Understanding the Impact of Image Quality in Face Processing Algorithms

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Abstract: Face processing algorithms are becoming more popular in recent days due to the great domain of application they can be used in. As a consequence, research about the quality of face images is also increasing. Several papers concluded that image quality does impact the performance of face processing algorithms, with low-quality images having a detrimental effect on performance. However, there is still a need for a comprehensive understanding of the extent of the impact of specific distortions like noise, blur, JPEG compression, and brightness. We've conducted a study evaluating the performance of three face processing algorithms with images under different levels of the aforementioned distortions. The study's results placed noise and blur with Gaussian distributions, as the main distortions affecting performance. A detailed description of the adopted methodology, as well as the results obtained from the study, is presented in this paper.

1 INTRODUCTION

In 2020, an increase in the use of efficient face processing algorithms was evidenced due to the demand for this technology in many services that require a type of personal identification. This was due to the social distancing and confinement caused by the epidemiological issues related to the COVID-19 virus worldwide. Face processing technology is widely used for security and access control through identification, verification, and liveness processes. Other methods like gender classification, age estimation, and emotion detection are also gaining attention thanks to their application in advertising and recommendation systems. As a consequence, research about the quality of face images is also increasing, with the general consensus being that image quality is an important factor in the performance of face processing algorithms.

A recent study by (Mehmood and Selwal, 2020) made a review about face recognition methods and the factors affecting their accuracy. The study divided the algorithms into appearance-based methods, feature-based methods, and hybrid methods; and evaluated their strengths and limitations while listing the main factors affecting face recognition. According to the authors, the main factors related to image quality affecting face recognition performance are illumination, occlusion, noise, and low-resolution.

In a survey by (Li *et al.*, 2019) about image quality in face recognition, the authors stated that the main challenges lay in the first stages of the face recognition pipeline: face detection and face alignment. According to this survey, face detection is particularly impacted by low-resolution images, and for the case of face alignment, the best performing algorithms aren't trained to consider image distortions, so it could be concluded that in the presence of low-quality images, their performance will suffer.

A paper by (Jaturawat and Phankokkruad, 2017) evaluated the face recognition accuracy of three well-known algorithms: Eigenfaces (Turk and Pentland, 1991), Fisherfaces (Belhumeur, Hespanha and Kriegman, 1997), and LBPH (Chen *et al.*, 2009), under unconstrained conditions, considering a variety of pose and expressions, as well as different light exposures, noise levels, and resolution. All three algorithms showed poor performance across the experiments.

Research has also been conducted to tackle this issue outside of the face recognition domain. In

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(Mahmood *et al.*, 2019), the authors placed occlusion, illumination, and noise as the main factors affecting facial expression recognition in unconstrained environments. Similarly, a paper by (Kang *et al.*, 2018), concluded that optical and motion blur negatively affect the performance of age estimation algorithms.

Relevant work on the topic of image quality was conducted by (Dodge and Karam, 2016). The authors studied the effects of several distortions on the performance of four deep learning architectures focused on image classification. The authors concluded that Gaussian blur and Gaussian noise had the biggest impact on deep learning architectures, while the other distortions affected to a lesser degree.

The literature available on this matter supports the premise that image quality does influences face processing performance. However, there is still a lack of comprehension about the impact of specific image distortions. With the exception of resolution, whose impact is been greatly researched and documented (Li *et al.*, 2019), our knowledge about other distortions' impact on face processing algorithms is limited. We know that images degraded by distortions such as noise, blur, lack or excess of brightness, etc, might be poorly processed by these algorithms, as is outlined in the papers above. However, a deeper understanding of that impact and the extent to which it is relevant for face processing would be useful to accurately address this issue and propose adequate solutions.

With that motivation, we've conducted a study to further comprehend the impact of image quality in face processing algorithms. Three face processing algorithms were tested with images under different levels of Gaussian noise, Gaussian blur, motion blur, low and high brightness, and JPEG compression. The results of the study are presented in this paper. Section 2 describes the adopted methodology, Section 3 presents the results obtained with each type and degree of distortion, and Sections 4 and 5 outline the summary and the conclusions of the study.

2 EXPERIMENTAL SETUP

The methodology adopted for the study is based on the work of (Dodge and Karam, 2016). However, a few changes were made to adapt it to our goal. The main differences in our approach are that the selected algorithms are focused on different tasks as opposed to one, and that each algorithm was tested with a dataset and a set of metrics corresponding to the task in question. Also, three additional distortions were considered as a part of our study: motion blur, low brightness, and high brightness.

Details about the algorithms, the datasets, the metrics, and the distortions are discussed below.

2.1 Face Processing Algorithms

The algorithms evaluated in the study are FaceNet, Deep Age Estimation (DEX), and Deep Alignment Network (DAN), focused on face recognition tasks, age estimation, and face alignment respectively. These algorithms are based on Deep Learning architectures and have achieved state-of-the-art results in their respective tasks.

FaceNet is a deep learning system that generates face embeddings for face recognition tasks, such as face identification and face verification, proposed by (Schroff and Philbin, 2015). The main contribution of this work is the introduction of a new loss for deep learning architectures, specifically made for face recognition purposes: the triplet loss. FaceNet uses two DCNN as base architectures: the Zeiler&Fergus (Zeiler and Fergus, 2014) style networks and the Inception (Szegedy *et al.*, 2015) type networks. For this study, an implementation of the FaceNet system based on the Inception architecture was chosen, and the algorithm's performance was evaluated using the accuracy, and the validation rate under a fixed False Alarm Rate (FAR) of 0.001.

The DEX algorithm consists of a deep learning architecture for apparent and real age estimation from a single face image and without the use of facial landmarks (Rothe, Timofte and Van Gool, 2018). The pipeline of the entire system consists of four main stages: face detection, face alignment and resize, feature extraction, and age estimation. To measure the model's performance the authors used the mean absolute error (MAE) in years and the e-error (Escalera *et al.*, 2015) for datasets where there is no ground-truth. In this study, we evaluate the MAE values for the real and the apparent age estimations.

The DAN method consists of a Convolutional Neural Network for image alignment proposed by (Kowalski, Naruniec and Trzcinski, 2017). The proposal is inspired by the Cascade Shape Regression (CSR) (Xiong and De La Torre, 2013) framework, which consists of a combination of a sequence of regressors to approximate nonlinear mapping between the initial shape of the face and the desired frontal face (Xiong and De La Torre, 2013). In the DAN algorithm, those regressors are implemented using deep neural networks. The authors used the Mean Error, as well as the Failure

Rate as metrics to support their results, so for this study, we evaluate its performance using both metrics.

2.2 Datasets

As stated before, for each algorithm, a corresponding set of images was selected according to their task. Additionally, the chosen datasets had previously been used to validate the algorithms, as is exposed in (Schroff and Philbin, 2015), (Clapes *et al.*, 2018), and (Kowalski, Naruniec and Trzcinski, 2017).

The Labelled Faces in the Wild (LFW) (Huang *et al.*, 2007) was employed to evaluate the performance of the FaceNet algorithm. The LFW dataset is composed of 13233 face images corresponding to 5749 individuals. All images were extracted from the internet, available as 250x250 pixel JPEG images, most of them in color. The images are the result of the Viola-Jones (Viola and Jones, 2001) face detection algorithm and have been rescaled and cropped to the aforementioned size. The dataset comprehends a variety of scenarios in head pose, lighting, focus, resolution, facial expression, age, gender, race, accessories, make-up, occlusions, background, and photographic quality.

To evaluate the performance of the DEX algorithm, the Real and Apparent Age (APPA-REAL) dataset (Clapes *et al.*, 2018) was used. The dataset contains 7591 images of 7000 individuals with ages ranging from 0 to 91 years, in unconstrained environments, and with varying resolutions. The APPA-REAL allows testing age estimation algorithms in both real and apparent age. For the study, the validation set containing 1978 images was used.

Lastly, the challenging subset of the 300W dataset was used to assess the performance of the DAN method. This subset is called IBUG (Sagonas *et al.*, 2013) and consists of 135 images obtained from the Internet, with variations in pose, expression, illumination condition, and resolution. The dataset provides landmark annotations for face alignment, obtained employing the Multi-PIE annotation scheme (Gross *et al.*, 2010).

2.3 Distortions

To illustrate the effects of image quality in face processing algorithms, four different distortions were contemplated: noise, blur, brightness, and JPEG.

Noise can be caused by low-quality camera sensors, or by the environmental conditions at the moment of the acquisition (Mehmood and Selwal, 2020). For this study, we modeled the noise as a Gaussian distribution with 0 mean and variance ranging from 0.01 to 0.1 in steps of 0.01.

Blur can result from unfocused camera lenses or moving targets (Huang *et al.*, 2019). Additionally, blurred images can simulate low-resolution images due to the lack of details. For this study, we simulated both motion blur and Gaussian blur. The motion blur was achieved by filtering the images with different sized kernels with value 1/(kernel size), and the Gaussian noise effect was achieved by varying the kernel's standard deviation from 1 to 9 in steps of 1.

One way to simulate low and high illumination conditions is through brightness. In that sense, we simulated 10 stages for both high and low brightness by altering the brightness factor using the Pillow library for Python. For low brightness we altered the brightness factor from 1 to 0, in steps of 0.1; and for high brightness, the established range was 1.2-3.0, with steps of 0.2.

JPEG compression is often cited as a distortion to study due to its intrinsic characteristics, meaning, it is a type of compression that provokes loss in the final result. As was stated in the study carried on by (Dodge and Karam, 2016), it is interesting to analyze if the algorithms are affected by the quality of the compression and in what measure it is relevant. To evaluate the influence of JPEG compression in the performance of the algorithms, the Pillow library was used to obtain 10 levels of quality ranging from 5 to 95 in steps of 10.

3 RESULTS

To comprehend the results obtained from the experiments, it is important to understand their methodology. The DEX and DAN algorithms are focused on one task each, so the experiments consisted of evaluating their performance on their specific task, through the selected metrics, and under images with different distortions at different magnitudes. However, FaceNet is a more complex system designed to generate embedding for face recognition tasks such as face identification and face verification. Face identification consists of assigning an identity to a face through a one-to-many operation, where the embeddings of the unknown face are compared with the ones in the dataset in order to output the corresponding identity. Face verification, on the other hand, is a one-to-one operation, where the task is to check if the person's embeddings are close enough to the embeddings of the identity he or she claims to be.

To evaluate the FaceNet performance, the experiments followed the same methodology proposed by (Huang *et al.*, 2007), where the system has to classify a pair of images as belonging to the same person or different ones, according to previously established pairs of matched and mismatched persons from the dataset. In other words, the experiments will be evaluating the algorithm's performance in a verification-like operation.

The website for the LFW (*LFW Face Database : Main*, 2018) dataset states that it is "*very difficult to extrapolate from performance in verification to performance in 1:N recognition*", although, given the nature of these two tasks, it is safe to assume that any changes in the algorithm performance during verification, will be more noticeable during identification.

The results obtained with each experiment are shown in tables 1 to 6. The values in the first rows correspond to the algorithms' performance with the original images, which was considered as the reference for comparison.

3.1 Noise

Table 1 shows the behavior of all metrics across the different levels of Gaussian noise. A significant decrease in performance can be observed in all three algorithms.

For the case of FaceNet, both metrics were affected, however, there is a noticeable difference between the accuracy of the model and the validation rate when the FAR is set to 0.001. Even at the lowest variance levels, the validation rate suffers considerably more compared to the accuracy. The algorithm appears to be robust in terms of accuracy, however, as was stated before, a bigger impact could be seen in the identification task.

The results obtained with the DEX algorithm show the mean absolute error significantly increasing in both classifications. In both cases, a 100% drop in performance was quickly reached, as the values doubled rapidly. On the other hand, after variance = 0.06, the errors plateaued.

Similar to the previous algorithms, DAN's performance worsens under the presence of noise. Both metrics were greatly impacted even at the lower variance values, however, the failure rate was significantly more affected than the mean error.

3.2 Blur

3.2.1 Gaussian Blur

Table 2 shows the results obtained with images with Gaussian blur. Like the previous experiment, all the metrics were severely affected.

The results obtained with FaceNet show a bigger decrease in performance than in the previous experiment. A significant decline in both accuracy and validation rate is observed after a standard deviation of 3.0, where up to that point the accuracy stayed above 0.97, and the validation rate was approximately 0.85, however, from that on, both metrics started decreasing at a higher rate.

The MAE values for the apparent and the real age classification with the DEX algorithm are also shown in Table 2. It is interesting to observe a slight improvement in both metrics at the lowest levels of gaussian blur. Since blurring techniques are used for denoising, might be the case that some of the images in the dataset were noisy, and the smoothness caused by those levels of blur helped achieve better results. From that point on, both metrics worsen significantly.

Similar to the noise experiments, the DAN's performance worsens under the presence of gaussian blur. However, an interesting phenomenon occurred where the mean error was more affected by Gaussian blur than by noise, but the failure rate, although poor in performance, achieved better results during this experiment than the one before.

3.2.2 Motion Blur

The results obtained with the motion blur experiment are shown in Table 3. Contrary to the behavior observed with noise and blur with Gaussian distributions, motion blur impacted significantly less than the previous distortions.

The overall accuracy in the FaceNet algorithm stayed almost constant across all kernel sizes, slightly decreasing towards the bigger ones. The validation rate at FAR = 0.001 suffered more than the accuracy, however, its minimum value was considerably higher than the values obtained in the previous experiments.

Motion blur also had a lesser impact on the DEX algorithm than the previous distortions. Table 3 shows a slight improvement in both metrics under the smaller kernels, as was the case with gaussian blur. After that, both metrics worsen as the kernel size increase.

A smaller impact on performance was observed in the DAN algorithm as well. Both metrics increase as the kernels get bigger, however, their behavior differs from each other as the failure rate increases at a higher rate than the mean error.

3.3 Brightness

3.3.1 Low Brightness

Low brightness's effect is shown in Table 4. The FaceNet and the DAN algorithms proved to be robust when dealing with this type of image. Their metrics display little variation for most of the brightness factors, changing only with severely degraded images, which correspond to images with little to no brightness.

For the case of the DEX algorithm, although less affected than in previous experiments, a more noticeable decrease in performance was observed when compared with the other algorithms.

3.3.2 High Brightness

The performance achieved with high brightness images is shown in Table 5. The results indicate that excess brightness has a slightly bigger impact than the opposite situation. All algorithms experienced a greater drop in performance at the lower and medium levels of brightness degradation during this experiment than during the previous one. However, the overall impact of high brightness is still relatively small, especially when compared with Gaussian blur and Gaussian noise.

3.4 JPEG Compression

The last distortion analyzed was the JPEG compression. In this case, the goal was to observed the effect of different qualities of compression in the performance of the algorithms. Table 6 shows that the three algorithms are robust under different compression qualities. The only noticeable impact occurred, in all three of them, at the lowest quality factors.

4 SUMMARY

The results obtained with the experiments show that even though the distortions did not affect the algorithms' performance in the same measure, patterns can be observed. In that sense, a series of remarks can be outlined regarding the impact of each distortion in these algorithms.

First, noise and blur, in their Gaussian distribution, constitute the bigger threats to face processing performance in terms of image quality. Both distortions noticeably impacted the algorithms' metrics even at the lowest levels of degradation.

Second, even though Gaussian blur severely impacted the performance of all three algorithms, motion blur didn't have the same effect. The results show significantly less influence throughout the majority of kernel sizes. This is an interesting result because it indicates that not all blur constitutes a threat to performance, unfocused images and lack of detail have a bigger impact on performance than motion.

Third, brightness and JPEG compression seem to have a small impact on performance. According to the graphs, noticeable impact is perceived only when the images are severely degraded.

5 CONCLUSIONS

The focus of this paper was to study the behavior of three different face processing algorithms under the presence of noise, blur, brightness, and JPEG compression, at different magnitudes. The goal was to draw conclusions about the impact of these distortions on face processing algorithms and obtain a more insightful understanding of the influence of image quality in these types of algorithms.

Based on the results, a series of remarks were summarized in the previous section. From that, we can conclude that the analyzed algorithms, and potentially others, are unsuited for unconstrained environments where noise and blur resembling Gaussian distributions might be present. On the positive side, their deployment in scenarios with different conditions of JPEG compression and brightness, would not be as compromised unless the images are severely distorted.

The main contribution of this work is providing a comprehensive study about the impact of several image distortions in face processing algorithms. Where most studies focused on one task, ours comprehended several ones within the face processing domain, which allowed us to extract common patterns that arise when dealing with low-quality images.

The information presented in this paper is useful to develop adequate solutions for face image quality assessment methods, oriented to improve face processing performance with images of different qualities. In that sense, our future work will be focused on identifying the type and degree of the distortions present in face images. We believe that having that information beforehand, in conjunction with the results presented in this paper, would lead to the development of more robust face processing systems.

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APPENDIX

Table 1: Gaussian noise experiment results.

	FACENET		DEX		DAN	
Noise Variance	**Accuracy**	**Validation Rate**	**MAE Apparent Age (Years)**	**MAE Real Age (Years)**	**Mean Error**	**Failure Rate**
0,00	**0,9965**	**0,98567**	**6,46788**	**7,6086**	**0,052**	**0,0518**
0,01	0,989	0,926	11,835	12,659	0,075	0,237
0,02	0,977	0,853	13,219	14,062	0,108	0,415
0,03	0,965	0,751	14,087	14,940	0,134	0,556
0,04	0,948	0,618	14,511	15,361	0,164	0,659
0,05	0,924	0,393	14,757	15,551	0,197	0,763
0,06	0,897	0,330	14,958	15,778	0,233	0,844
0,07	0,876	0,183	15,096	15,913	0,255	0,867
0,08	0,845	0,109	15,112	15,948	0,289	0,911
0,09	0,825	0,052	15,196	16,012	0,312	0,963
0,10	0,782	0,048	15,129	15,956	0,342	0,985

Table 2: Gaussian blur experiment results.

	FACENET		DEX		DAN	
Standard deviation	**Accuracy**	**Validation Rate**	**MAE Apparent Age (Years)**	**MAE Real Age (Years)**	**Mean Error**	**Failure Rate**
0	**0,9965**	**0,9857**	**6,4679**	**7,6086**	**0,0524**	**0,0519**
1	0,9957	0,9747	6,3348	7,5249	0,0553	0,1111
2	0,9899	0,9348	7,7535	8,6961	0,0866	0,2222
3	0,9758	0,8490	8,7475	10,0413	0,1508	0,4148
4	0,9587	0,6483	9,7207	11,0002	0,2484	0,5138
5	0,9192	0,4717	10,5318	11,8231	0,3410	0,5630
6	0,8515	0,2130	11,1935	12,4259	0,4268	0,6296
7	0,7840	0,0920	11,7378	12,9049	0,4960	0,7407
8	0,7388	0,0610	12,2777	13,3167	0,5495	0,7926
9	0,7055	0,0437	12,6175	13,6724	0,5942	0,8222
10	0,6792	0,0390	12,9041	13,9599	0,6312	0,8596

Table 3: Motion blur experiment results.

	FACENET		DEX		DAN	
Kernel Size	**Accuracy**	**Validation Rate**	**MAE Apparent Age (Years)**	**MAE Real Age (Years)**	**Mean Error**	**Failure Rate**
0	**0,9965**	**0,9857**	**6,4679**	**7,6086**	**0,0524**	**0,0519**
3	0,9953	0,9853	6,2926	7,4780	0,0527	0,0593
5	0,9942	0,9767	6,3769	7,6107	0,0548	0,0889
7	0,9927	0,9650	6,6799	7,9063	0,0624	0,1556
9	0,9925	0,9417	7,0470	8,2531	0,0730	0,2296
11	0,9890	0,9240	7,4316	8,6433	0,0875	0,2963
13	0,9852	0,9043	7,7827	9,0208	0,1028	0,3556
15	0,9810	0,8623	8,1101	9,3635	0,1207	0,3926
17	0,9748	0,7930	8,4178	9,6787	0,1399	0,4444
19	0,9663	0,7397	8,7187	9,9900	0,1584	0,5037
21	0,9583	0,6803	8,9849	10,2712	0,1546	0,5333

Table 4: Low brightness experiment results.

	FACENET		DEX		DAN	
Brightness Factor	**Accuracy**	**Validation Rate**	**MAE Apparent Age (Years)**	**MAE Real Age (Years)**	**Mean Error**	**Failure Rate**
1,0	**0,9965**	**0,9857**	**6,4679**	**7,6086**	**0,0524**	**0,0519**
0,9	0,9963	0,9850	6,7060	7,8234	0,0525	0,0519
0,8	0,9965	0,9850	6,8995	8,0156	0,0528	0,0667
0,7	0,9963	0,9830	7,1050	8,2215	0,0529	0,0667
0,6	0,9962	0,9760	7,4271	8,5286	0,0534	0,0667
0,5	0,9960	0,9753	7,6763	8,8173	0,0543	0,0963
0,4	0,9953	0,9683	8,1112	9,2502	0,0558	0,0963
0,3	0,9935	0,9610	8,7266	9,8644	0,0627	0,1407
0,2	0,9857	0,9267	9,6779	10,8681	0,0878	0,2815
0,1	0,5475	0,0003	12,3576	13,4337	0,2446	0,7556

Table 5: High brightness experiment results.

	FACENET		DEX		DAN	
Brightness Factor	**Accuracy**	**Validation Rate**	**MAE Apparent Age (Years)**	**MAE Real Age (Years)**	**Mean Error**	**Failure Rate**
1,0	**0,9965**	**0,9857**	**6,4679**	**7,6086**	**0,0524**	**0,0519**
1,2	0,9952	0,9863	6,4763	7,6331	0,0524	0,0519
1,4	0,9942	0,9767	6,8012	8,0657	0,0532	0,0667
1,6	0,9920	0,9480	7,4323	8,6951	0,0547	0,0741
1,8	0,9822	0,8830	8,1965	9,4396	0,0591	0,0963
2,0	0,9695	0,7690	9,0058	10,2465	0,0623	0,1111
2,2	0,9540	0,6890	9,7599	11,0076	0,0651	0,1333
2,4	0,9318	0,5743	10,3806	11,6264	0,0687	0,1778
2,6	0,9085	0,4737	10,8840	12,0786	0,0729	0,1926
2,8	0,8882	0,3850	11,2700	12,4501	0,0764	0,2148
3,0	0,8618	0,3043	11,6299	12,7698	0,0819	0,2667

Table 6: JPEG compression experiment results.

	FACENET		DEX		DAN	
JPEG Quality	**Accuracy**	**Validation Rate**	**MAE Apparent Age (Years)**	**MAE Real Age (Years)**	**Mean Error**	**Failure Rate**
0	**0,9965**	**0,9857**	**6,4679**	**7,6086**	**0,0524**	**0,0519**
3	0,9958	0,9857	6,4862	7,6254	0,0524	0,0519
5	0,9962	0,9850	6,6462	7,7662	0,0525	0,0519
7	0,9957	0,9843	6,4717	7,6117	0,0527	0,0519
9	0,9960	0,9873	6,8818	7,9820	0,0528	0,0519
11	0,9957	0,9837	7,3550	8,4265	0,0530	0,0593
13	0,9955	0,9837	6,5798	7,7979	0,0530	0,0741
15	0,9958	0,9793	6,6900	7,8536	0,0536	0,0667
17	0,9955	0,9830	7,3014	8,4085	0,0535	0,0593
19	0,9932	0,9670	7,4256	8,6271	0,0552	0,0741
21	0,9507	0,5370	10,226	11,371	0,0848	0,2889