Exploring Facial Expressions and Affective Domains for Parkinson Detection

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Abstract—Parkinson’s Disease (PD) is a neurological disorder that affects facial movements and non-verbal communication. Patients with PD present a reduction in facial movements called hypomimia which is evaluated in item 3.2 of the MDS-UPDRS-III scale. In this work, we propose to use facial expression analysis from face images based on affective domains to improve PD detection. We propose different domain adaptation techniques to exploit the latest advances in face recognition and Face Action Unit (FAU) detection. The principal contributions of this work are: (1) a novel framework to exploit deep face architectures to model hypomimia in PD patients; (2) we experimentally compare PD detection based on single images vs. image sequences while the patients are evoked various face expressions; (3) we explore different domain adaptation techniques to exploit existing models initially trained either for Face Recognition or to detect FAUs for the automatic discrimination between PD patients and healthy subjects; and (4) a new approach to use triplet-loss learning to improve hypomimia modeling and PD detection. The results on real face images from PD patients show that we are able to properly model evoked emotions using image sequences (neutral, onset-transition, apex, offset-transition, and neutral) with accuracy improvements up to 5.5% (from 72.9% to 78.4%) with respect to single-image PD detection. We also show that our proposed affective-domain adaptation provides improvements in PD detection up to 8.9% (from 78.4% to 87.3% detection accuracy).

Index Terms—Parkinson’s disease, Hypomimia, Facial expressions, Face Action Unit, Affective domains, Triplet loss.

1 INTRODUCTION

Parkinson’s Disease (PD) is a neurological disorder characterized by motor and non-motor impairments that affects between 1 and 2 percent of people over 65 years old [7]. Motor deficits include bradykinesia, rigidity, postural instability, tremor, and dysarthria; and non-motor deficits include depression, anxiety, sleep disorders, and slowing of thought. Besides the extensive list of symptoms, most patients with PD exhibit also difficulties to express emotions or specific expressions on their faces. Possible signs of those abnormalities include less range of facial muscle movement, wider opening of eyes, half-open mouth, and slower blinking. All of these phenomena in their facial expression are grouped in the literature and called hypomimia [5], which is the result of motor impairments at the facial muscles level. It is typically not noticed in early stages of PD, but once there is a significant deterioration, orofacial movements are highly reduced which can result in expressionless faces, with a very limited capability to smile, to express other emotions or feelings like happiness, sadness, anger, fear, disgust, and surprise [13]. The main effect of these impairments is in difficulties with non-verbal communication which also produces social isolation in a mid to long term.

Clinical evaluation of PD patients is mainly performed by expert neurologists according to the Movement Disorder Society - Unified Parkinson’s Disease Rating Scale (MDS-UPDRS) [22]. This scale is the global standard for the clinical evaluation of PD patients and it considers both motor and non-motor symptoms. Items of the MDS-UPDRS scale range between 0 and 4, where 0 means completely healthy and 4 means completely impaired. Section III in MDS-UPDRS has a maximum value of 132 and covers motor examination including facial expression in one item. According to the guidelines given by the Movement Disorder Society, the five levels of the item where hypomimia is evaluated can be used to assess facial expressions in PD patients [22]. The following list indicates the correspondence between possible values of the item and their meaning in terms of facial expression evaluation:

0) Normal: Normal facial expression.
1) Slight: Minimal masked facies manifested only by decreased frequency of blinking.
2) Mild: In addition to decreased eye-blink frequency, masked facies present in the lower face as well, namely fewer movements around the mouth, such as less spontaneous smiling, but lips not parted.
3) Moderate: Masked facies with lips parted some of the time when the mouth is at rest.
4) Severe: Masked facies with lips parted most of the time when the mouth is at rest.

Neurological evaluation highly depends on the clinician’s expertise, which causes variability and possible bias in the rating procedure. Therefore, the development of computerized systems to objectively support the evaluation of the disease progression is now growing in importance. There are several contributions in the state of the art where computerized systems are introduced to evaluate different aspects of Parkinson’s patients including speech [35, 34], gait [20, 12], handwriting [45, 9, 16, 11], hands movement [49], and facial expression [4]. Among all, facial expression and hypomimia seem to be the least covered. Facial Expression Recognition (FER) refers to the evaluation of the capability of PD patients to effectively recognize different expressions or emotions when watching at faces. Facial Expressivity Evaluation (FEE) refers to the capability of the patient to produce different facial expressions or emotions. Both aspects have a very important role in social
interaction and non-verbal communication. The first one has been studied for several decades mainly by psychologists in different works and the main findings are summarized in a relatively recent study [3]. On the other hand, FEE has become a popular field among engineers and computer scientists, which opens space for research in different applications related to Affective computing.

During the past two decades, the Affective computing community has made great advances in developing novel technologies to model facial expressions and emotional information [39, 32, 42]. One of the goals of affective technologies is to create computational models with the ability to recognize, interpret, and process human emotions, making human-computer interaction more useful. Sentiment analysis and affective computing have been continuously studied since the 20th century, helping in the development of computer vision systems [10, 31, 26], in the creation of entertainment [41], and in the development of systems to aid different areas of medicine including neurology [52, 28, 37].

Our work is focused on the study of FEE in PD patients, the main aim is to consider videos collected from patients to evaluate their capability to produce specific emotions and to compare such a capability with respect to healthy subjects using recent advances in Affective domains.

2 Related Works

One of the earliest studies about FEE in PD patients was conducted in 2004 by Simons et al. [46]. The authors evaluated the capability of 19 PD patients and 25 healthy subjects to pose and imitate different facial expressions. Videos with social interactions were used to evoke emotional responses in the patients faces. The videos were manually analyzed and the participants’ expressiveness was rated according to subjective rating scales, objective facial measurements, and self-questionnaires. The objective measurement was based on the facial action coding system presented in [19], where the facial expression is decomposed according to specific facial muscle movements like rising eyebrows and wrinkling the nose. The results of the study indicated that patients with PD have reduced capability to produce spontaneous facial expressions in all experimental situations. Two years later in [6], the authors presented a work where expressivity and bradykinesia were studied. The authors hypothesized that intentional facial expressions are slowed (bradykinetic) and with less movement in PD patients than in healthy controls. This hypothesis was basically inspired in other intentional movements performed by PD patients, e.g., walking, where bradykinesia is also observed. Digitized videos were evaluated frame-by-frame and the entropy in temporal changes of pixel intensity was measured [44]. The authors found that PD patients had reduced entropy compared to healthy controls, and were significantly slower in reaching a peak expression ($p < 0.0001$), which is directly associated to bradykinesia.

In 2016 Almutiry et al. [2] presented perhaps the only longitudinal study about FEE in PD patients. A total of 8 subjects (4 PD and 4 healthy controls) participated in the study. Patients were recorded for five days per week (once per day) during six weeks while controls were recorded for five days within one week. Participants were requested to produce specific facial expressions while being recorded. The authors used two classical feature extraction methods to localise 27 facial features: Active Appearance Model (AAM) and Constrained Local Model (CLM). The results suggested that PD patients exhibit less movement than controls, which confirms the observations made ten years earlier by Bowers et al. [6].

In 2017, Gunnery et al. [27] studied the coordination of movements across regions of the face in 8 PD patients (4 female). They used the facial action coding system [19, 14] to measure spontaneous facial expressions. The number of activated frames per action unit and their intensity was manually labeled. Correlations were computed for activation values obtained across different regions of the face. The results showed that as severity of facial expression deficit increased, there was a decrease in number, duration, intensity, and co-activation of facial muscle action. In the same year, Bandini et al. [4] classified emotions expressed by 17 PD patients (13 male) and equal number of healthy controls (6 male). Different emotions were evaluated including happiness, anger, disgust, and sadness. Different areas of the face were modeled with 49 landmarks [50, 24], including: eyes, eyebrows, mouth, and nose. A total of 20 features were extracted to define a linear combination of specific reference points. Acted and imitated facial expressions were considered. An SVM was trained to automatically detect different emotions expressed by participants. The results with imitated expressions showed higher accuracies for healthy controls in most of the emotions. The only case where the PD patients displayed an expression better than the healthy subjects was sadness. When acted expressions were evaluated, the authors found also higher accuracies for healthy subjects than for PD patients.

Other contributions in the topic of FEE in PD include the study of Kang et al. [30]. The authors evaluated whether deficiencies in the orofacial movements of PD patients occur in spontaneous and voluntary expressions. Muscular activation (related with specific regions in the face) were studied considering electro-myography signals. Data from the East Asian Dynamic Facial Expression Stimuli (EAD-FES) database was used [33]. A group with 20 PD patients and 20 healthy controls was evaluated; the authors report limitations of patients to express emotions spontaneously, although the observed dynamics in the movement of the face are similar across all subjects. The study also highlighted the deterioration in the patient’s quality of life due to the presence of “masked face”, affecting social and psychological aspects and increasing their risk to develop depression-related symptoms.

More recently, in another line of work, Grammatikopoulou et al. [25] analyzed facial expressions from images captured with smartphones. Geometric features of the face were extracted and stored in the cloud. A total of 34 participants were recruited, 23 with PD and 11 healthy controls. Patients were divided into three groups according to the facial expression score of the MDS-UPDRS-III scale. The authors extracted two feature sets: one by using the Google Face API and the other one using the Microsoft Face API [23]. The feature sets were composed by reference points on the faces, then two linear regression models were
developed (one per feature set) to estimate two different values of the Hypomimia Severity index, namely HSi1 and HSi2. These two indexes were used to classify between Parkinson’s patients and healthy people. The reported sensitivity and specificity values were 0.79 and 0.82, respectively for HSi1 while 0.89 and 0.73 for HSi2. In 2020 Sonawane and Sharma [48] presented a review of automatic techniques and the use of machine learning in detecting emotional facial expressions in PD patients. The authors show that the use of deep learning in this field has not been adequately addressed yet in the classification between healthy people and PD patients. Also, they conducted a pilot experiment based on the use of one CNN from scratch for masked faces detection. The pilot experiment shows that deep learning-based models can be very useful to perform the classification.

2.1 Contributions of this Work

As shown in the literature review, there is a lack of work in the field of FEE for modeling hypomimia in Parkinson’s Disease (PD) patients with latest affective models including deep learning techniques. One of the main reasons for this lack of deep approaches is the absence of large scale databases with Parkinson’s Disease patients. In contrast, Face Recognition and Affective Computing research communities have made great efforts to release databases with millions of samples. In this work, we propose to use facial expression analysis and Affective domains to improve the PD detection. We propose different domain adaptation techniques [18] [47] to exploit the latest developments in face recognition and Face Action Unit (FAU) detection [43].

The main contributions of this paper are: (1) a novel framework to exploit deep face architectures to model hypomimia in PD patients; (2) we experimentally compare PD detection based on single images vs. image sequences while the patients are evoked various face expressions; (3) we explore different domain adaptation techniques to exploit existing models initially trained either for Face Recognition or to detect FAUs for the automatic discrimination between PD patients and healthy subjects; and (4) a new approach to use triplet-loss learning to improve hypomimia modeling and PD detection.

3 EXPERIMENTAL FRAMEWORK

Let’s assume that $w_{FR}$ is a model trained for Face Recognition tasks and the representation $x_{FR}$ is a feature vector generated by the model (typically from the last layers of a Convolutional Neural Network) from an input face image. This representation $x_{FR}$ is learned to describe the face image in a projected space where faces from the same person remain closer than faces from different persons. Similarly, models and representations can be trained for different tasks such as Affect recognition ($w_{AF}$) (e.g., in the form of facial gestures) or Parkinson’s Disease detection ($w_{PD}$). Domain adaptation refers to methods that serve to adapt a representation $x_A$ trained for the domain A to a new domain B (typically a domain with similar characteristics to A but less information to train). The resulting representation $x_B$, adapted from $x_A$, is expected to perform better than a representation trained from scratch for the domain B.

We propose an experimental framework where Affective features are explored at different levels (or domains). The list of domains and the corresponding underlying hypotheses to be explored are presented below. (See also Figure 1).

Face Recognition Domain (Level 1). Our acquisition protocol introduces emotional tasks including evoked emotional states (smiling, anger, and surprise) and coordinated face gestures (right eye wink, left eye wink):

- Hypothesis (H1): evoked responses intensify the features necessary to model hypomimia in Parkinson’s patients. The representation $x_{FR}$ can be improved by incorporating different facial gestures during the acquisition protocol.

- Experiment: we evaluate the performance of PD detection for different sequences of face gestures using pre-trained Face Recognition models ($w_{FR}$ trained with VGGFace2 [8]).

Affective Domain (Level 2). We propose to improve the learned Face Recognition representations ($x_{FR}$) for Parkinson Detection by incorporating an Affective domain adaptation $w_{AF}$ training process:

- Hypothesis (H2): automatic detection of hypomimia is improved when features from the emotion domain are incorporated to the representations. The representation $x_{AF}$ performs better for Parkinson Detection than the representation $x_{FR}$.

- Experiment: the pre-trained models ($w_{FR}$) are adapted to the Affective domain ($w_{AF}$) using the EmotioNet database [15] and FAU detection. Both, the performance of $x_{FR}$ and $x_{AF}$ are evaluated for Parkinson Detection.

Parkinson Domain (Level 3). We evaluate the performance obtained by representations $x_{PD}$ trained with Healthy and Parkinson patients and the Triplet Loss function:

- Hypothesis (H3.1): similarity learning functions designed to enhance the Parkinson features can serve to improve the capability to detect hypomimia. Experiment: the Affective model ($w_{AF}$) is adapted to the Parkinson domain using the Triplet Loss function and the FacePark-GITA database (see Section 3.1.3 for details).

The best performing facial representations are also used to classify patients with different levels of neurological impairment according to the MDS-UPDRS-III scores:

- Hypothesis (H3.2): facial representations learned in previous models have information to identify and evaluate different levels of neurological impairment in Parkinson’s Disease patients.

- Experiment: models created to represent hypomimia are used to evaluate three different neurological states according to the MDS-UPDRS-III scores.

Details of the methods implemented to validate all hypotheses are presented in Section 3.2.
3.1 Databases

Three different databases are considered in this work. VGGFace2 [8] and EmotioNet [15] which are popular for Face Recognition and Face Action Unit detection, respectively. The third one is a new database composed by PD patients and healthy subjects. It contains face videos of patients suffering from Parkinson’s disease and age-matched healthy controls. This new corpus is called FacePark-GITA. Details of each database are presented below.

3.1.1 Face Recognition Domain: VGGFace2

This database comprises more than 3.31 million faces from 9,131 different subjects. An average of 362.6 images per subject are included [8]. The images were downloaded from Google Image Search. The corpus has large variations in pose, age, lighting, ethnicity, and profession. This database is popular in the Face Recognition community and it has been extensively used to train competitive recognition models [40, 29].

3.1.2 Affective Domain: EmotioNet

This database was originally introduced by researchers from the Ohio State University who released the EmotioNet Challenge in 2017 [15]. This database contains one million facial expression images collected from the Internet. A total of 950,000 images were annotated by the automatic Action Unit (AU) detection model presented in [15], and the remaining 50,000 images were manually annotated by experts. A total of 12 AUs are included in the corpus.

3.1.3 Parkinson Domain: FacePark-GITA

The database was created by GITA Lab. The recording of patients is still ongoing and the most updated version of the corpus contains video recordings of 24 healthy participants and 30 PD patients. The videos were recorded at 30 frames per second in non-controlled environment conditions, i.e., light conditions and the background were not controlled prior the recording and differ among participants. PD patients were diagnosed by a neurologist expert and were

Table 1: Demographic and clinical information of the participants included in the FacePark-GITA database.

|                  | PD patients | Healthy participants |
|------------------|-------------|----------------------|
| # of Participants| 18          | 12                   |
| # of Participants| 12          | 12                   |
| # of Participants| 12          | 12                   |
| Age [years]      | 70.2 ± 10.4 | 67.4 ± 10.9          |
| Age range [years]| 52 – 90    | 53 – 87              |
| t [years]        | 8.7 ± 5.4  | 15.6 ± 17.3          |
| t range [years]  | 2 – 20     | 1 – 45               |
| MDS-UPDRS-III    | 35.4 ± 13.9| 29.7 ± 12.3          |
| MDS-UPDRS-III    | 16 – 65    | 15 – 54              |
| H&Y              | 2.3 ± 0.5  | 2.5 ± 0.5            |
| H&Y range        | 2 – 3      | 2 – 3                |

MDS-UPDRS: Movement Disorder Society - Unified Parkinson’s Disease Rating Scale. H&Y: Hoehn & Yahr scale. t: Years since diagnosis
evaluated according to the MDS-UPDRS-III scale and the Hoehn and Yahr scale (H&Y) [21]. A summary of the clinical and demographic information is presented in Table 1. All participants gave written informed consent. The study is in accordance with the Declaration of Helsinki and it was approved by the Ethical Research Committee at the University of Antioquia.

The participants of this study were asked to produce different facial expressions while being recorded. A total of five video-task recordings are included: right eye wink, left eye wink, smile, anger, and surprise. The average duration of each video is 6 seconds. Patients have an average age of 69 years old and healthy subjects were chosen with a similar range of age. Possible bias introduced by age or gender were discarded via a chi-square statistical test ($p = 0.44$) and a Welch’s t-test ($p = 0.15$), respectively.

3.2 Methods

3.2.1 Face Recognition pre-trained model

In this work we employ the ResNet50 architecture [29], with 50 layers and 25.6M parameters. This model is used to generate an initial face representation.
was originally proposed for general image recognition tasks and later it was retrained with the VGGFace2 database [8] for Face Recognition. The model is used as feature extractor by removing the final decision layer. For each face image, the model generates a $1 \times 2048$ feature vector.

In our experiments we apply Transfer Learning (TL) [38] to adapt from one domain to another (e.g. from Face Recognition to the Affective domain). TL are methods where weights from a model originally learned for one task are used as initialization before adjusting the model for a different task. One of the transfer learning techniques consists in freezing intermediate and initial layers to retain their capability to extract general characteristics and retrain the last layers closer to the network output. Re-training of those last layers allows to adapt the original feature space for the new task. These methods are suitable for problems where data is scarce and end-to-end learning approaches fail to find the optimal feature space. The number and size of available databases to model hypomimia in patients suffering from PD are very small (typically less than 100 subjects and less than 1,000 images in total), so we expect that TL techniques will be very useful here to adapt to the Parkinson domain from the Face Recognition domain, where massive datasets are available for learning (millions of images).

### 3.2.2 Face Action Unit detection models

In addition to the ResNet50 Face Recognition model, in this work we employ two deep neural networks trained from scratch for Face Action Unit (FAU) detection. The architectures employed are based on the popular VGG and ResNet models [53, 43]. The details of the two models are described below:

**VGG-8**: This model contains 8 convolutional layers divided into groups of 2 layers. Each group is followed by a Max pooling layer. Convolutional layers apply a variety of filters to the images and Max-Pooling layers reduce the size of the filtered images. Additionally, dropout is used in the regularization layers to randomly discard neurons in the model and make it less prone to overfitting. The final part of the architecture has a total of 6 convolutional layers (fully-connected) before the decision layer. The number of neurons per layer is 1024, 512, 256, 128, 64, and 32. The number of parameters of this model is 295,448.

**ResNet-7**: The ResNet model is composed of a total of 7 residual blocks. Each block can be defined as an identity-block or a conv-block. The identity-blocks are the standard blocks used in ResNet, they have a set of convolutional filters and a shortcut connection which bypasses these blocks. This block has the same input and output dimensions. Conv-blocks are the block types where the input and output dimensions do not match. The difference with the identity-block is a convolutional layer in the shortcut to the output. The benefit of these architectures is that in traditional architectures by having a high amount of layers in the training, the problem of error degradation appears. ResNet models with their previous layer shortcut connections are effective in solving this problem [29]. The number of parameters of this model is 366,026.

### 3.2.3 Affective Triplet Loss

Due to the limited number of samples in the FacePark-GITA database, for the Parkinson domain adaptation we opted for a Triplet Loss learning approach. The Triplet Loss function consists in applying a linear transformation over the data before taking the distance among samples. Given a training data set $S = \{(x_i, y_i)\}$ with inputs $x_i \in \mathbb{R}^d$ and discrete class labels $y_i \in \mathbb{Z}$, the goal is to find a transformation to the input data such that reduces the distance between pairs from the same class while increases the distance between pairs from different classes. The Mahalanobis distance defined in Equation 1 is the similarity measure used in this work.

$$d_M^2(x_i, x_j) = (x_i - x_j)^T M (x_i - x_j)$$  \hspace{1cm} (1)

where $M$ is a positive semi-defined symmetric matrix that can be decomposed as $M = T^T T$, where $T$ denotes a linear transformation matrix. Equation 1 can be rewritten as:

$$d_M^2(x_i, x_j) = \|T(x_i - x_j)\|_2^2 = \|x'_i - x'_j\|_2^2$$  \hspace{1cm} (2)

The linear transformation $T$ can be generalized as $\Phi(x_i)$, where $\Phi$ indicates a kernel function. The resulting distance metric is as follows:

$$d_M^2(x_i, x_j) = \|\Phi(x_i) - \Phi(x_j)\|_2^2$$  \hspace{1cm} (3)

The process to determine the transformed vector $\Phi(x_i)$ requires to find a transformation that makes the intra-class distance smaller than the inter-class distance. The general rule which is applied over the data set consists in the following triplets $S_T$:

$$S_T = \{(x^a, y^a), (x^n, y^n), (x^p, y^p) | y^a = y^p, y^a \neq y^n\}$$  \hspace{1cm} (5)

where $a, p$ are samples belonging to the same class, and $n$ is a sample from a different class. In our Parkinson detection experiments, the number of classes is two (healthy and Parkinson). However, we propose to introduce an additional restriction in the triplet. In our experiments, $a, p$ belong to the same class, but present different face expression. In this way, we introduce facial gestures into the learning objective. The generation of the triplet $S_T$ can be seen as a data augmentation technique. The high number of possible combinations of three elements in a dataset enriches the training process, especially when low number of samples are available. The triple loss function to be minimized is defined as:

$$\mathcal{L} = \sum_{S_T} [d_M^2(x^a, x^p) - d_M^2(x^a, x^n) + \alpha]_+$$  \hspace{1cm} (6)

where $[z]_+ = \max(z, 0)$, and $\alpha \geq 0$ is the minimum margin required between classes.

### 3.3 Classification and Parameter Optimization

The automatic classification between healthy people and PD patients is performed using Support Vector Machines (SVMs). The classification of patients with different degree of impairment is performed using SVMs
4 EXPERIMENTS AND RESULTS

FacePark-GITA includes 5 videos for each participant. Each video corresponds to a different facial expression: smile, anger, surprise, left eye wink, and right eye wink. Five frames per video-task were extracted with the software Affectiva. The curve of valence provided by the software is used as the criterion to select the following sequence of five images/frames per participant on each expression: (i) Neutral; (ii) transition from Neutral to the Apex (i.e., onset); (iii) Apex; (iv) transition from the Apex to Neutral (i.e., offset); and (v) Neutral. The sequence of images and their direct relation with the valence curve are illustrated in Figure 2.

4.1 Experiment 1: Face Recognition Domain

4.1.1 PD detection based on single face images

Individual frames corresponding to each valence level shown in Figure 2 are considered to evaluate whether specific frames provide relevant information to discriminate between PD patients and healthy subjects. Feature vectors are obtained from the last layer of the ResNet-50 model (see Section 3.2.1). Table 2 summarizes the results.

Table 2: Results of the classification using a single image from the extracted image sequence.

| S.E. | Kernel* | Accl [%] | Sens [%] | Spec [%] | F1 [%] |
|------|---------|----------|----------|----------|--------|
| Neutral | C=1e+01; γ=1e-04 | 69.0 ± 10.1 | 74.0 ± 11.6 | 63.0 ± 9.7 | 67.8 ± 10.1 |
| Apex | C=1e+01; γ=1e-04 | 70.0 ± 9.1 | 84.4 ± 7.4 | 53.3 ± 24.0 | 61.0 ± 18.6 |
| Onset | C=1e+01; γ=1e-04 | 71.4 ± 3.2 | 88.6 ± 7.0 | 50.0 ± 9.0 | 63.1 ± 6.6 |
| Offset | C=1e+01; γ=1e-04 | 71.6 ± 5.2 | 79.5 ± 3.3 | 61.9 ± 13.5 | 68.6 ± 8.2 |
| Neutral | C=1e-03 | 70.8 ± 9.6 | 77.3 ± 10.2 | 63.0 ± 9.7 | 69.3 ± 9.7 |
| Apex | C=1e-03 | 70.8 ± 9.1 | 83.7 ± 7.3 | 55.7 ± 21.6 | 63.8 ± 16.3 |
| Onset | C=1e-02 | 72.9 ± 4.2 | 88.6 ± 7.8 | 53.4 ± 7.7 | 66.1 ± 5.9 |
| Offset | C=1e-01 | 72.8 ± 4.3 | 81.5 ± 4.5 | 61.9 ± 13.5 | 69.2 ± 7.9 |

*Column with optimal hyper-parameters.

Note that there is almost no difference among the accuracies obtained with the frames of each expression stage.

1. https://www.affectiva.com/
4.2 Experiment 2: Affective Domain

This experiment intends to incorporate information from the Affective domain to improve Parkinson’s Disease (PD) detection. In this case the EmotioNet database is used to create an appropriate facial representation space. The first step consists in selecting AUs that provide suitable information to perform the automatic classification between PD patients and healthy subjects. We selected a subset of AUs according to [14] adequate for the facial expressions included in the recording tasks of the FacePark-GITA database. Figure 3 shows the set of selected AUs.

4.2.1 Adaptation from Face Recognition models

The process to adapt the convolutional models from one domain to another consists in freezing different percentages of the layers and retraining the remaining portion. The data with the selected AUs from the EmotioNet dataset are used here to retrain the models. In this case we evaluate three percentages of layers frozen during the retraining of the ResNet50 model (originally trained for Face Recognition): freezing 50% (Freeze 50), freezing 75% (Freeze 75), and freezing 100%. Note that the freezing 100% model is taken as the Baseline and corresponds to the case where no affective information is incorporated ($x_{FR}$). After the convolutional layers, a fully connected layer is added for the classification of the 8 selected AUs (see Figure 3). The result of the retraining process and its performance to classify the AUs is shown in Table 4 in terms of AUC and EER values. The accuracy varies depending of the FAU and the percentage of layers frozen. The FAUs numbers 6, 12, and 25 reached accuracies around 90%, while the rest of the FAUs achieved performances around 80%.

The representations $x_{AF}$ obtained by the retrained models are further used to classify between PD patients and healthy subjects of the FacePark-GITA corpus. The results obtained with the Freeze 75 and Freeze 50 models are shown in Table 5 and Table 6, respectively. The results for the Baseline model correspond to those previously shown in Table 3. Optimal hyper-parameters found in the 5-fold cross-validation process are also included in every experiment.

Note that the Freeze 75 exhibits higher accuracies than the Freeze 50, indicating that considerable information from the Face Recognition domain is still useful to obtain good results in the classification between PD patients and healthy subjects. More interestingly, note that the best accuracy obtained with the Freeze 75 model in Table 5 (87.3%) is 8.9% higher than the best result obtained when only a Face Recognition model is considered (Table 3). This result supports our second hypothesis (H2), the idea of incorporating information from the Affective domain to the Face Recognition domain to improve detection of hypomimia in PD patients. The benefits of including information of the Affective domain are also shown in Figure 4, where the ROC curves obtained with the Freeze 75, Freeze 50, and Baseline models are presented.

Note that the models used until this point of the study are based on architectures originally trained for Face Recognition tasks (ResNet50). Now we want to evaluate the importance of this initialization based on a Face Recognition training processes.
The previous scenario studied the performance of pre-trained models with high number of parameters learned from the Face Recognition domain after adaptation to the Affective domain. In this section we will train FAU detection models from scratch. ResNet50 requires to optimize more than 20M parameters. Conversely, the VGG-8 and ResNet-7 architectures proposed in Section 3.2.2 require the optimization of 295,448 and 366,026 parameters respectively.

### 4.2.2 Training Affective models from scratch

The previous scenario studied the performance of pre-trained models with high number of parameters learned from the Face Recognition domain after adaptation to the Affective domain. In this section we will train FAU detection models from scratch. ResNet50 requires to optimize more than 20M parameters. Conversely, the VGG-8 and ResNet-7 architectures proposed in Section 3.2.2 require the optimization of 295,448 and 366,026 parameters respectively.
Figure 5: Comparison between PD classification ROC curves obtained using the NOnAOffN sequence in the Freeze 75, ResNet-7 and VGG-8.

Table 9: PD classification results using the ResNet-7 model.

| Sequence   | Kernel* | Acc[%] | Sens[%] | Spec[%] | F1[%] |
|------------|---------|--------|---------|---------|-------|
| NOnA       | C=1e+03, γ=1e-04 | 73.0 ± 9.5 | 75.9 ± 18.7 | 69.7 ± 17.8 | 68.9 ± 12.3 |
| AOffN      | C=1e+01, γ=1e-02 | 73.4 ± 9.9 | 81.7 ± 15.6 | 63.6 ± 8.9 | 70.5 ± 9.5 |
| NOnAOffN   | C=1e+03, γ=1e-04 | 78.8 ± 6.4 | 79.3 ± 9.8 | 78.2 ± 12.8 | 77.6 ± 6.7 |
| NOnA       | C=1e-02 | 74.1 ± 6.9 | 82.2 ± 19.4 | 64.5 ± 11.4 | 69.3 ± 6.1 |
| AOffN      | C=1e-02 | 72.4 ± 10.8 | 84.2 ± 16.5 | 58.2 ± 8.6 | 68.1 ± 9.6 |
| NOnAOffN   | C=1e-01 | 78.3 ± 7.3 | 80.1 ± 10.6 | 76.2 ± 10.1 | 77.3 ± 7.4 |

First three rows: Gaussian kernel. Last three rows: Linear kernel.
*Column with optimal hyper-parameters.

Table 10: PD classification results of classification with the Triplet 75 model.

| Sequence   | Kernel* | Acc[%] | Sens[%] | Spec[%] | F1[%] |
|------------|---------|--------|---------|---------|-------|
| NOnA       | C=1e+01, γ=1e-04 | 85.2 ± 7.4 | 87.6 ± 5.8 | 82.5 ± 12.6 | 84.5 ± 8.2 |
| AOffN      | C=1e+01, γ=1e-04 | 86.0 ± 6.1 | 91.4 ± 6.9 | 79.5 ± 7.1 | 84.9 ± 6.2 |
| NOnAOffN   | C=1e+01, γ=1e-04 | 86.0 ± 9.0 | 92.1 ± 6.9 | 78.7 ± 13.4 | 84.5 ± 10.1 |
| NOnA       | C=1e-01 | 84.4 ± 6.6 | 87.2 ± 4.4 | 78.9 ± 13.3 | 83.4 ± 7.6 |
| AOffN      | C=1e-01 | 85.9 ± 5.9 | 90.3 ± 6.4 | 78.7 ± 7.1 | 84.0 ± 6.1 |
| NOnAOffN   | C=1e-01 | 86.1 ± 9.5 | 91.4 ± 7.5 | 79.9 ± 13.5 | 85.0 ± 10.5 |

First three rows: Gaussian kernel. Last three rows: Linear kernel.
*Column with optimal hyper-parameters.

Table 11: PD classification results of classification with the Triplet 50 model.

| Sequence   | Kernel* | Acc[%] | Sens[%] | Spec[%] | F1[%] |
|------------|---------|--------|---------|---------|-------|
| NOnA       | C=1e+01, γ=1e-04 | 78.9 ± 5.5 | 84.3 ± 10.9 | 72.4 ± 11.3 | 76.7 ± 6.1 |
| AOffN      | C=1e+01, γ=1e-04 | 73.2 ± 8.7 | 69.1 ± 16.9 | 78.3 ± 4.0 | 72.2 ± 8.3 |
| NOnAOffN   | C=1e+02, γ=1e-04 | 75.8 ± 11.8 | 77.4 ± 15.5 | 74.3 ± 16.2 | 74.2 ± 10.5 |
| NOnA       | C=1e-01 | 80.7 ± 6.6 | 86.4 ± 13.2 | 73.9 ± 11.8 | 78.3 ± 7.4 |
| AOffN      | C=1e-01 | 76.3 ± 8.7 | 79.1 ± 17.4 | 73.3 ± 7.4 | 74.5 ± 8.6 |
| NOnAOffN   | C=1e-01 | 77.1 ± 10.2 | 83.0 ± 10.7 | 69.9 ± 19.8 | 73.9 ± 13.2 |

First three rows: Gaussian kernel. Last three rows: Linear kernel.
*Column with optimal hyper-parameters.

Table 8 and Table 9 show the results obtained when the aforementioned models, created with the reduced architectures, are used to discriminate between PD patients and healthy subjects. Note that no additional training is performed with data from Parkinson’s disease patients. The best results are obtained when the ResNet-7 architecture is considered with features extracted from the NOnAOffN sequence. Although 78.3% could be considered a good accuracy, it is still far from the best result obtained with the ResNet50 Freeze 75 model (87.3%) in Table 5, indicating that the FAU domain is missing certain features present in the Face Recognition domain.

Figure 5 shows three ROC curves where results with Freeze 75, ResNet-7, and VGG-8 are compared. The superiority of the Freeze 75 model is clearly observed, supporting the advantages of initializing the models using the Face Recognition domain.

4.3 Experiment 3: Parkinson Domain (PD Detection)

The triplet loss function is explored for learning in this experiment with the aim to evaluate whether the classification performance of PD patients vs. Healthy Control (HC) subjects can be improved with respect to previous experiments. The triplet loss function modifies the original representation space such that the inter-class separability is increased while the intra-class separability is reduced. The modified feature vectors are called *embedded vectors*.

4.3.1 Triplet Loss in Face Recognition models adapted to the Affective domain

The Freeze 75 and Freeze 50 models are trained with the triplet loss function strategy and two new models are obtained, namely Triplet 75 and Triplet 50, respectively. The FacePark-GITA database is divided into a 5-fold partition for the training of each Triplet model and the SVM classifier. The classification results obtained when using the embedded vectors are shown in Table 10 for the Triplet 75 model, and in Table 11 for the Triplet 50 model.

Note that the Triplet 75 model exhibits better accuracy (86.0%) than the Triplet 50 (80.7%). Since the best accuracies in the previous experiments with the Freeze 75 and Freeze 50 models were 87.3% and 83.1%, these new results obtained with the triplet loss strategy likely indicate that the embedding approach does not provide advantages over the use of transfer learning and freezing of layers. This observation is also supported in the fact that the number of parameters to be optimized has not been reduced, so in principle, there is no reason for using the triplet loss function in these two scenarios.

4.3.2 Triplet Loss in FAU detection trained from scratch

In this experiment the VGG-8 and ResNet-7 models are retrained considering the triplet loss function, creating two new models, namely Triplet-VGG8 and Triplet-ResNet7, respectively. These new models are used to extract embedded vectors for further classification between PD patients and healthy subjects. The results obtained with the Triplet-VGG8 and Triplet-ResNet7 embedded vectors are shown in Table 12 and Table 13, respectively.

Note that there is an improvement in both models compared to those based on VGG-8 and ResNet-7 where the triplet loss function was not applied. In the first case the improvement is around 5.1% (from 67.6% to 72.7%) and in the second case is around 3.6% (from 78.8% to...
82.4%). These results partially validate our third hypothesis (H3) indicating that loss functions designed to learn from the PD domain serve to improve the performance of PD classification. It is not only interesting to highlight the improvement achieved when using the triplet loss function, but also to note that the best result obtained with the Triplet-ResNet7 model is competitive compared to the best accuracy previously obtained with the Freeze 75 model.

Although the accuracy in the second one is 4.9% above the first one, Freeze 75 requires 17,815,520 more parameters to be optimized than Triplet-ResNet7, which might indicate a better generalization capability. Further experiments with additional data are required to validate this hypothesis.

PCA is now used to create a 2D representation of the feature spaces learned in previous experiments. Figure 6 shows the feature spaces and the distribution of the classification scores. The figure shows a superior discrimination capability of the $x_{AF}$ feature space (ResNet50 adapted to the FAU domain). The representation obtained by the Triplet-ResNet7 model shows a larger margin between classes but the misclassification errors decrease the performance.

### 4.4 Experiment 4: Parkinson Domain (PD Impairment Estimation)

Given the promising results obtained with the above presented experiments in the automatic discrimination between PD patients and healthy subjects, especially with the Freeze 75 and the Triplet-ResNet7 models, with accuracies of 87.3% and 82.4%, respectively, we want to evaluate in this section the suitability of those models to discriminate between three different degrees of impairment: mild (PD-1), intermediate (PD-2), and severe (PD-3). These three groups are defined considering the scores of the MDS-UPDRS-III provided by the expert neurologist. The mild group includes patients with scores in the range from 0 to 23, the intermediate group is defined for patients with scores between 23 and 33, and the severe group for patients with scores greater than 33. Figure 7 shows the distribution of the MDS-UPDRS-III scores for the three groups of patients.

The tri-class classification experiments are performed considering the feature vectors extracted with the Freeze 75 model on the NOnAOOffN sequence, and the Triplet-ResNet7 model on the NOnA sequence. Optimization of hyper-parameters is performed as indicated in Section 3.3.
The confusion matrices and results obtained with the Freeze 75 and the Triplet-ResNet7 models are shown in Table 14 and Table 15, respectively. Values of accuracy, F1 score, and κ index are included in the bottom part of each table. These results show that the Freeze 75 model is better than the Triplet-ResNet7. There is a difference of 4% points in the accuracy, and 0.07 in the F1 score when using the SVM.

The accuracies obtained are around 43% for a problem with three classes (33% random chance). These results are far to be optimal but suggest there is certain useful information in the models that can help to estimate the degree of impairment (our fourth hypothesis H4). Figure 8 shows the projected space. Note that there is a relatively clear separability between mild and severe patients. In the middle between these two groups there are samples of the intermediate group, which are not accurately classified but clearly appear in between, which likely indicates that the proposed approach is able to find a trend regarding the neurological state of the patients.

5 Discussion and Conclusion

This study presents a novel approach where deep learning methods are used to model hypomimia in PD patients. Videos with the face of people while evoking emotions are considered for the study. Frames of the recorded videos are segmented in different stages during the production of evoked emotions: neutral, onset-transition, apex, offset-transition, and neutral. This approach exhibits improvements of up to 5.5% in accuracy (from 72.9% to 78.4%) with respect to classical approaches where single frames are considered. These results suggest that dynamics information is more suitable to model hypomimia in PD patients. We are aware of the fact that the presented approach does not completely exploit the video dynamics; however, the incorporation of frames in different stages during the production of emotions shows to be a good and computationally affordable approach.

Later, information from the Affective domain is incorporated in the model by means of transfer learning methods. Transfer learning was performed considering the complete architecture of a base model previously trained with massive data and then freezing some layers to fine-tune the remaining layers with the smaller emotion data. Results freezing 75% and 50% of the layers are reported. The results show that the Affective domain adaptation provides an improvement of 8.9%, from 78.4% to 87.3% of accuracy in PD detection. These results confirm that domain adaptation via transfer learning methods is a good strategy to model hypomimia in PD patients. Considering the good results and also the fact that only up to four images per participant are considered in the experiments, we believe that this work is a step forward in the development of inexpensive computational systems suitable to model and quantify problems of PD patients to express emotions.

With the aim of finding lighter approaches suitable to be
used in portable devices, other experiments with reduced architectures like VGG-8 and ResNet7 were also addressed, however, the results were not as good as before, the maximum achieved accuracies in this case were 67.6% and 78.8%, respectively. These results were further improved up to 72.7% and 82.4% when the triplet loss strategy is considered for training the VGG-8 and ResNet7 models, respectively.

Finally, the neurological state of the patients was evaluated considering the best approach found in the classification experiments. The patients were grouped into three groups according to their MDS-UPDRS-III scores and a tri-classification strategy showed a maximum classification accuracy of 44% (F1=0.45).

Future work includes more sophisticated methods to integrate the information provided by the full video sequences, including video tracking of facial features. We will also investigate multiple classifier approaches to combine the information provided by face videos for PD detection and PD impairment estimation with other sources of information [17], like speech, gait, handwriting [16], and human-computer interaction signals [1].

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COMPLIANCE WITH ETHICAL STANDARDS

Ethical approval

All of the signals considered in this work were collected in compliance with the Helsinki Declaration and the procedure was approved by the Ethics Committee at the University of Antioquia in Medellín, Colombia. Written informed consent was signed by each participant.

REFERENCES

[1] Alejandro Acien et al. “Smartphone Sensors For Modeling Human-Computer Interaction: General Outlook And Research Datasets For User Authentication”. In: IEEE Conf. on Computers, Software, and Applications (COMPSAC). July 2020.
[2] R. Almutiy et al. “Facial Behaviour Analysis in Parkinson’s Disease”. In: Lecture Notes in Computer Science 9805 (2016), pp. 329–339.
[3] S. Argaud, M. Véris, P. Sauleau, and D. Grandjean. “Facial Emotion Recognition in Parkinson’s Disease: A Review and New Hypotheses”. In: Movement Disorders 33.4 (2018), pp. 554–567.
[4] A. Bandini, S. Orlandi, H. J. Escalante, F. Giovannelli, et al. “Analysis of facial expressions in Parkinson’s disease through video-based automatic methods”. In: Journal of Neuroscience Methods 281 (2017), pp. 7–20.
[5] M. Bologna et al. “Facial bradykinesia”. In: J Neurol Neurosurg Psychiatry 84.6 (2013), pp. 681–685.
[6] D. Bowers et al. “Faces of emotion in Parkinson’s disease: Micro-expressivity and bradykinesia during voluntary facial expressions”. In: Journal of the International Neuropsychological Society 12 (2006), pp. 765–773.
[7] R. Cacabelos. “Parkinson’s disease: from pathogenesis to pharmacogenomics”. In: International Journal of Molecular Sciences 18.3 (2017), p. 551.
[8] Q. Cao et al. “Vggface2: A dataset for recognising faces across pose and age”. In: 2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018). IEEE. 2018, pp. 67–74.
[9] R. Castrillon et al. “Characterization of the Handwriting Skills as a Biomarker for Parkinson Disease”. In: IEEE Intl. Conf. on Automatic Face and Gesture Recognition (FG). May 2019.
[10] O. Celiktutan, E. Skordos, and H. Gunes. “Multimodal human-human-robot interactions (mhhri) dataset for studying personality and engagement”. In: IEEE Transactions on Affective Computing (2017).
[11] C. De Stefano et al. “Handwriting analysis to support neurodegenerative diseases diagnosis: A review”. In: Pattern Recognition Letters 121 (2019), pp. 37–45.
[12] V. Dentamaro, D. Impedovo, and G. Pirlo. “Gait Analysis for Early Neurodegenerative Diseases Classification Through the Kinematic Theory of Rapid Human Movements”. In: IEEE Access 8 (2020), pp. 193966–193980.
[13] P. Ekman. “Strong evidence for universals in facial expressions: a reply to Russell’s mistaken critique.” In: Psychological Bulletin 115 2 (1994), pp. 268–87.
[14] P. Ekman, W. V. Friesen, and J. C. Hager. “Facial action coding system: The manual on CD ROM”. In: A Human Face, Salt Lake City (2002), pp. 77–254.
[15] C. Fabian Benitez-Quiroz, S. Srinivasan, and A. M. Martinez. “Emotionet: An accurate, real-time algorithm for the automatic annotation of a million facial expressions in the wild”. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2016, pp. 5562–5570.
[16] M. Faundez-Zanuy et al. “Handwriting Biometrics: Applications and Future Trends in e-Security and e-Health”. In: Cognitive Computation (Aug. 2020).
[17] J. Fierrez, A. Morales, R. Vera-Rodriguez, and D. Camacho. “Multiple Classifiers in Biometrics. Part 1: Fundamentals and Review”. In: Information Fusion 44 (Nov. 2018), pp. 57–64.
[18] J. Fierrez, A. Morales, R. Vera-Rodriguez, and D. Camacho. “Multiple Classifiers in Biometrics. Part 2: Trends and Challenges”. In: Information Fusion 44 (Nov. 2018), pp. 103–112.
[19] E. Friesen and P. Ekman. Facial Action Coding System: A technique for the measurement of facial movement. 1978.
[20] H. Gaßner et al. “Perturbation Treadmill Training Improves Clinical Characteristics of Gait and Balance in
Parkinson’s disease”. In: Journal of Parkinson’s Disease 9.2 (2019), pp. 413–426.

[21] C. G. Goetz et al. “Movement Disorder Society Task Force report on the Hoehn and Yahr staging scale: status and recommendations: The Movement Disorder Society Task Force on rating scales for Parkinson’s disease”. In: Movement Disorders 19.9 (2004), pp. 1020–1028.

[22] C. G. Goetz et al. “Movement Disorder Society-sponsored revision of the Unified Parkinson’s Disease Rating Scale (MDS-UPDRS): scale presentation and clinimetric testing results”. In: Movement Disorders 23.15 (2008), pp. 2129–2170.

[23] E. Gonzalez-Sosa, J. Fierrez, R. Vera-Rodriguez, and F. Alonso-Fernandez. “Facial Soft Biometrics for Recognition in the Wild: Recent Works, Annotation and COTS Evaluation”. In: IEEE Trans. on Information Forensics and Security 13.8 (Aug. 2018), pp. 2001–2014.

[24] E. Gonzalez-Sosa, R. Vera-Rodriguez, J. Fierrez, and J. Ortega-Garcia. “Exploring Facial Regions in Unconstrained Scenarios: Experience on ICB-RW”. In: IEEE Intelligent Systems 33.3 (May 2018), pp. 60–63.

[25] A. Grammatikopoulou, N. Grammalidis, S. Bostaniopoulos, and T. Katsarou. “Detecting hypomimia symptoms by selfie photo analysis: for early Parkinson disease detection”. In: Proceedings of the 12th ACM International Conference on PErvasive Technologies Related to Assistive Environments. 2019, pp. 517–522.

[26] S. S. Guillen, L. L. Iacono, and C. Meder. “Affective Robots: Evaluation of Automatic Emotion Recognition Approaches on a Humanoid Robot towards Emotionally Intelligent Machines”. In: Energy 3643 (2018).

[27] S. D. Gunnery, E. N. Naumova, M. Saint-Hilaire, and L. Tickle-Degnen. “Mapping spontaneous facial expression in people with Parkinson’s disease: A multiple case study design”. In: Cogent Psychology 4 (2017), pp. 1–15.

[28] J. Hamm, C. G. Kohler, R. C. Gur, and R. Verma. “Automated facial action coding system for dynamic analysis of facial expressions in neuropsychiatric disorders”. In: Journal of Neuroscience Methods 200.2 (2011), pp. 237–256.

[29] K. He, X. Zhang, S. Ren, and J. Sun. “Deep residual learning for image recognition”. In: Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition. 2016, pp. 770–778.

[30] J. Kang, D. Derva, D. Y. Kwon, and C. Wallraven. “Voluntary and spontaneous facial mimicry toward other’s emotional expression in patients with Parkinson’s disease”. In: PloS One 14.4 (2019).

[31] K. Li, W. Tao, and L. Liu. “Online Semantic Object Segmentation for Vision Robot Collected Video”. In: IEEE Access 7 (2019), pp. 107602–107615.

[32] S. Li and W. Deng. “Deep facial expression recognition: A survey”. In: IEEE Transactions on Affective Computing 2010.20 (2020).

[33] Y. J. Lim, Y. G. Ko, H. C. Shin, and Y Cho. “Prevalence and correlates of complete mental health in the South Korean adult population”. In: Mental Well-Being. Springer, 2013, pp. 91–109.

[34] L. Moro-Velazquez et al. “Phonetic relevance and phonemic grouping of speech in the automatic detection of Parkinson’s Disease”. In: Scientific Reports 9.1 (2019), pp. 1–16.

[35] J. R. Orozco-Arroyave et al. “NeuroSpeech: An open-source software for Parkinson’s speech analysis”. In: Digital Signal Processing 77 (2018), pp. 207–221.

[36] J.R. Orozco-Arroyave. Analysis of speech of people with Parkinson’s disease. Logos-Verlag, Berlin, 2016.

[37] A. Pampouchidou et al. “Automatic assessment of depression based on visual cues: A systematic review”. In: IEEE Transactions on Affective Computing (2017).

[38] S. J. Pan and Q. Yang. “A survey on transfer learning”. In: IEEE Transactions on Knowledge and Data Engineering 22.10 (2009), pp. 1345–1359.

[39] M. Pantic and L. J. Rothkrantz. “Expert system for automatic analysis of facial expressions”. In: Image and Vision Computing 18.11 (2000), pp. 881–905.

[40] O. M. Parkhi, A. Vedaldi, A. Zisserman, et al. “Deep Face Recognition”. In: British Machine Vision Conference (BMVC). Swansea, UK, 2015.

[41] A. Parnandi and R. Gutierrez-Osuna. “Visual biofeedback and game adaptation in relaxation skill transfer”. In: IEEE Transactions on Affective Computing 10.2 (2017), pp. 276–289.

[42] A. Peña, J. Fierrez, A. Lapedriza, and A. Morales. “Learning Emotional-Blind Face Representations”. In: IAPR Intl. Conf. on Pattern Recognition (ICPR). Jan. 2021.

[43] R. Ranjan et al. “Deep learning for understanding faces: Machines may be just as good, or better, than humans”. In: IEEE Signal Processing Magazine 35.1 (2018), pp. 66–83.

[44] C. Richardson et al. “Digitizing the moving face during dynamic expressions of emotion”. In: Neuropsychologia 38 (2000), pp. 1026–1037.

[45] C. D. Rios-Urrego et al. “Analysis and evaluation of handwriting in patients with Parkinson’s disease using kinematic, geometrical, and non-linear features”. In: Computer Methods and Programs in Biomedicine 173 (2019), pp. 43–52.

[46] G. Simons, M. C. S. Pasqualini, V. Reddy, and J. Wood. “Emotional and nonemotional facial expressions in people with Parkinson’s disease”. In: Journal of the International Neuropsychological Society 10.4 (2004), pp. 521–535.

[47] R. Singh, M. Vatsa, V. M Patel, and N. Ratha. Domain Adaptation for Visual Understanding. Springer, 2020.

[48] B. Sonawane and P. Sharma. “Review of automated emotion-based quantification of facial expression in Parkinson’s patients”. In: The Visual Computer (June 2020).

[49] S. Spasojevic et al. “Quantitative Assessment of the voice in Parkinson’s disease”. In: Parkinson's Disease: The South Korean adult population”. In: Scientific Reports 9.1 (2019), pp. 1–16.

[50] P. Tome, J. Fierrez, R. Vera-Rodriguez, and D. Ramos. “Identification using Face Regions: Application and Assessment in Forensic Scenarios”. In: Forensic Science International 233 (2013), pp. 75–83.
[51] J.C. Vásquez-Correa et al. “Multimodal assessment of Parkinson’s disease: a deep learning approach”. In: *IEEE Journal of Biomedical and Health Informatics* 23.4 (2019), pp. 1618–1630.

[52] P. Wu et al. “Objectifying facial expressivity assessment of Parkinson’s patients: preliminary study”. In: *Computational and Mathematical Methods in Medicine* (2014).

[53] M. Yan et al. “Vargfacenet: An efficient variable group convolutional neural network for lightweight face recognition”. In: *Proceedings of the IEEE International Conference on Computer Vision Workshops*. 2019.

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