbb{E}_h((A_L * \Delta A)^+)$
- $R = R + A_L \bullet R$

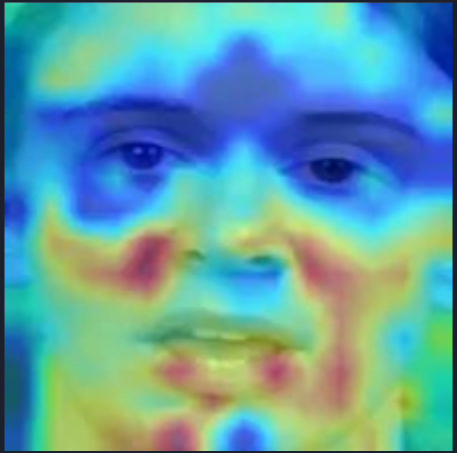
Experiments and results

Adapting and testing visual techniques

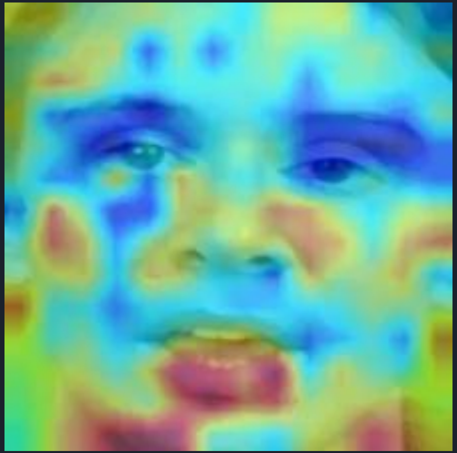
- Adaptation relatively simple.
- Divided space-time attention.
- Spacial attention encapsulates the temporal attention.

Adapting and testing visual techniques

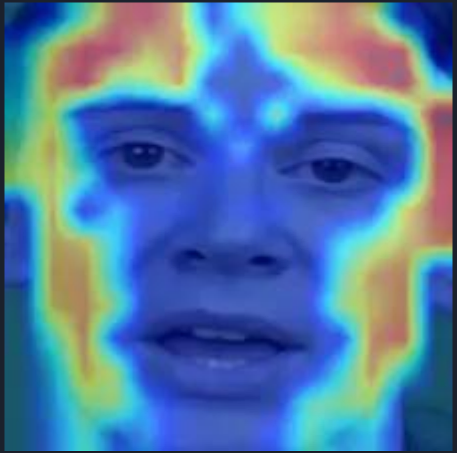
Anger



Grad-CAM



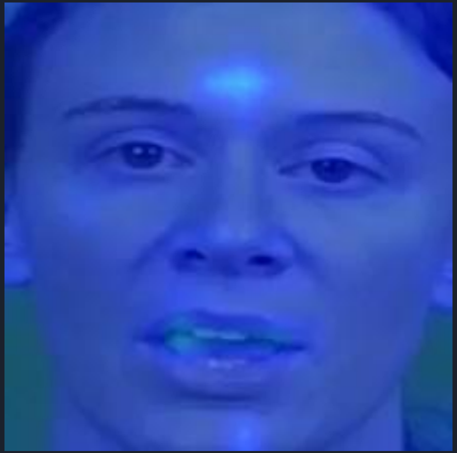
Grad-CAM ++



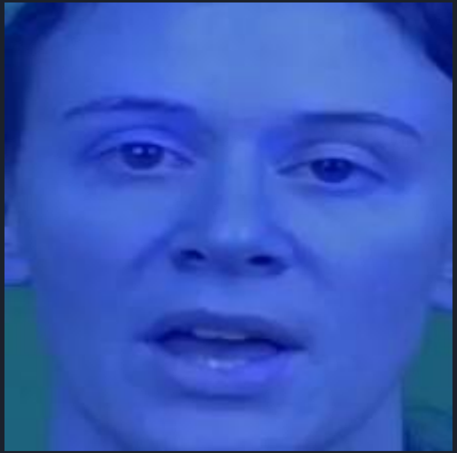
Eigen-CAM

Adapting and testing visual techniques

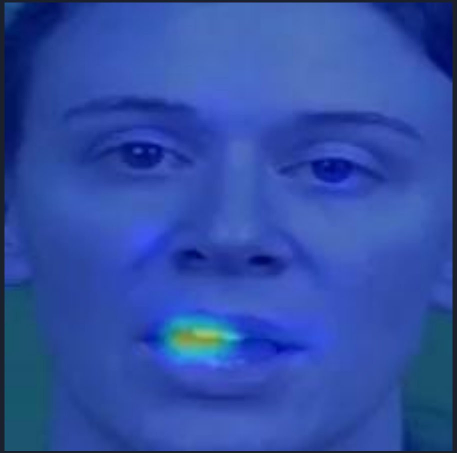
Anger



Rollout



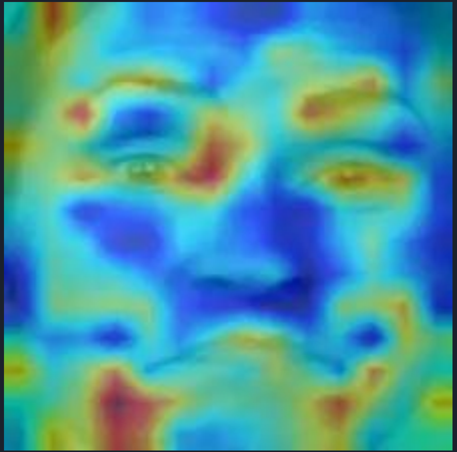
Rollout-Grad



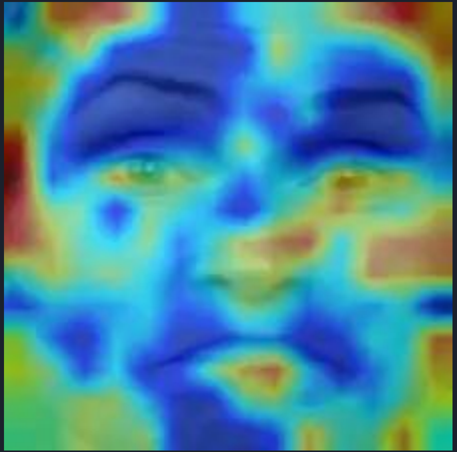
TIBAV

Adapting and testing visual techniques

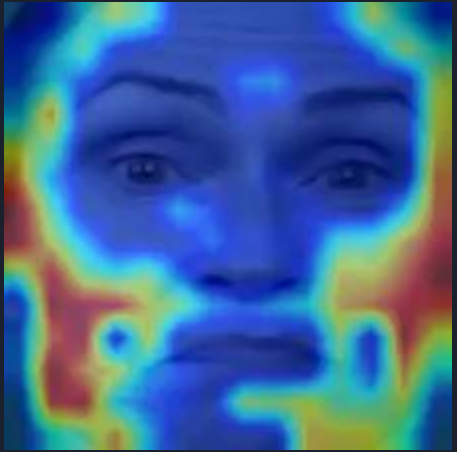
Happy



Grad-CAM



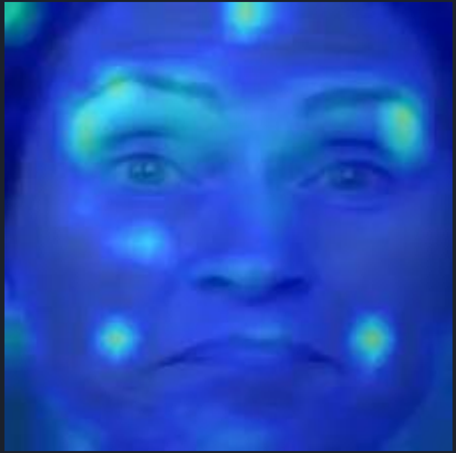
Grad-CAM ++



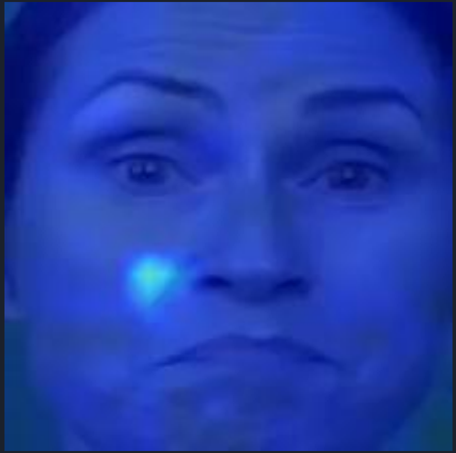
Eigen-CAM

Adapting and testing visual techniques

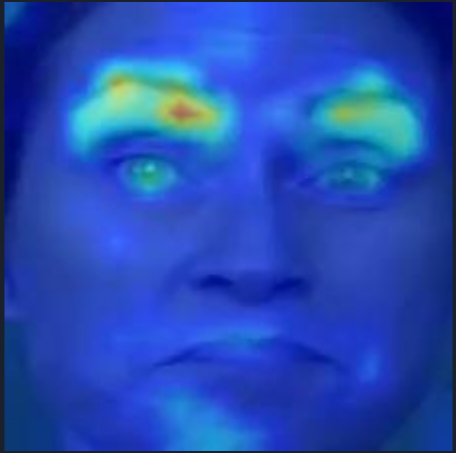
Happy



Rollout



Rollout-Grad

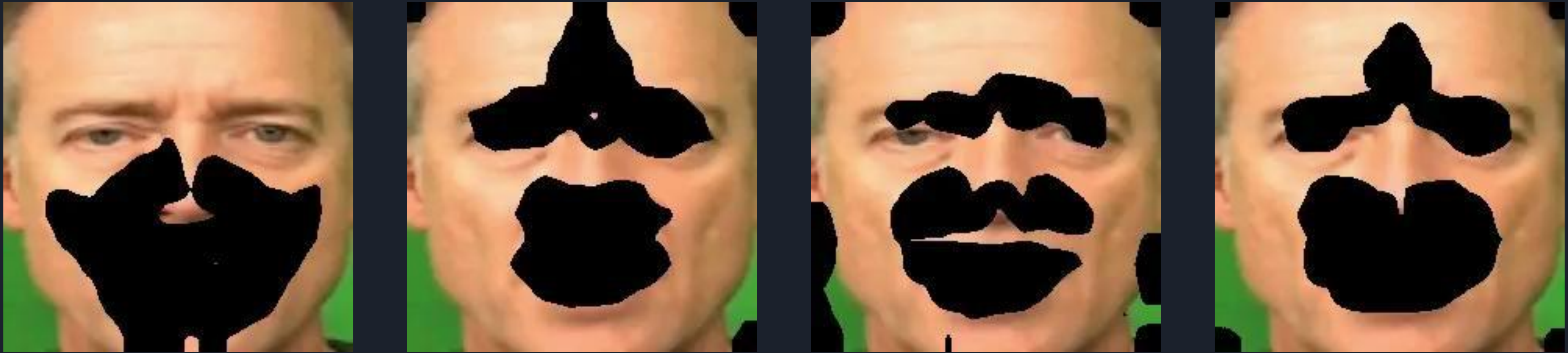


TIBAV

Visual technique occlusion testing

- Quantitative comparison.
- Occluded most important patches.
- Check testing accuracy.
- Repeat for least important patches.
- Grad-CAM acts as baseline - should perform badly.

Visual technique occlusion testing



Grad-CAM

Rollout

Rollout-Grad

TIBAV

30% spacial and 2 frames occluded.

Visual technique occlusion testing

Grad-CAM

Rollout

Rollout-Grad

TIBAV

30% spacial and 2 frames occluded.

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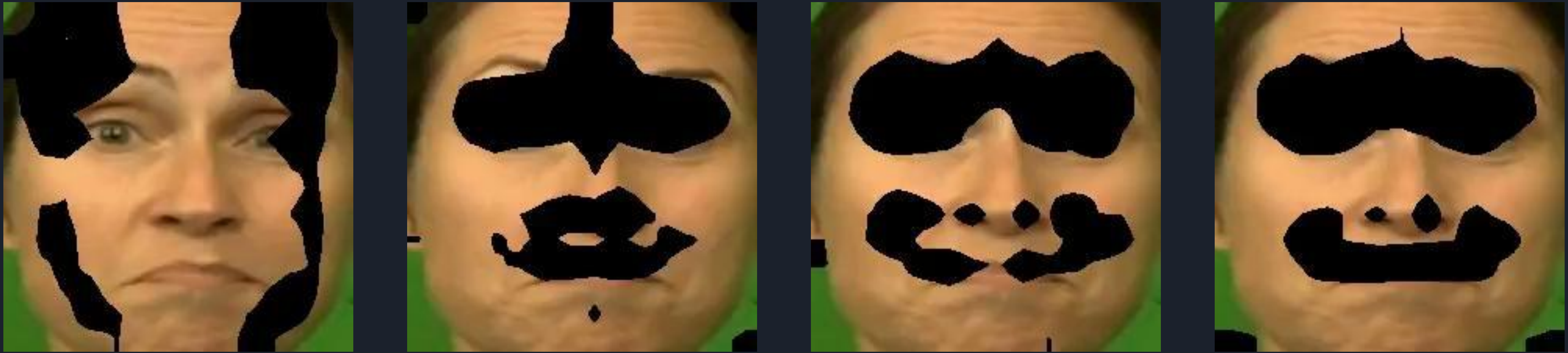
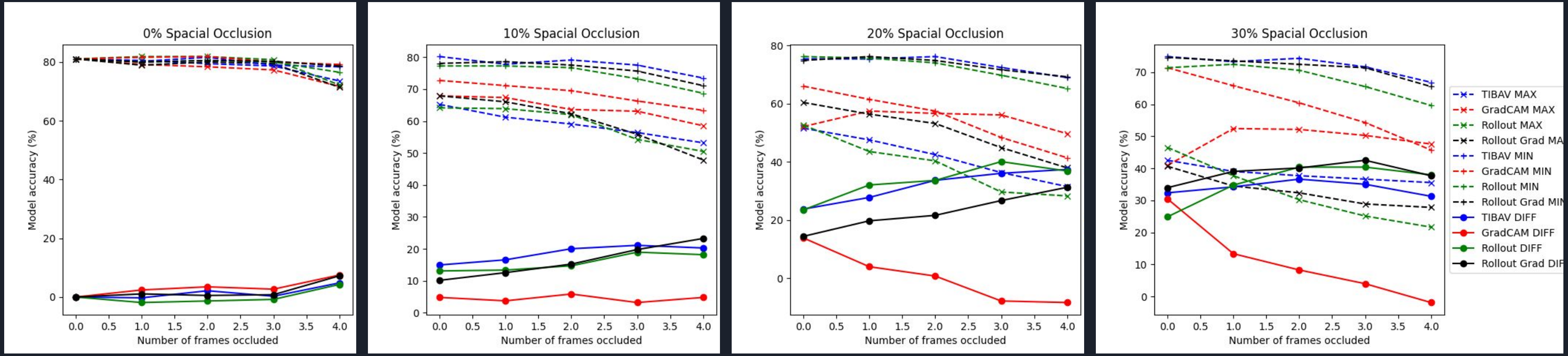


30% spacial and 2 frames occluded.

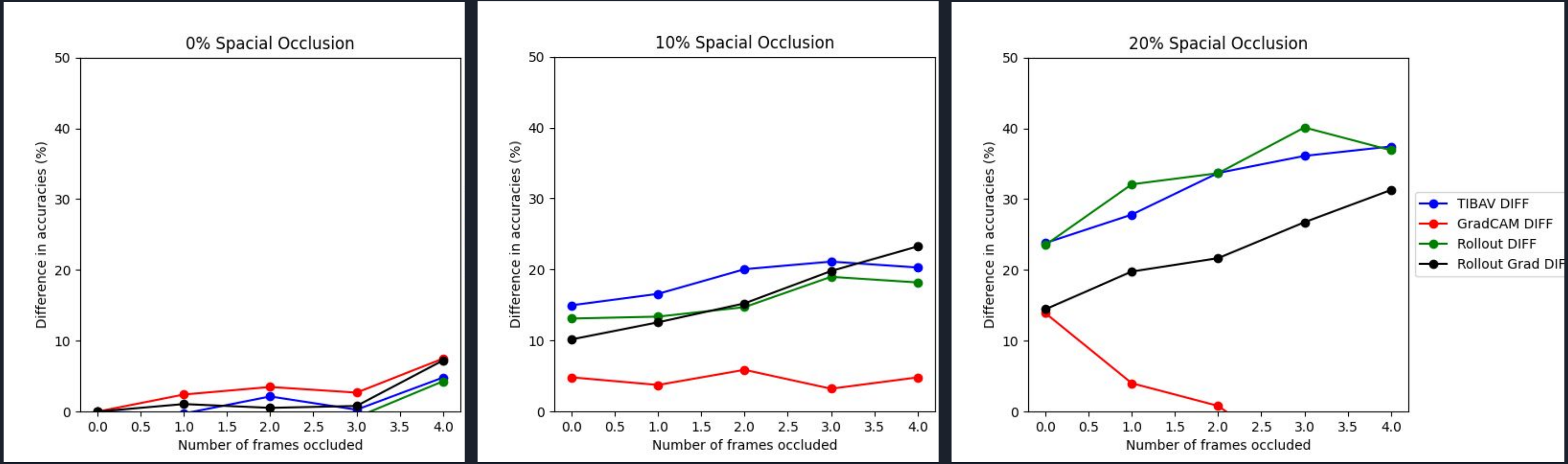
Visual technique occlusion testing

30% spacial and 2 frames occluded.

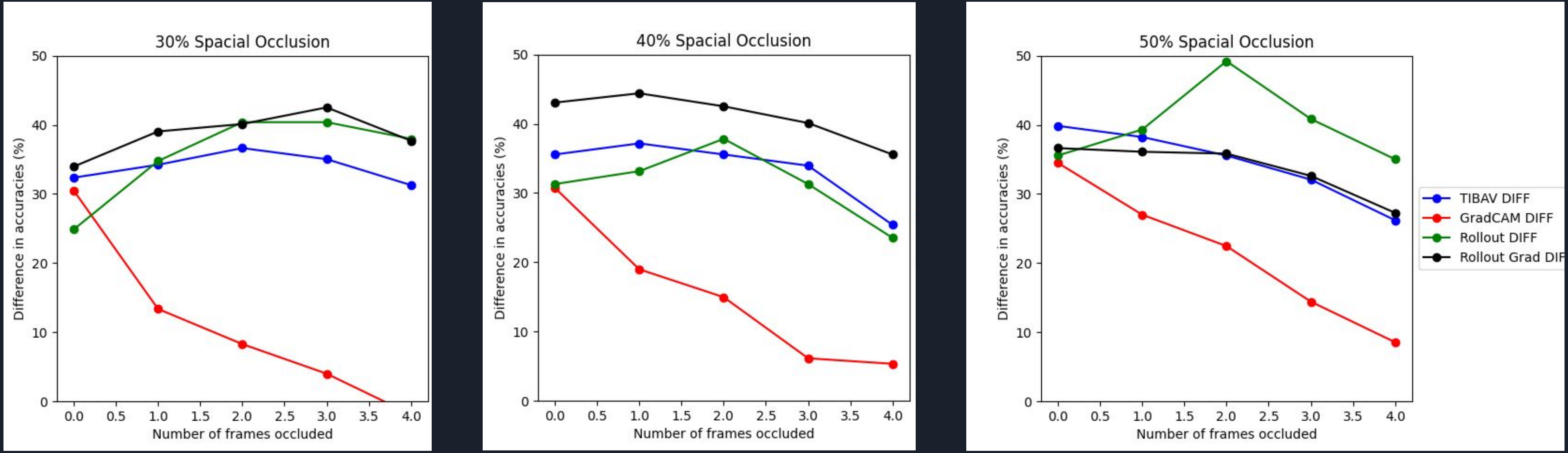
Visual technique occlusion testing



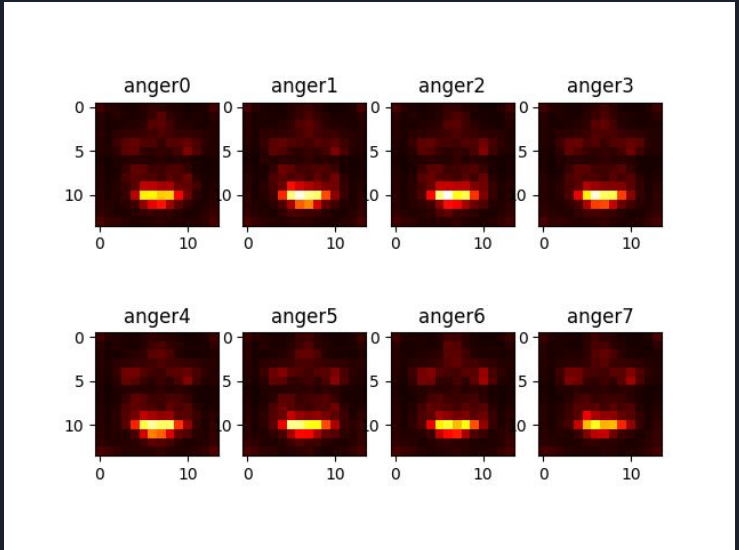
Visual technique occlusion testing

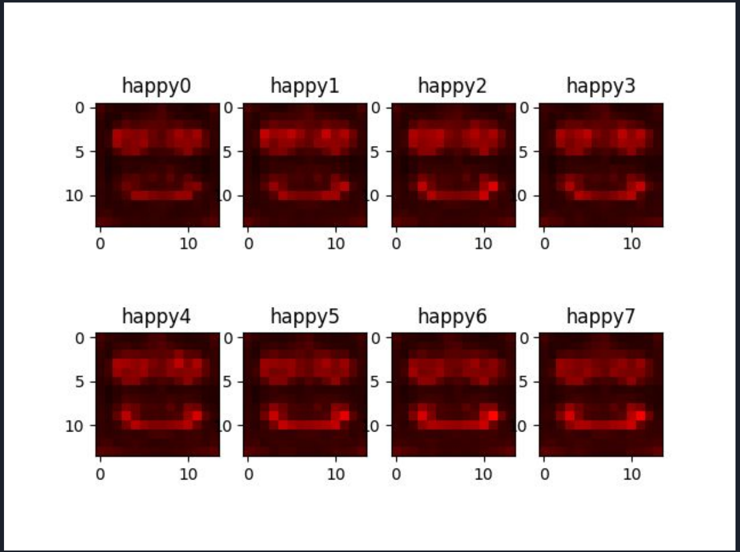


Visual technique occlusion testing



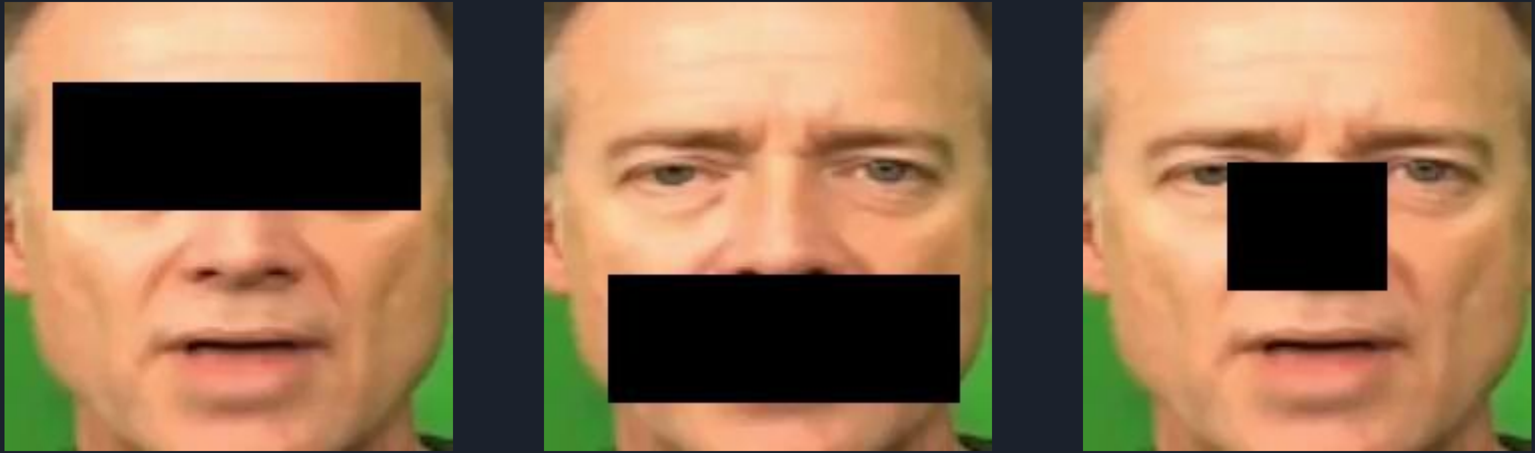
Emotion trends



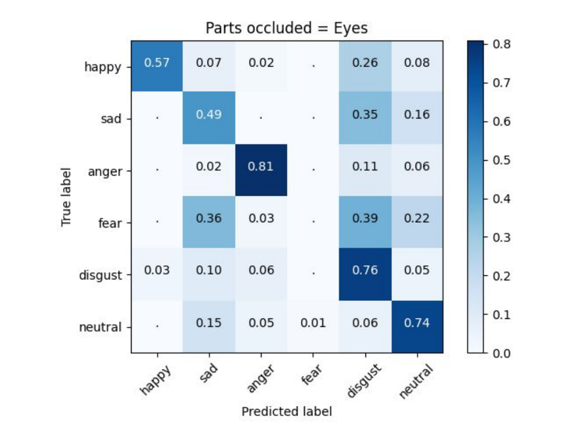


Plots are to scale

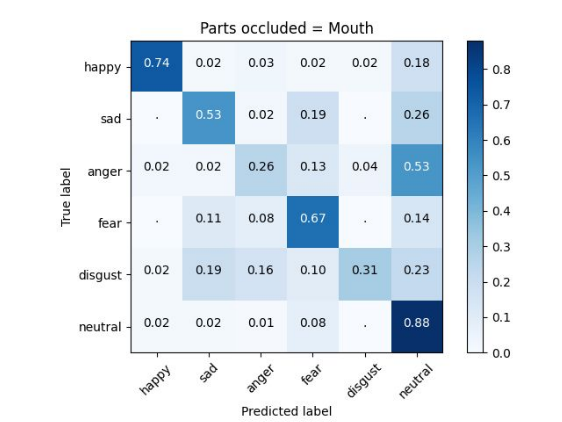
Facial part occlusion testing



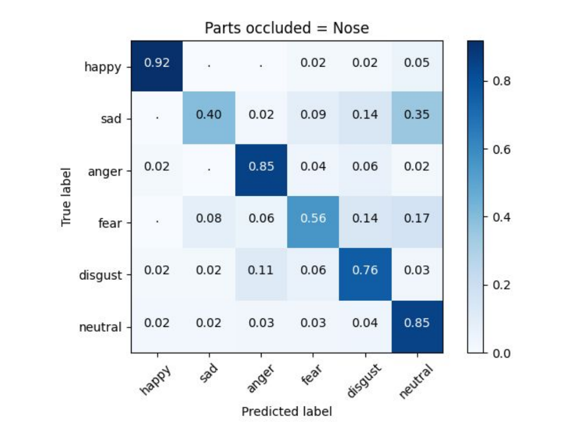
Facial part occlusion testing



Parts occluded = Eyes

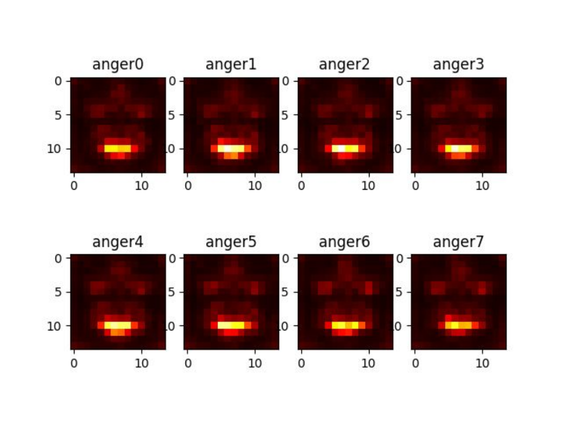


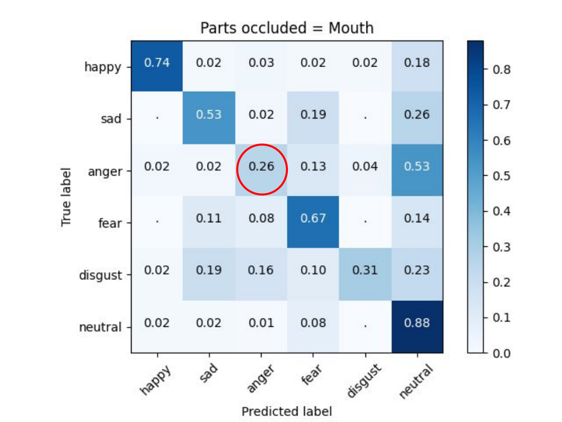
Parts occluded = Mouth



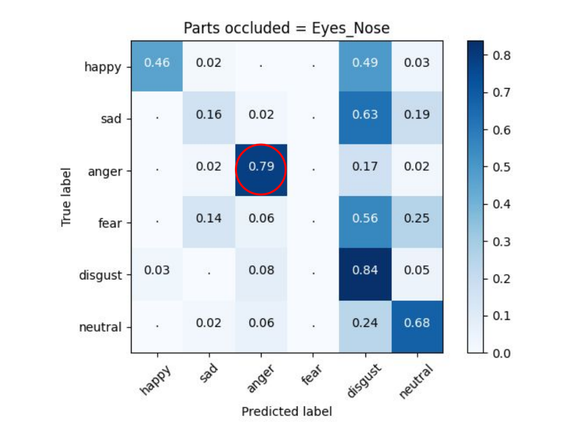
Parts occluded = Nose

Facial part occlusion testing



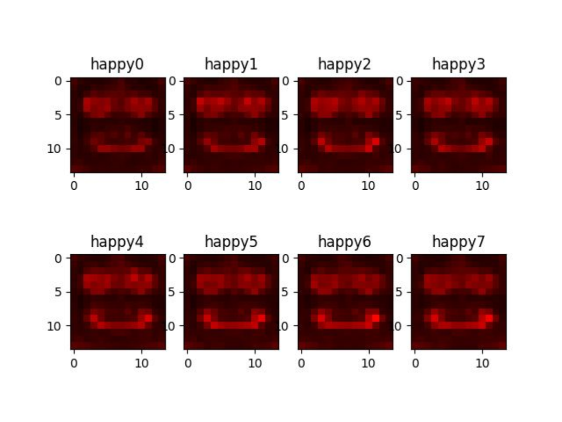


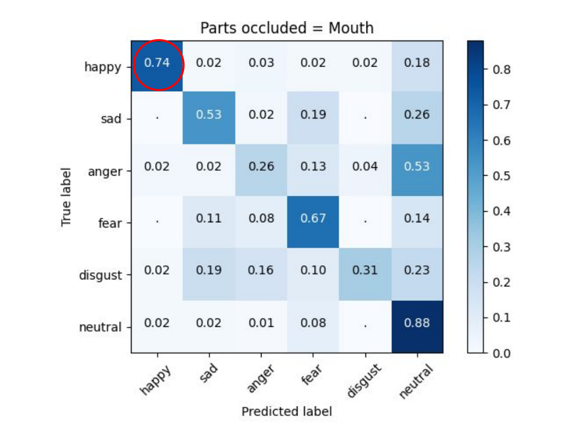
	happy	sad	anger	fear	disgust	neutral
happy	0.74	0.02	0.03	0.02	0.02	0.18
sad	.	0.53	0.02	0.19	.	0.26
anger	0.02	0.02	0.26	0.13	0.04	0.53
fear	.	0.11	0.08	0.67	.	0.14
disgust	0.02	0.19	0.16	0.10	0.31	0.23
neutral	0.02	0.02	0.01	0.08	.	0.88

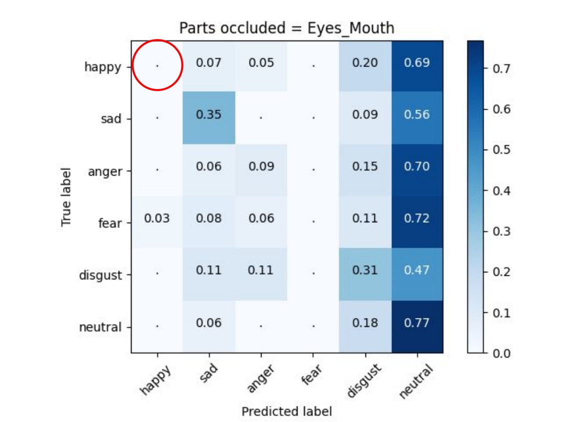


	happy	sad	anger	fear	disgust	neutral
happy	0.46	0.02	.	.	0.49	0.03
sad	.	0.16	0.02	.	0.63	0.19
anger	.	0.02	0.79	.	0.17	0.02
fear	.	0.14	0.06	.	0.56	0.25
disgust	0.03	.	0.08	.	0.84	0.05
neutral	.	0.02	0.06	.	0.24	0.68

Facial part occlusion testing







Discussion and further research

Discussion

- Divided attention makes it simple.
- Temporal attention had little influence.
- Trends:

Happy	Eyes and mouth
Anger	Mouth
Sad	Eyes and nose
Fear	Eyes
Disgust	Mouth
Neutral	Whole face - not well defined

- Trends inline with affective computing [11].

Further research

- Fine tune model on spontaneous emotion dataset.
- Repeat and compare results.
- Come up with an improved visual technique.
- Multimodal visualization with sound.

Conclusion

Conclusion

- TimeSformer 81% accuracy on CREMA-D dataset.
- Grad-CAM, Rollout and TIBAV adapted and analyzed.
- TIBAV performs best overall with occlusion testing.
- TIBAV visuals agree with facial occlusion trends.

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