AFFDEX 2.0: A Real-Time Facial Expression Analysis Toolkit

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Abstract—In this paper we introduce AFFDEX 2.0—a toolkit for analyzing facial expressions in the wild, that is, it is intended for users aiming to: a) estimate the 3D head pose, b) detect facial Action Units (AUs), c) recognize basic emotions and 2 new emotional states (sentimentality and confusion), and d) detect high-level expressive metrics like blink and attention. AFFDEX 2.0 models are mainly based on Deep Learning, and are trained using a large-scale naturalistic dataset consisting of thousands of participants from different demographic groups. AFFDEX 2.0 is an enhanced version of our previous toolkit [36], that is capable of tracking faces at challenging conditions, detecting more accurately facial expressions, and recognizing new emotional states (sentimentality and confusion). AFFDEX 2.0 outperforms the state-of-the-art methods in AU detection and emotion recognition. AFFDEX 2.0 can process multiple faces in real time, and is working across the Windows and Linux platforms.

I. INTRODUCTION

Facial expression is one of the most informative behaviour in non-verbal communication, that can reveal human affection, emotions, and personality [2]. There are typically two main approaches commonly used for studying facial expressions: the first includes detecting the facial muscle movements (i.e. AUs), described by the Facial Action Coding System (FACS) [12], while the second interprets the message delivered by a facial expression, where the message is an emotional state (e.g. anger, joy). Automatic Facial Expression Analysis (AFEA) focuses on detecting expressions described by both approaches, and has been an active research area in Computer Vision in the last 20 years [28, 24]. AFEA is a vital processing step in a wide range of applications such as ad testing [34, 33, 30, 11], driver state monitoring [10, 44, 27], and health care [15, 19, 5, 7].

Several architectures and toolkits have been developed for AFEA [28, 24], however, the datasets that have been used for training most of those architectures have several limitations. First, many datasets were captured in controlled recording conditions (limited illumination levels and camera poses), which subsequently affects the robustness of the AFEA architectures in naturalistic conditions. Second, the number of subjects available in those datasets is relatively limited, making the machine learning models vulnerable to training problems like overfitting. Third, most of the available datasets have participants from specific demographic groups, limiting the AFEA performance on other demographic groups that have not been included in the training. Furthermore, many of those architectures extracted hand-crafted features for AFEA, which have achieved lower performance compared to the deep learning features. AFEA is also lacking for a reliable and standalone toolkit that is capable of doing the different AFEA tasks (e.g. face detection, head pose estimation, AU detection, emotion recognition, etc) in real time.

In this paper, we build a toolkit (named AFFDEX 2.0) for analyzing facial expressions in the wild. AFFDEX 2.0 can accomplish many of aforementioned AFEA tasks, while overcoming many of the issues highlighted above. Specifically, we use for training and testing our models a large-scale dataset consisting of thousands of videos, that were captured at different recording conditions (i.e. in the wild), and with fully spontaneous facial expressions – participants in those videos span different demographic groups. Having access to a large-scale dataset allows us to train efficiently Deep Learning based models for facial expression analysis, those models have shown significant improvement compared to AFFDEX 1.0 [36], and other state-of-the-art methods in AFEA. Figure 1 shows an overview of AFFDEX 2.0.

AFFDEX 2.0 has three main components: face tracker, AU detector, and high-level metrics estimator. First, the face tracker has a deep-based model that is trained on a large dataset for detecting and tracking faces at challenging conditions, as well as estimating the 3D head pose. The AFFDEX 2.0 tracker has better performance (by ∼3%) than our previous toolkit [36]. Similarly, the AU detector has a deep-based model that is trained with thousands of videos for detecting 20 AUs. The AU detector boosts the AU detection performance by ∼4% compared to [36]. The improved tracking and AU detection performance can be seen across the different demographic groups. In addition, the AU detector shows better performance than the state-of-the-art methods on the DISFA dataset [29].

The tracker and AU detector predictions are used for estimating some high-level expressive and data quality metrics. These metrics can be categorized into 4 groups: a) 7 basic emotions, b) two new emotional states (sentimentality and confusion), c) other expressive metrics (e.g. blink, valence, attention), and d) data quality metrics (measuring the quality of the detected face images). The different expressive metrics are estimated by aggregating the AU predictions related to the target metric. Our emotion recognition model outperforms the state-of-the-art methods on the AffWild2 dataset [22]. The inclusion of two additional emotional states (sentimentality and confusion), beyond those typically in published literature, is based on the application area of our technology, i.e. analyzing participants watching advertising
In AFFDEX 2.0, all the video frames are scaled to a fixed resolution, and passed as input to the face detector. Then, the landmark detector is applied on the detected faces in the frames. As the face detector operates on the whole frame and requires a relatively large amount of computations, while the landmark detector operates only on the face region, and has much lower computations than the face detector. Consequently, we apply the face detector every 0.5s to find lost/new faces, while the landmark detector is applied every frame on the proposals given by the face detector (in the last timestamp being applied).

### Results
A large in-house testing set consisting of ~8.2K videos (~6M frames) of participants watching commercial ads worldwide is used for evaluating our face tracker. The testing set has labels for gender, ethnicity, age band, and glasses. The average tracking performance across the testing set has increased from 91.3% for AFFDEX 1.0 [36] to 94.6% for AFFDEX 2.0 (~3% increase). Table I show the tracking performance across the different demographic groups. From Table I, we can first conclude that the improvement in face tracking can be seen across all demographic breakdowns. Second, some groups like African ethnicity, people with glasses, and older age bands (55-64, 65+) got largely improved by ~9-12% in the new tracker. Figure 2 shows a qualitative comparison between the AFFDEX 1.0 and 2.0 trackers. Figure 2 highlights how the new tracker can detect faces at more challenging conditions (harder head poses, hand occlusions, darker illumination).

### III. AU detection
AUs are the building blocks for most of the facial expressions. In this section, we build an AU detector that detects 20 different AUs at naturalistic recording conditions. The AU detector consists of a deep based model that is trained and tested using a large-scale dataset.

![Diagram of AFFDEX 2.0 pipeline](image)

**Fig. 1: The full pipeline of AFFDEX 2.0.**

### Table I: The face tracking and AU detection average performance across different demographic groups.

| Age band | Ethnicity | Gender | Glasses |
|----------|-----------|--------|---------|
| 18-24    | Caucasian | Male   | False   |
| 25-34    | East Asian| Male   | False   |
| 35-44    | Latino    | Male   | False   |
| 45-54    | South Asian| Male | False  |
| 55-64    | South Asian| Male | False  |
| 65+      | South Asian| Male | False  |

| AUs | AFFDEX 1.0 | AFFDEX 2.0 |
|-----|------------|------------|
| True | 92.1       | 96.4       |
| False| 91.1       | 96.4       |
A. Dataset.

Most of the datasets available in the literature (e.g. DISFA [29], UNBC [26], BP4D [49]) have relatively limited number of participants, recording conditions, and/or diversity in demographics. In our analysis, we use a large-scale dataset that was captured in the wild, and has spontaneous facial expressions. The web-based approach described in [35] is used for collecting thousands of videos for participants watching commercial ads worldwide (from 90+ countries). This dataset has \( \approx 55K \) videos of participants with diverse age, gender and ethnicity.

The collected videos were annotated for the presence of AUs using trained FACS coders. In addition, videos were labelled for gender, ethnicity, age band, and glasses. For our analysis, we divide the dataset into 40.9K videos for training, 5.9K for validation, and 8.2K for testing. Note that the face tracker and the AU detector have the same testing set. A part of this dataset was made available to the research community through AM-FED [35] and AM-FED+ [32].

B. Modelling

Our AU detection pipeline consists of 3 main stages; preprocessing, modeling, and postprocessing.

In the preprocessing stage, we first detect the face region and the 4 facial landmarks using the face tracker introduced in Section II. Second, the landmarks are used for aligning horizontally the face image. Third, the aligned faces are scaled to a fixed size of 96x96, and passed as an input to two CNNs.

Modeling. We train two identical CNNs for detecting 20 different AUs. Each CNN has 5 convolutional and 1 fully-connected layers, and is trained for detecting some AUs, using a sampling strategy that compensates for imbalanced AU frequency found in spontaneous data and as a result, our labeled data. In order to avoid the classifier biasing to the most frequent classes, we use two different sampling strategies. The first strategy uses the oversampling technique used in [6] for sampling an equal number of positive and negative examples across each AU, and subsequently balancing the severely imbalanced AUs. The second strategy samples from our large dataset with a condition of having at least a positive label for one of the AUs in each sampled example. The sampled batches in the second strategy are not totally balanced, however the AU frequency in the training batches has been improved compared to the random sampling, in addition, the sampled batches maintain the correlations incorporated between the different AU labels.

Using the first sampling strategy retains the AUs equally represented and balanced in the training batches, but discards the correlations incorporated between the different AUs, while the opposite is the second strategy. Subsequently, we trained two CNNs, one using the first strategy, while the other using the second one. The first strategy is better for AUs with highly imbalanced positive to negative ratio, while the second strategy is better for the rest of the AUs. We use severe augmentation in the training to avoid overfitting problems, and Binary Cross Entropy for calculating the loss. Most of the pre-processing and classification settings are chosen based on the recommendations given in [3], [4].

In the postprocessing stage, we apply some operations in order to de-noise the individual frame predictions, as well as compensate for activations caused by individual or environmental differences. Specifically, we first smooth the AU predictions using a 1-dimensional moving mean filter – this helps in having a more consistent predictions and reducing the noisy AU predictions. Second, the smoothed...
Facial Expressions

| AFFDEX 1.0 [36]| AFFDEX 2.0 |
|----------------|------------|
| Inner Brow Raise (AU1) | 0.76 | 0.79 |
| Outer Brow Lower (AU2) | 0.79 | 0.86 |
| Forehead Wrinkle (AU4) | 0.67 | 0.78 |
| Upper Lid Raise (AU6) | 0.87 | 0.92 |
| Cheek Raise (AU10) | 0.91 | 0.95 |
| Nose Wrinkle (AU12) | 0.91 | 0.94 |
| Upper Lip Raise (AU14) | 0.86 | 0.94 |
| Lip Corner Puller (AU12) | 0.36 | 0.38 |
| Blinker (AU14) | 0.78 | 0.81 |
| Lip Corner Depressor (AU15) | 0.90 | 0.93 |
| Lip Press (AU20) | 0.70 | 0.76 |
| Lip Press (AU23) | 0.70 | 0.78 |
| Lip Smirk (AU26) | 0.59 | 0.61 |
| Lip Smirk (AU26) | 0.59 | 0.61 |
| Eyes Closed (AU16) | 0.92 | 0.92 |
| Smirk | 0.92 | 0.92 |
| Average | 0.82 | 0.84 |

*Smirk is defined as the asymmetric lip corner puller (AU12) or dimpler (AU14).*

### Table II: The ROC-AUC obtained by the AFFDEX 1.0 [36] and AFFDEX 2.0 on the AU testing set.

| AFFDEX 2.0 | DSIN [9] | LP [37] | SREBL [23] | EAC [25] | JAA [41] | ARl [42] | PT-MT [18] | SEV-NET [46] |
|------------|----------|---------|------------|---------|---------|---------|-----------|-----------|
| AU1        | 0.366    | 0.424   | 0.299      | 0.457   | 0.415   | 0.437   | 0.439     | 0.461     |
| AU2        | 0.623    | 0.39    | 0.247      | 0.478   | 0.264   | 0.462   | 0.421     | 0.486     |
| AU4        | 0.781    | 0.612   | 0.555      | -       | 0.275   | 0.325   | 0.131     | 0.365     |
| AU6        | 0.625    | 0.416   | 0.475      | -       | 0.337   | 0.328   | 0.259     | 0.413     |
| AU12 (Smile) | 0.783   | 0.444   | 0.624      | 0.59    | 0.474   | 0.497   | 0.443     | 0.537     |
| AU17       | 0.832    | -       | 0.26       | -       | -       | -       | -         | -         |

### Table III: The F1-score obtained by AFFDEX 2.0 and state-of-the-art methods on the DISFA dataset (cross-dataset testing).

| AFFDEX 2.0 | DSIN [9] | LP [37] | SREBL [23] | EAC [25] | JAA [41] | ARl [42] | PT-MT [18] | SEV-NET [46] |
|------------|----------|---------|------------|---------|---------|---------|-----------|-----------|
| AU1        | 0.366    | 0.424   | 0.299      | 0.457   | 0.415   | 0.437   | 0.439     | 0.461     |
| AU2        | 0.623    | 0.39    | 0.247      | 0.478   | 0.264   | 0.462   | 0.421     | 0.486     |
| AU4        | 0.781    | 0.612   | 0.555      | -       | 0.275   | 0.325   | 0.131     | 0.365     |
| AU6        | 0.625    | 0.416   | 0.475      | -       | 0.337   | 0.328   | 0.259     | 0.413     |
| AU12 (Smile) | 0.783   | 0.444   | 0.624      | 0.59    | 0.474   | 0.497   | 0.443     | 0.537     |
| AU17       | 0.832    | -       | 0.26       | -       | -       | -       | -         | -         |

### Table IV: The F1-score obtained by AFFDEX 2.0 and state-of-the-art methods on the DISFA dataset (within-dataset testing).

C. Results.

We first compare the AU detectors of AFFDEX 1.0 [36] and AFFDEX 2.0 on our large testing set. The area under the ROC curve (ROC-AUC) is used for evaluating the performance. Table II shows the performance across the different AUs for both detectors. AFFDEX 2.0 achieves better performance than AFFDEX 1.0 for most of the AUs (by ~4% on average). Table I shows the average performance across the different demographic groups. From Table I, we can see that all the groups got improved by AFFDEX 2.0. In addition, some specific groups got largely improved, like the African and South Asian ethnicity who got improved by ~8-9%. Figure 3 shows a qualitative comparison between the two detectors on 5 AUs (each image has a face with an active AU). AFFDEX 2.0 can detect AUs at more challenging conditions than AFFDEX 1.0.

Second, we compare our AU detector to the state-of-the-art methods in the literature. For our comparison, we use the DISFA dataset [29], which contains videos recorded for subjects watching short video clips. The DISFA dataset has in total around 130K frames, and was annotated in terms of 12 AUs. Two settings are commonly used for testing, one setting includes testing an architecture on the same dataset used in the training (named within-dataset testing), while the other includes testing the architecture on a dataset different from the one used for training (named cross-dataset testing).

In this paper, we compare our performance to both the methods tested using the within-dataset setting [9], [37], [23], [25], [41], [42], [18], [46], and those using the cross-dataset setting [13], [13], [1], [43]. F1-score is used for evaluating performance, as it is a common KPI reported in the literature. Table III and Table IV compares the performance across the two settings. Note that there are some values missing in Table III, as the different state-of-the-art methods have not reported their performance on all the AUs in the DISFA dataset. Although, AFFDEX 2.0 has used a different dataset for training than DISFA, it still can achieve better performance than the state-of-the-art methods in both settings.

#### IV. High-Level Metrics Estimation

In this section, we estimate some high-level expressive and data quality metrics based on the tracker and AU predictions are normalized by subtracting a baseline classifier output determined by analyzing the previous frames – this helps in reducing the relatively high activations emerging from objects occluding some participants’ faces (e.g. glasses, hats, or/and hands). Third, we apply a soft-threshold using a sigmoid function. The purpose of the threshold is two-fold: a) to report a low-false positive rate as our toolkit is required to have reliable predictions, and b) to achieve consistent output between versions of our toolkit. A grid search was conducted to find the best set of postprocessing parameters over the AU validation set. The postprocessing stage typically results in around 2% improvement in the overall ROC-AUC.
detector predictions. These metrics can be categorised into 4 groups; a) basic emotions, b) sentimentality and confusion, c) other expressive metrics, and d) data quality metrics. In the following we will explain how we detect the different high-level metrics.

A. Basic Emotions

Emotion recognition in AFEA includes mainly detecting 7 basic emotions (Anger, Disgust, Fear, Joy, Sadness, Surprise and Contempt), and the neutral expression. In AFFDEX 2.0, we predict the 7 basic emotions as combinations (i.e. a normalized weighted sum) of the 20 AUs predictions. The used weights are deduced from the Emotional Facial Action Coding System (EMFACS) [14], which defines the combinations of AUs related to each emotion. We add negative weights for opposite AUs so as to minimise the false positives. For example, anger consists of the activation of brow furrow (AU4), lip corner depressor (AU15) and lip pressor (AU24) – in order to reduce the false positives we add negative weights for opposite expressions like inner and outer brow raiser (AU1 and AU2) which are not typically co-firing with brow lowerer (AU4), and the same for smile (AU12) and lip corner depressor (AU15). Finally, the neutral expression is considered active when the 7 basic emotions are absent.

We evaluate our emotion recognition model on the AffWild2 challenge [22]. Using the AffWild2 challenge allows all participants to evaluate their methods in similar conditions, for a better and fair comparison. AffWild2 includes around 550 conversational and non-conversational videos, that have been labelled for basic emotions, as well as an other emotion category (i.e. representing other non-basic emotions). AFFDEX 2.0 is not tuned for neither the other category, nor the conversational emotion analysis, and subsequently we have excluded all the other and conversational samples from our analysis. F1-score is used for evaluating performance. Table V compares the results obtained by the AFFDEX 2.0 and state-of-the-art methods in the literature [48], [20], [45], [40], [38], [21], [47], [22]. Results show that AFFDEX 2.0 outperforms the other methods in emotion recognition, although our model has not been trained on the AffWild2 dataset – this is in contrast to other methods that have been trained using the AffWild2 dataset.

B. Sentimentality and Confusion

In AFFDEX 2.0, we introduce and detect two new affective states; sentimentality and confusion, as evoking those emotions is common across different contexts (e.g. watching ads and movies) [31]. Sentimentality and confusion models are built on the top of the AU predictions. In the following, we will clarify the dataset and models developed for sentimentality and confusion detection.

Datasets. Affectiva in collaboration with global market agencies have collected thousands of commercial ads. For
each ad, several participants were hired to watch the ad, and then fill a survey about how they feel about the ad. A consent was given by the participants to get video recorded while they were watching the ad. Out of the collected ads, experienced ad testers in Affectiva have selected 30 ads (15 sentimental and 15 non-sentimental), and 4.65K participants’ videos to form a dataset for sentimentality. Similarly, they have selected 40 ads (19 confusing and 21 non-confusing) and 7.2K participants’ videos for confusion analysis. The selected ads for sentimentality and confusion span different markets/countries and have participants with diverse demographics. Non-sentimental and non-confusing ads are typically informative, funny, or musical ads. The sentimental moments in the sentimental ads were labelled by 3 labellers, while for confusion it was hard to find and label specific confusing moments.

**Sentimentality Detection.** Sentimentality is detected by first analyzing the participants watching the ads using the face tracker and AU detector, and then the activation frequency of the different expressions (i.e. AUs and combinations of AUs) is compared across the sentimental and non-sentimental ads. The expressions are compared using the two ad-level KPIs introduced in [8]. The first KPI measures how separable is the aggregated sentimentality across sentimental and non-sentimental ads (named ROC-Ad), while the second measures if the aggregated sentimentality is firing high at the right sentimental moments (named ROC-Sent). The two KPIs are calculated on the top of the aggregated sentimentality across different ads. The KPI calculation is based on the area under the ROC curve (ROC-AUC).

By comparing the sentimental and non-sentimental ads, we found 12 combinations of AUs that are significant for sentimentality, those combinations include mostly Joy and sad related AUs. Sentimentality is considered active if any of those 12 combinations were active. We found that combining mainly positive expressions with negative expressions discriminates well sentimental from non-sentimental ads. Some partners used Inner brow raiser (AU1) of AFFDEX 1.0 as a sentimentality score. Table VI compares the performance of our model to the one achieved by using AU1 of AFFDEX 1.0 and 2.0. On average, our sentimentality model has better performance than the chance level and AU1. Figure 4 (top row) shows some of the detected sentimental faces by AFFDEX 2.0.

**Confusion Detection.** For confusion, we repeat the same processing steps used for sentimentality, where we compare the confusing and non-confusing ads in terms of different combinations of AUs, so as to highlight the significant combinations for confusion. We use for the analysis only one KPI (i.e. ROC-Ad), as it was hard to define specific confusing moments in the ads. Comparing the ads shows 6 combinations of AUs that are significant for confusion. In AFFDEX 2.0, the activation of any of those 6 combinations activates confusion. Two of these combinations have brow furrow (AU4), which is similar to other works that have shown a good relation between confusion and AU4 [16], [17]. Some partners used brow furrow (AU4) of AFFDEX 2.0 as a confusion score. Table VI shows the performance achieved by our confusion model and AU4 detected by AFFDEX 1.0 and 2.0. Our confusion model has better performance than the chance level and AU4. Figure 4 (bottom row) shows some of the detected confusing faces. Note that all the faces used in the figures belong to Affectiva employees who have been recorded while watching some ads. Both the sentimentality and confusion models shows promising qualitative and quantitative results.

### Other Expressive Metrics

In this section we focus on detecting some other expressive metrics. First, the **Blink** is detected when the eye closure (AU43) score gets above and then below a certain threshold during a specific time range. Second, the **Blink Rate** is calculated on the top of the blink output, and it is the number of blinks happening per minute. Third, the participants’ **Attention** is estimated by calculating the amount of time the participant spent looking at versus looking away from

![Fig. 4: The positive moments of sentimentality and confusion detected using AFFDEX 2.0.](image-url)
a screen, specifically turning the head left and right (i.e. yaw angle) is used for calculating attention. Fourth, Expressiveness is an overall score of the participant’s engagement. The more the face reacts, the more engaged is someone. Expressiveness is calculated as a normalized weighted sum of some upper face AUs (e.g. AU1, AU4) and lower face AUs (e.g. AU12, AU15). Finally, Valence is a score for measuring the intrinsic attractiveness or avereness of a situation, and is calculated based on the activation level of the positive expressions (e.g. AU6, AU12) versus the negative expressions (e.g. AU4, AU15).

D. Data Quality Metrics

AFFDEX 2.0 introduces five metrics for measuring the quality of the detected face images. First, the Mean Face Luminance measures how dark or bright is the detected face, and is calculated as the average pixel intensity across the detected face. Second, the Mean Face Luminance Diff LR measures the difference in luminance (i.e. mean pixel intensity) between the right and left parts of the face. Third, the Variance Face Luminance measures the contrast of the face by calculating the variance in the face pixel intensity. Fourth, the High Frequency Power measures the amount of noise available in the face image by summing the square of the high frequency components. Finally, the Inter Ocular Distance is the distance between the two eyes, and is calculated by measuring the normalised distance between the 2 landmarks located on the outer eye corners.

V. INTERFACE

AFFDEX 2.0 toolkit is available as an SDK for Windows and Linux platforms. The SDK allows easy integration of the software into other applications. The memory and computational power of a device can impacts the number of faces and frames that can get processed per second. On a Dell-5520 Precision laptop with i7-7820HQ CPU we can process on average ~62 video Frames per Second (FPS), and ~26-29 FPS using internal and USB webcams with 720p and 1080p resolutions. Figure 5 shows an example for a desktop demo. The SDK output highlights for each detected face the tracker output (the bounding box and head pose), and the confidence scores for the a) 20 AUs, b) 7 basic emotions, c) sentimentality and confusion, and d) other high-level metrics (e.g. blink and attention), as you can see in Figure 5.

VI. CONCLUSION

AFFDEX 2.0 is based on a new, more robust face tracker and AU detector, which has deep-based models trained and tested using a large-scale dataset. AFFDEX 2.0 improved the face tracking by ~3% and the AU detection performance by ~4%, compared to AFFDEX 1.0. The improved face coverage and AU detection performance is apparent across all demographic groups, and is reflected on the different high-level metrics (e.g. basic emotions, blink, attention). Comparing the performance of AFFDEX 2.0 to other methods in the literature shows that AFFDEX 2.0 achieves the state-of-the-art results in AU detection and emotion recognition.

Fig. 5: Screenshot of the real-time multi-face expression analysis of AFFDEX 2.0.

AFFDEX 2.0 also introduces and detects two new emotional states; sentimentality and confusion. Furthermore, AFFDEX 2.0 can process multiple faces in real time, and is working across 2 different platforms (Linux and Windows).

REFERENCES

[1] T. Baltrusaitis, M. Mahmoud, and P. Robinson. Cross-dataset learning and person-specific normalisation for automatic action unit detection. In 2015 11th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG), volume 6, pages 1–6. IEEE, 2015.
[2] M. S. Banllett et al. Real time face detection and facial expression recognition: development and applications to human computer interaction. In 2003 Conference on computer vision and pattern recognition workshop, volume 5, pages 53–53. IEEE, 2003.
[3] M. Bishay, A. Ghoneim, M. Ashraf, and M. Mavadati. Choose settings carefully: Comparing action unit detection at different settings using a large-scale dataset. In 2021 IEEE International Conference on Image Processing (ICIP), pages 2883–2887. IEEE, 2021.
[4] M. Bishay, A. Ghoneim, M. Ashraf, and M. Mavadati. Which cnns and training settings to choose for action unit detection? a study based on a large-scale dataset. arXiv preprint arXiv:2111.08320, 2021.
[5] M. Bishay, P. Palasek, et al. Schinet: Automatic estimation of symptoms of schizophrenia from facial behaviour analysis. IEEE Transactions on Affective Computing, 2019.
[6] M. Bishay and I. Patras. Fusing multilabel deep networks for facial action unit detection. In 2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017), pages 681–688. IEEE, 2017.
[7] M. Bishay, S. Priebe, and I. Patras. Can automatic facial expression analysis be used for treatment outcome estimation in schizophrenia? In ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 1652–1656. IEEE, 2019.
[8] M. Bishay, J. Turcot, G. Page, and M. Mavadati. Automatic detection of sentimentality from facial expressions. In 2022 IEEE International Conference on Image Processing (ICIP), pages 321–325. IEEE, 2022.
[9] C. Corneanu, M. Madadi, and S. Escalera. Deep structure inference network for facial action unit recognition. In Proceedings of the european conference on computer vision (ECCV), pages 298–313, 2018.
[10] D. Dai, A. U. Nambi, C. Jawahar, and V. Padmanabhan. Autorate: How attentive is the driver? In 2019 14th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2019), pages 1–8. IEEE, 2019.
[11] N. Effremova, N. Hajimirza, D. Bassett, and F. Thomaz. Understanding consumer attention on mobile devices. In 2020 15th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2020), pages 919–919. IEEE, 2020.
[12] P. Ekman and E. L. Rosenberg. What the face reveals: Basic and applied studies of spontaneous expression using the Facial Action Coding System (FACS). Oxford University Press, USA, 1997.
