
Exploring Super-Resolution for Face Recognition

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Abstract— Biometric recognition is part of many aspects of modern society. With the smartphones popularization, facial recognition gains space in this environment of biometric technologies. With the diversity of image capture devices, of different brands and qualities, the images will not always be in the ideal standard to be recognized. This article tests and compares different scenarios and situations to assess the results obtained by facial recognition in different environments. For this, the quantitative method of data analysis was used. In the first scenario, all images were submitted without changes. In the following, we have the reduction of image resolution, which may or may not be followed by enlargement to the original resolution via bicubic interpolation or through the Image Super-Resolution algorithm, these images can be all, or only that undergo tests. Results indicate that the first scenario obtained the best performance, followed by only the tests images change. The worst performance occurs where the properties of all images are affected. In situations where there is a reduction and enlargement optional, the enlargement option performs better, so the bicubic enlargement has an advantage over the ISR, the situation in which only the reduction occurs has the worst performance.

Keywords— Facial Recognition, Deep Learning, Super-Resolution, Images and Videos, Image Processing, Computer Vision

I. INTRODUCTION

Due to the Sars-CoV-2 pandemic, the adoption of digital resources has expanded and becoming more evident in many aspects of everyday life. In Brazil, for example, there were 15,632,584 cases and 436,001 deaths¹ due to COVID-19, after 447 days since the first national case, alternative solutions are needed, considering that, until May 18, 2021, vaccines were injected in 18.54%² of the population and are in short supply and sometimes missing due to the shortage of imported goods³.

Even before this sad event, the paths were already paved: systems that monitor individuals through cameras, recog-

nize their faces and activities, go beyond Chinese borders⁴, a country well known for superb use of technologies, especially those that use biometric resources in surveillance of the population. Free of charge, mobile devices, social networks, and other services can recognize their users and even non-users.

Regardless of the current controversies in which the use of technologies has been present, its proper use can help in poignant issues, especially about issues such as the pandemic itself, an example are systems that can identify body temperature and prevent non-carriers of masks that do not enter public spaces⁵, thus preventing the spread of the virus and, therefore, new infected ones. These technologies depend on concepts such as Deep Learning, biometrics, and super-resolution.

According to [1], with the popularization of smartphones, the adoption of biometric resources is observed in these devices to grant usage. [2] complement that facial recognition

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¹Data from May 18, 2021. (Monitor do coronavírus - saúde. **Folha de São Paulo**. Available at: <<https://arte.folha.uol.com.br/equilibrioesaude/2020/casos-mortes-coronavirus-brasil-mundo/#/local/brasil>>. Accessed on May 18, 2021.)

²Data from May 18, 2021. (Mapa da vacinação contra Covid-19 no Brasil | Vacina. **G1 - O portal de notícias da Globo (globo.com)**. Disponível em: <<https://especiais.g1.globo.com/bemestar/vacina/2021/mapa-brasil-vacina-covid/>>. Accessed on May 18, 2021.)

³CoronaVac vaccine is suspended due to lack of imported substances. (Declarações da gestão Bolsonaro contra a China afetam liberação de insumos de vacinas, diz Butantan. **Folha de São Paulo**. Available at: <<https://www1.folha.uol.com.br/equilibrioesaude/2021/05/declaracoes-da-gestao-bolsonaro-contra-a-china-afetam-liberacao-de-insumos-diz-butantan.shtml>>. Accessed on May 18, 2021.)

⁴A recent use of artificial intelligence for facial recognition occurred recently at Carnival in Salvador, which at the time helped to apprehend a criminal. (OH, S. Hyeon. Reconhecimento facial ajuda a prender criminoso no Carnaval de Salvador. **Canaltech**, São Bernardo do Campo, March 6, 2019. Available at: <<https://canaltech.com.br/seguranca/reconhecimento-facial-ajuda-a-prender-criminoso-no-carnaval-de-salvador-134189/>>. Accessed on: May 18, 2021.)

⁵A device has a system that can measure body temperature and identify a person who does not wear a mask. (ZARAMELA, Luciana. COVID-19: dispositivo indica quem está com febre em empresas ou instituições. **Canaltech**, São Bernardo do Campo, June 1, 2020. Available at: <<https://canaltech.com.br/saude/covid-19-dispositivo-indica-quem-esta-com-febre-em-empresas-ou-instituicoes/>>. Accessed on: May 18, 2021.)

is applied in different scenarios such surveillance, border patrol, and forensic science. Currently “[...] millions of images have been generated opening a range of possibilities for the most diverse purposes [...]” [3].

Facial recognition is understood as a set of techniques/algorithms that, through images, can recognize faces. Face data can be compared with data in a database to identify the individual with those characteristics. Facial recognition performed by machines is “[...] biometric techniques that consist in identifying facial patterns [...]” [4]. The main algorithms are named by their methodological approaches which can be holistic (based on appearance), structural (based on features) or hybrid (mixture of holistic and structural type). In the holistic type, there are the Eigenfaces, Fisherfaces and TensorFaces algorithms, in the structural type, the main algorithm is the Elastic Bunch Graph-Matching.

Deep Learning is a subfield of artificial intelligence. According to [5], this sub-area seeks, through its algorithms, to imitate the way the human brain works and its structure. A neural network in the context of Deep Learning is where the information goes through and gets processed, the first layer is the input layer, while the last layer it is called the output layer. A convolutional neural network (CNN) is a class inside Deep Learning and it is very used in many aspects of visual imagery.

Biometrics, on the other hand, is concerned with “[...] identifying people using their physical or behavioral characteristics” [5], to detect the bearer of the characteristic. This is done by transforming these characteristics into various statistical measures. An example might be fingerprint detectors in banks: a device that captures the biometric reading of an individual’s hand and replaces the password in banking operations.

Super-resolution “[...] refers to the process of creating clear and high-resolution (HR) images from a single low-resolution (LR) image or from a sequence of low-resolution observations” [6]. An image that has undergone super-resolution processes allows for greater detail of the content displayed in the image. “The use of deep learning, specifically convolutional neural networks (CNNs) to perform the mapping between LR and HR images/patches have been extensively explored in recent years” [3].

In the context of digital images, “[...] interpolation is basically the process that uses known data to estimate values in points [...]” [7] not known.

Bicubic interpolation uses all 16 pixels (4x4 neighbors) closest to a pixel to make its estimate. Once these are at many ranges from the unspecified pixel, nearby pixels receive a bigger weighting in the computation. The resizing algorithms that use the bicubic interpolation logic carry out enlargement or reduction of the images. When compared to Bilinear and Nearest Neighbor interpolation, the Bicubic interpolation are more efficient and produces sharper images, that is why many image manipulation and edition programs implement the Bicubic interpolation.

It is noticeable that there is a symbiosis between the concepts. Normally, image resolution changes are performed using specific algorithms. However, an image obtained in low resolution can be transformed into a high-resolution image (super-resolution) using Deep Learning techniques and submitted to a facial recognition algorithm to detect biometric

characteristics.

The super-resolution of images can be of paramount importance for the area of public security and commercial applications, as the images captured from conventional cameras and used in these areas are, according to [8], small and they differ from reduced low-resolution images from high-resolution images. This is occasioned by several factors, whether because the object of the captured images is far away, the environment does not help with lighting conditions, images that need to be reduced in their specificities to be transmitted in real-time, or the type of camera.

There is currently little research on super-resolution, therefore, this article proposes to deepen the studies of Deep Learning algorithms as well as super-resolution algorithms testing their integration to further increase their effectiveness in low-resolution images and videos. This project can bring new understandings about the subject discussed and, in the future, new applications in various areas, especially about public safety.

Specifically, this article will test different scenarios and situations involving images, their specifications and their content formed by pixels, to observe and choose a solution that best fits the criteria of effective and more accurate facial recognition, which makes the algorithm of face recognition correctly identify and recognize faces.

In an initial survey, authors [9] report that low-resolution images make face recognition a challenge. However, the researchers proposed a method to increase the resolution of images that differs from others that seek to investigate the direct relationship between high-resolution and low-resolution images. The researchers’ method estimates high-frequency components that are not present in other methods.

The [10] research discusses the issue of invariant recognition of face posture using an MRF. An acronym that means Markov Random Field and is known for its computational complexity. For this, it was used the daisy descriptor for facial image representation in image recognition and created an implementation of a graphical processing unit of the MRF multiresolution matching process. Efficiency made the MRF approach viable and facilitates extensive empirical optimizations and evaluation studies.

It is proposed to transfer the pixel domain super-resolution reconstruction to face space with a smaller dimension in [11] research. This approach has the advantage of decreasing computational complexity regarding super-resolution image reconstruction, since the focus of the algorithm is not a visually improved image, but rather to search for the necessary information for the recognition system.

Paying attention to the impact of layer loss of artificial neural networks in the context of image processing, authors [12] show other alternatives for image restoration and, specifically, the importance of perceptually motivated losses when the resulting image is evaluated by a human observer. The performance of different types of losses is compared and a new differentiable error function is proposed. Furthermore, the authors show that image quality improves with more elaborate loss functions.

Finally, the research by [13] describes a system for recognizing and detecting human faces using real-time security cameras. The system uses the Viola-Jones face detector and then extracts local features and creates a shape-based feature

vector. The authors considered improving the performance and accuracy of the recognition and detection phases.

II. MATERIALS AND METHOD

As stated in the previous section, the aim of this study is to verify whether the use of super-resolution in low-quality images can improve the accuracy of a facial recognition algorithm. In this work, the quantitative method of data analysis was used with the support of the Face Recognition recognition algorithm, this algorithm uses the Python language and the dlib library. The choice of a solution that fits the criteria of effective facial recognition and better precision made this algorithm become the preference, in the algorithm documentation, it is said that the model has 99.38% accuracy⁶.

For the tests to be carried out, a database widely used in the literature it is necessary for the optimal functioning of the algorithm.

A face database called Georgia Tech face database have been used for training and tests the image recognition system, which contains 750 images of 50 different people, each with 15 images of 640x480 resolution, totaling 128MB of images. These images were taken from photo sessions between 06/01/1999 and 11/15/1999 at the Center for Signal and Image Processing at the Georgia Institute of Technology. “The pictures show frontal and/or tilted faces with different facial expressions, lighting conditions, and scale”. [14].

These images are used by changing their properties, modifying their resolutions to compare different scenarios, and quantitatively evaluate these different situations. They are then only reduced or reduced and increased, the reduction occurs in a bicubic way, stretching happens or in a bicubic form, or using a super-resolution algorithm.

Classic algorithms work so that captured images go through a face detection process. Finally, face detection data are compared with data in a database to identify the subjects of the image in question as seen in Figure 1.

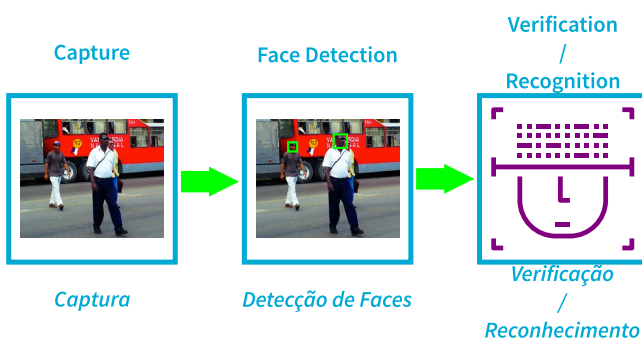


Fig. 1: Representation of how classical face recognition algorithms work.

The proposed system, represented in Figure 2, adds a step to the recognition process, which is the application of the super-resolution process to the images before their recognition in an attempt to improve image quality and, consequently, sophisticate the accuracy of the system of recognition.

⁶Documentation of the Face Recognition algorithm. (GEITGEY, Adam. **Face Recognition**: ageitgey/face_recognition. 2017. Available at: <https://github.com/ageitgey/face_recognition>. Accessed on Feb. 1, 2021.)

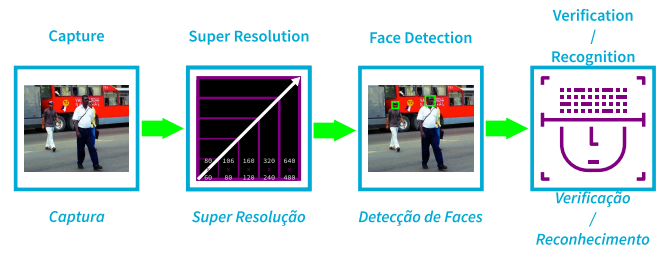


Fig. 2: Representation of the functioning of the proposed face recognition system.

The chosen algorithm needs, as input, images that will train the face recognition system for the tests to be executed in a controlled manner, in addition, to test images, that will be identified by the system. As part of the training of the images, they are found in an exclusive folder, where there are subfolders dedicated, each, for a single individual. As for the test images, they are also found in an exclusive folder, with no subfolders. In this context 200/750 images are dedicated to training and 550/750 images goes to the test process.

With this division done, the algorithm starts the training process and, when this part is finished, the detection of faces and recognition of identified faces begins.

Initially, the images were trained and tested according to the original specifications, keeping their resolutions.

Then, new directories were generated through the system, where each destination contains the same images from the database of faces, with the images contained in each directory of lower resolution. Each folder represents a resolution lower than the original resolution, as a result of dividing the original resolution by 2, 4, 6, and 8, resulting in resolutions 320x240, 160x120, 106x80, and 80x60, respectively. This means that both the images that are in the testing directory and the images that are in the training directory will have the same resolutions. However, it is possible that only the images found in the testing directory undergo this downsampling process, with the original resolution and properties being maintained in the images in the training directory.

Images that undergo the process of reducing their resolution can return to their original resolution, through bicubic interpolation or the Image Super-Resolution (ISR) algorithm. In this case, the ISR CNN is already trained and ready to use (also called in the literature off-the-shelf CNN). Both the techniques, algorithms and architecture are explained in the following.

The bicubic interpolation process is well known to be traditionally implemented in image manipulation applications, where the image is suppressed of detail making it blurry depending on how much the image is reduced.

Interpolation techniques constitute one of the components of Super-Resolution. Basically, with interpolation, new pixels are created from existing pixels. Although Super-Resolution uses interpolation, “say[...] interpolation techniques (nearest neighbor, bilinear and cubic convolution) differ from SR because in the first, only one image is used as a source of information for generate an image in higher resolution, different than what is used to produce an image using SR” [15].

Bicubic interpolation, uses all 16 pixels (4x4 neighboring pixels) closest to a pixel to perform its estimate. Since they are at various unspecified pixel ranges, nearby pixels

are given a higher weight in the calculation. Resizing algorithms that use bicubic interpolation logic perform enlargement or reduction of images. When compared to Bilinear and Nearest Neighbor interpolation, Bicubic interpolation is more efficient and produces sharper images, so many image manipulation and editing programs implement Bicubic interpolation.

On the other hand, images submitted through the ISR algorithm undergo more elaborate processing to recover details in low-resolution images. One of the objectives of this work is the generation of images from a super-resolution algorithm. From images that had their quality and specifications lowered, the super-resolution algorithm, namely Image Super-Resolution (ISR), makes the reconstruction of these images in high resolution. Then, these images will go through the face recognition algorithm to see if the use of super-resolution changes the effectiveness of facial recognition. The ISR project “[...] contains Keras implementations of different Residual Dense Networks for Single Image Super-Resolution (ISR), as well as scripts to train these networks using content and adversarial loss components” [16]. The choice of this solution is based on its availability, considering how expensive other solutions are, which implies adjusting the ideal settings for running the solution, installing libraries, etc. In the scope of super-resolution, we have what are called models; different implementations to obtain the super-resolution.

Specifically, for this work, the ISR network used is a off-the-shelf Convolutional Neural Network called Residual Dense Network for Image Super-Resolution [17]. Residual Dense Network extracts large local features through densely connected convolutional layers. RDN is composed of four elements, shallow feature extraction net (SFENet), residual dense blocks (RDBs), dense feature fusion (DFF), and the up-sampling net (UPNet).

This network architecture is formed by 6 convolutional layers stacked inside 20 Residual Dense Blocks (RDB) where each RDB contains 60 feature maps (of each convolutional layers inside the RDBs) and contains 64 feature maps for convolutions outside of RDBs (and of each RDB output). Also, this off-the-shelf network was pre-trained using the DIV2K Dataset [18] which contains 1000 super-resolution (2k) images with a great variety of contents. This network works very well with general images for Super-Resolution without any over-fitting during the training and testing phases.

These changes in image properties correspond to different scenarios to monitor the behavior of the face recognition algorithm. In real scenarios, the captured image may not be the best or there is an individual who is at a considerable distance even in images with considerable resolutions and properties. These techniques contribute to identification making the results more meaningful. In Figure 3 below, it is possible to observe in more detail the functioning of the proposed system.

The computer used to run the tests have 8 GB of RAM memory, 64 bits and an Intel®Core™ i7-7700 CPU @ 3.60GHz with 4 cores, 8 threads, and 8 MB of cache as its configuration. Specifically for the generation of super-resolution images due to the high computational cost, it became unfeasible to use the aforementioned computer, how-

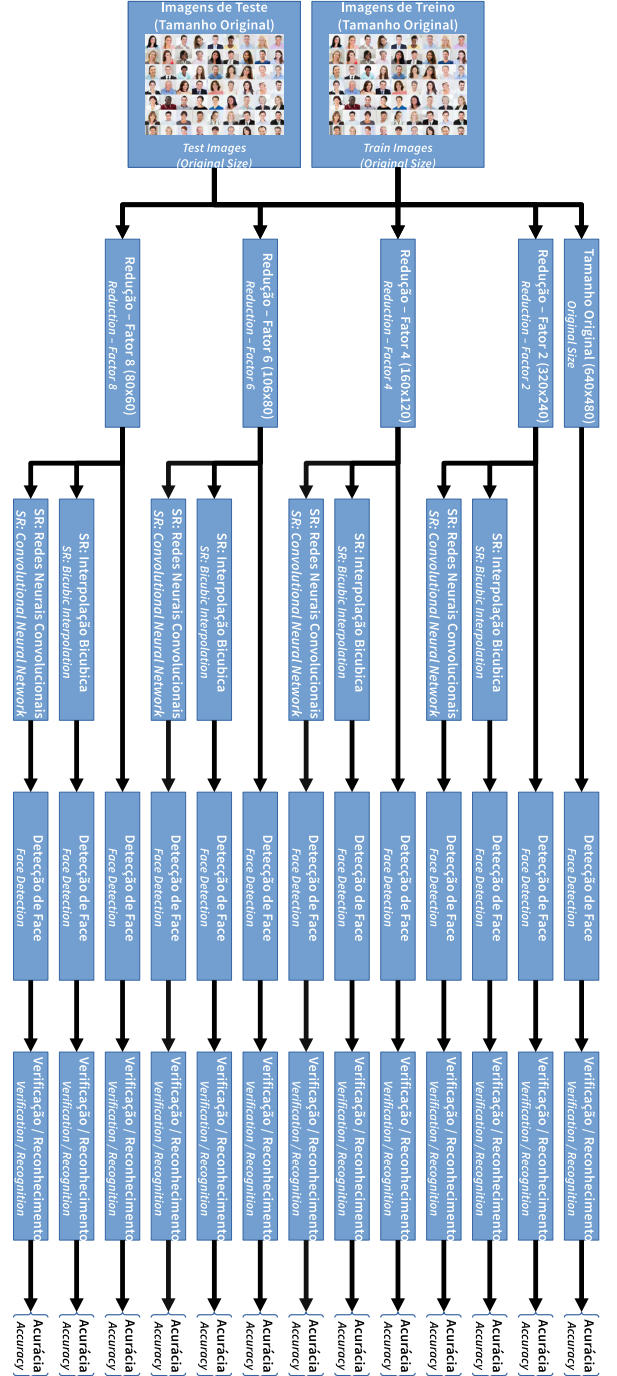


Fig. 3: Details of the operating of the proposed system.

ever, the Google Colab service was used, which allows outsourced processing, which made it necessary to send the images that would be performed in super-resolution to Google’s proprietary cloud, namely Google Drive.

III. RESULTS

In this section, the results of all scenarios and situations mentioned in the previous part will be shown:

- Set of test images and training of original size;
- Reduction of original resolution (640x480) by factors of 2 (320x240), 4 (160x120), 6 (106x80) and 8 (80x60):
 - Sets of test and training images:

- * reduced by bicubic interpolation;
 - * reduced and then increased to the original resolution by bicubic interpolation;
 - * reduced by bicubic interpolation and then increased to the original resolution using the ISR algorithm.
- Only images from the test directory being retained the original properties of the training directory images:
- * Reduction of images of the testing directory by bicubic interpolation;
 - * Reduction and then increasing the images of the test directory to the original resolution then by bicubic interpolation;
 - * Reduction by bicubic interpolation and then enlargement of the test directory images to the original resolution using the ISR.

With the images without any change in their original specifications, in the first scenario, with regard to training and testing, 100% correctness was obtained in face identifications, not resulting in any error. That is, all 550 images were successfully identified. Figure 4 exemplifies the result obtained from a given input image.

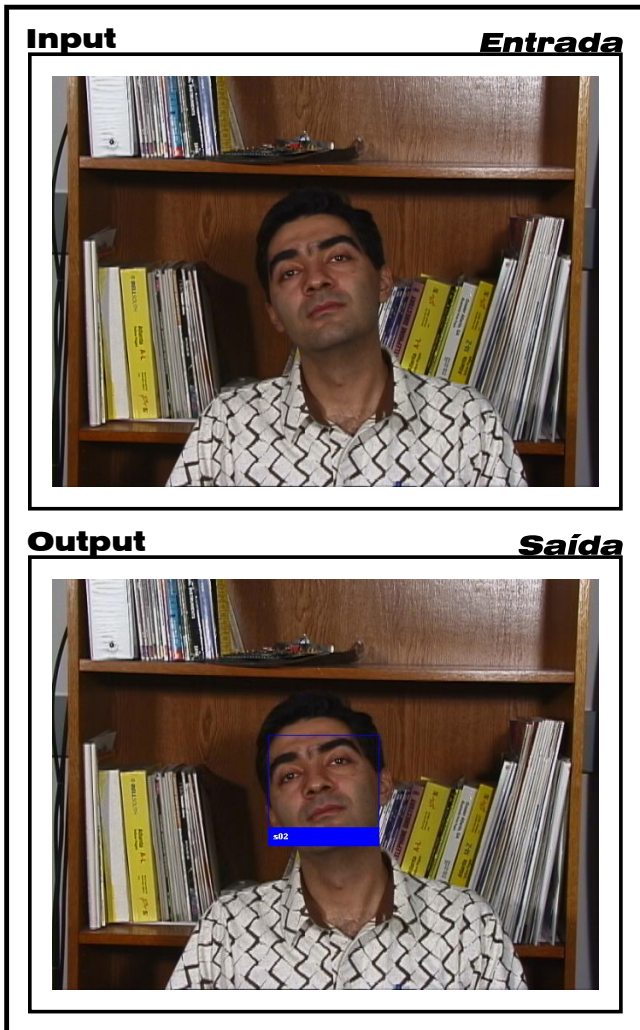


Fig. 4: Example of an image to be recognized and the recognition result.

Then, the scenario is changed, changing the image resolutions by dividing the original resolution by 2, 4, 6 and 8, as shown in Figure 5, the results vary.

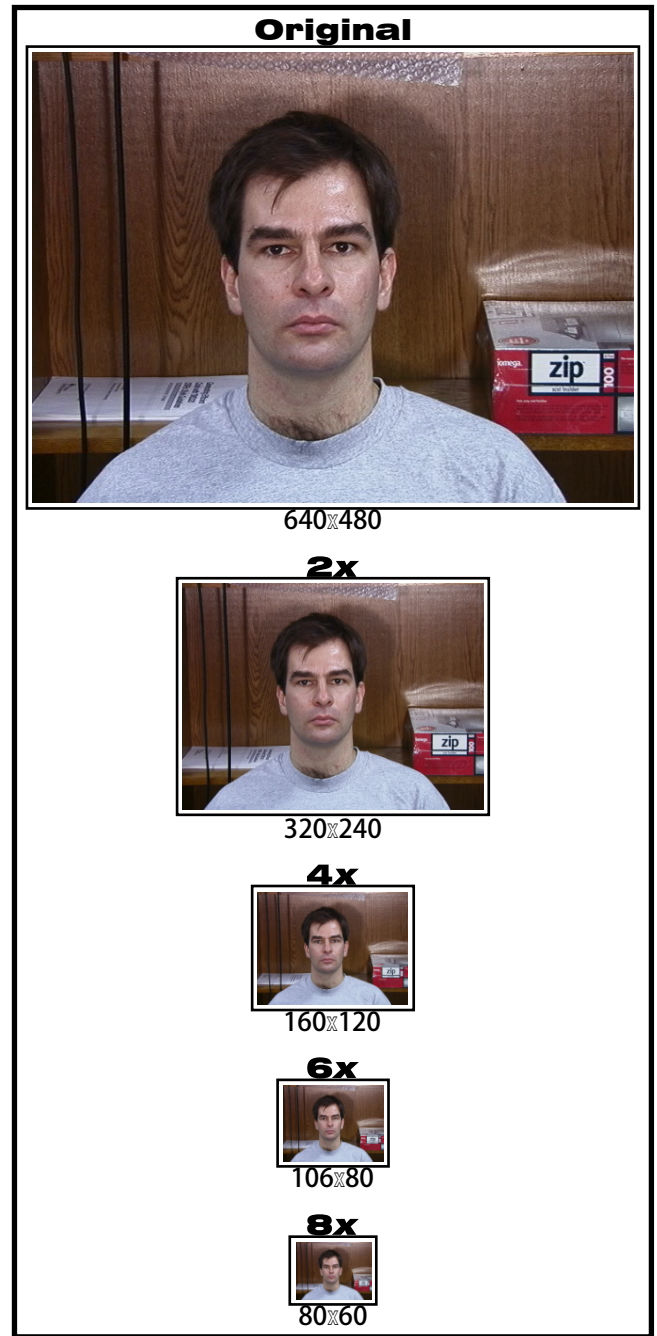


Fig. 5: Representation of an input image that goes through the bicubic interpolation process at a given lower resolution.

TABLE 1: RESULTS IN THE SCENARIO WHERE ALL IMAGES ARE BICUBICALLY DIMINISHED.

Configuration		Results	
Factor	Resolution	Hits	Errors
2	320x240	548	2
4	160x120	543	7
6	106x80	17	553
8	80x60	0	550

Initially, at 320x240 resolution, resulting from the original resolution divided by 2, 548 images are correctly identified,

resulting in 99.64% of the total 550 images, leaving 0.36% of the images that result in error, that is, two images. By factor 4 (160x120), 543 images result in correct answers (98.73%), remaining seven images that result in error (1.27%). About factor 6 (106x80), 17 images are correctly identified, that is, only 3.09% of the images result in correct answers while the majority of 96.91% of the images result in an error (533 images). Finally, no image is corrected, with all images resulting in error.

Differently from the previous situation, where only the resolution of the images was reduced, there is also a situation in which the images are reduced and, through bicubic interpolation, they are increased to the original resolution, thus losing the original properties. Figure 6 illustrates this process.

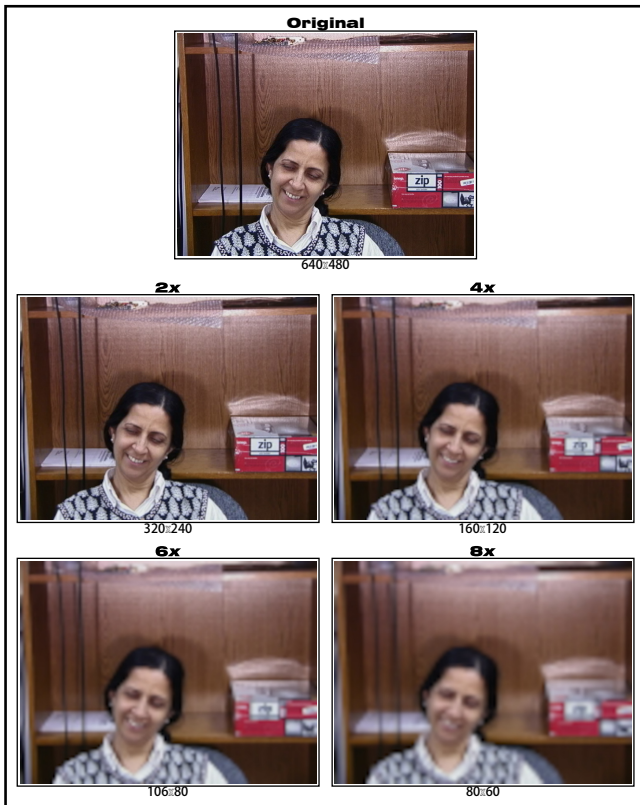


Fig. 6: Illustration of an image that is reduced and later enlarged by the interpolation process.

TABLE 2: RESULTS IN THE SCENARIO WHERE ALL IMAGES ARE DIMINISHED AND THEN BICUBICALLY ENLARGED.

Configuration		Results	
Factor	Resolution	Hits	Errors
2	320x240	550	0
4	160x120	546	4
6	106x80	497	53
8	80x60	370	180

In this context, at 320x240 resolution (factor 2), it shows 100% accuracy of the total of 550 images. By factor 4 (160x120) it is seen that 546 (99.27%) of the images resulted in correct answers and only four images (0.73%) in error. Thus, by factor 6 (106x80), 90.36% (497 images) of the images result in correct answers while 9.64% (53 images) result in an error. Finally, there is the factor 8 (80x60) where

67.27% (370 images) of the images are correct and 32.73% (180 images) result in an error.

In comparison with the images that do not go through the bicubic stretching (as seen in Table 2), it can be seen as an improvement. As the factors increase, so performs the images that are enlarged over images that are only downsampled. By factor 2 there is an 0.36% improvement, in factor 4 the difference goes by 0.54%, in factor 6 there is the best performance by 87.27%, and finally, in factor 8 there are 67.27% of improvement.

Now it is introduced the ISR algorithm. In this situation, the images are bicubic reduced and then increased to the original resolution with the ISR algorithm. Figure 7 characterizes this process.

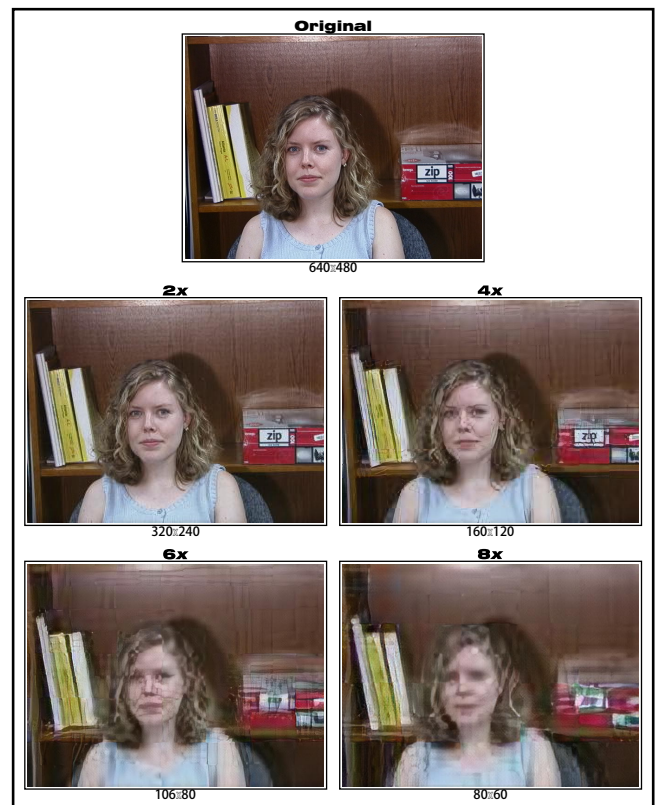


Fig. 7: Demonstration of an image that is reduced via bicubic interpolation and immediately increased to the original resolution using the ISR algorithm.

TABLE 3: RESULTS IN THE SCENARIO WHERE ALL IMAGES ARE BICUBICALLY DIMINISHED AND THEN AUGMENTED USING THE ISR ALGORITHM.

Configuration		Results	
Factor	Resolution	Hits	Errors
2	320x240	550	0
4	160x120	531	19
6	106x80	370	130
8	80x60	181	369

As it can be seen in Table 3, the results in this scenario with the resolution of 320x240 (factor 2), it shows 100% accuracy of the total of 550 images. By factor 4 (160x120), it can be seen that 531 (96.5%) of the images resulted in correct answers and 19 images (3.5%) in error. In factor 6

(106x80) 67.27% (370 images) of the images result in correctness while 23.63% (130 images) result in an error. Finally, there is the factor 8 (80x60) where 32.9% (181 images) of the images are correct and 67.1% (369 images) result in an error.

Ultimately, in the last scenario, only the images located in the test directory are resized, keeping the properties of the images in the training directory, this comes close to reality and in most applications. In real environments the images are controlled and captured initially when a person is registered in the database, so these images need to be in good resolutions.

TABLE 4: RESULTS IN SCENARIO WHERE ONLY TEST DIRECTORY IMAGES ARE SHRUNK.

Configuration		Results	
Factor	Resolution	Hits	Errors
2	320x240	550	0
4	160x120	549	1
6	106x80	110	440
8	80x60	0	550

As seen in the Table 4, starting with factor 2 of 320x240 resolution, the results achieved through the original resolution are maintained, there are 100% correct answers in the total of 550 images. By factor 4 of 160x120 resolution, the results change subtly, there is an error which corresponds to 0.2% of the 550 images, thus, 99.98% of the images result in correctness, which corresponds to 549 images. On the other hand, in factor 6 of 106x80 resolution, there is a considerable deterioration concerning correct answers, resulting in 80% of errors (440 images) and 20% (110 images) of correct answers. Finally, with factor 8 of 80x60 there is the worst performance, it does not result in any accuracy and with 100% (550 images) of images identified wrongly. In comparison with the Table 1 the results in this scenario proves an enhancement. This also means that high quality and resolution train images tends to improve the outcome, but for extreme low quality test images neither situation are shown as ideal. By factor 2 we have an 0.36% improvement, in factor 4 the difference goes by 1.09%, in factor 6 there are the best performance by 16.9%, and finally in factor 8 there are no improvement, in both cases no image was recognized.

Similarly, the previous situation, now in addition to decreasing the resolution, through bicubic interpolation, the images are increased to the original resolution, thus losing the original properties.

TABLE 5: RESULTS IN THE SCENARIO WHERE ONLY TEST IMAGES ARE REDUCED AND THEN ENLARGED.

Configuration		Results	
Factor	Resolution	Hits	Errors
2	320x240	550	0
4	160x120	545	5
6	106x80	527	23
8	80x60	399	151

As it is shown in Table 5, initially, at factor 2 (320x240), there is 100% correctness (550 images) and no errors. Continuing by factor 4 (160x120), there is 99.1% correctness

(545 images) and five images resulting from error. By factor 6, the images errors increase, resulting in 4.2% of the images (23 images) with 95.8% of the images correctly identified. Finally, with factor 8, we have that 72.5% of the images result in correct answers (399) and 27.5% of the images (151 images) correspond to errors. The comparison between Table 2 and 5 were both satisfy similar conditions, exhibit a better performance Table 2. By factor 2 both recognizes all images. In factor 4, the Table 2 takes advantage by 2.72%. Factor 6 there are 23.09% of difference. In the last factor, factor 8 there are 32.9% of variation. This means that the use of high quality images in the training does not improve the performance over images that are diminished and in sequence enlarged.

In the last situation of this scenario, the images of the tests and training directories were reduced and increased through the Image Super-Resolution algorithm, as seen in Table 6.

TABLE 6: RESULTS IN THE SCENARIO THAT TEST IMAGES ARE BICUBICALLY DIMINISHED AND THEN AUGMENTED USING THE IMAGE SUPER-RESOLUTION ALGORITHM.

Configuration		Results	
Factor	Resolution	Hits	Errors
2	320x240	550	0
4	160x120	544	6
6	106x80	432	118
8	80x60	234	316

The calculation in this configuration returns in factor 2 100% correctness. In factor 4 we have 544 correct answers (98.9%) and 6 errors (1.1%). With factor 6, the computation points to 432 correct answers (78.55%) and 118 errors (21.45%). Lately, in factor 8, there are 234 correct answers (42.55%) and 316 errors (57.45%). Comparing Table 3 and the Table 6 significant changes are shown in favor of Table 6. By factor 2 both recognizes all images. In factor 4 Table 6 shows an improvement of 2.36%. Factor 6 this difference goes by 11.27%. At last, in factor 8 are shown an improvement of 9.63%. This means that in the training process when the images are bicubically diminished and then enlarged using the ISR algorithm the results are better than when all images go through this process. But they are overcome by the results obtained by enlargement by bicubic interpolation.

The Figure 8 presents the summary of the main results by the number of correct answers of face recognition comparing the four main configurations: resampling the test and training images using bicubic interpolation (a) and super-resolution via CNN (b), and resampling only test images using bicubic interpolation (c) and super-resolution via CNN (d) for the four factors (2, 4, 6 and 8). Note that in all settings, reducing the image by half the size, the number of hits remains the same, ie 100 percent. As the resolution starts to decrease, the number of hits also decreases. In all cases the super-resolution using bicubic interpolation performed better than CNN mainly for the lowest factor when the image is almost all out of focus.

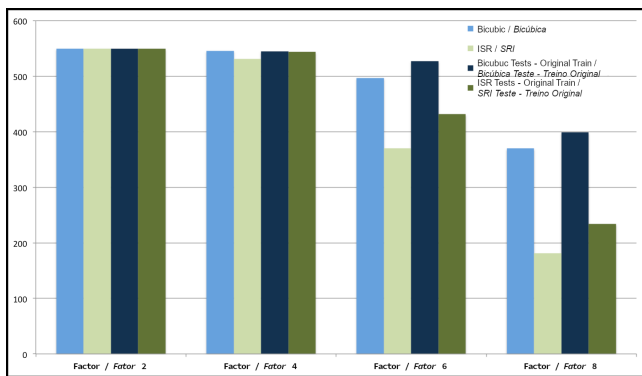


Fig. 8: Summary of Results in number of hits of the recognition process grouped in different test configurations by the two super-resolution algorithms.

IV. CONCLUSIONS

Given the results in different scenarios and situations, it is possible to observe that the ideal situation is that of images at high resolutions where the best results are obtained. However, in everyday situations, it is not always possible to rely on scenarios where there are images of excellent quality and resolutions.

With this in mind, even with images at low resolutions, the process of increasing the resolution considerably improves the results and performance of the algorithm in question.

The data indicate that, with the images that are trained in high resolution, even with the images that will be identified in lower resolution, the results are superior to the scenarios in which the training takes place with images in lower resolutions, which is the case of many applications used daily.

There was an expectation that the super-resolution would improve and enhance the results in terms of accuracy, which did not bring concrete results in this regard. Although visually, according to images that undergo super-resolution, as long as they have not very low resolutions, they show greater detail, which does not necessarily make the performance of face recognition more significant.

The bicubic interpolation used to increase images to the original resolutions with loss results in superior outcomes and, therefore, its use is justified in this context. Even without any new information, the interpolation uses the image's original pixels. The best result obtained in the interpolation process can be related to the chosen face recognition algorithm, which is based on fine detail. Deep Learning algorithms generate several artifacts that can confuse the recognition algorithm.

In future works, other facial recognition algorithms can be tested so other neural networks. Bicubic interpolation in comparison with Deep Learning can be cheaper and a faster alternative for low-budget systems that generate small quality and resolution images, improving the accuracy of results in a considerable way.

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REFERENCES

- [1] H. Hofbauer, L. Debiasei, and A. Uhl, "Mobile face recognition systems: Exploring presentation attack vulnerability and usability," in *2019 International Conference on Biometrics (ICB)*, 2019, pp. 1–7.
- [2] S. Kirchgasser, A. Uhl, Y. Martínez-Díaz, and H. Mendez-Vázquez, "Is warping-based cancellable biometrics (still) sensible for face recognition?" in *2020 IEEE International Joint Conference on Biometrics (IJCB)*, 2020, pp. 1–9.
- [3] E. Ribeiro, A. Uhl, and F. Alonso-Fernandez, "Iris super-resolution using cnns: is photo-realism important to iris recognition?" *IET Biom.*, vol. 8, no. 1, pp. 69–78, 2019. [Online]. Available: <https://doi.org/10.1049/iet-bmt.2018.5146>
- [4] T. D. Bissi, "Reconhecimento facial com os algoritmos eigenfaces e fisherfaces," *Uberlândia*, p. 41, 2018.
- [5] K. Sundararajan and D. L. Woodard, "Deep learning for biometrics: A survey," *ACM Comput. Surv.*, vol. 51, no. 3, pp. 65:1–65:34, 2018. [Online]. Available: <https://doi.org/10.1145/3190618>
- [6] R. R. Schultz and R. L. Stevenson, "Extraction of high-resolution frames from video sequences," *IEEE Trans. Image Processing*, vol. 5, no. 6, pp. 996–1011, 1996. [Online]. Available: <https://doi.org/10.1109/83.503915>
- [7] W. B. Dourado, "Avaliação de técnicas de interpolação de imagens digitais," Master dissertation, Universidade Estadual Paulista (UNESP), Universidade Estadual Paulista (UNESP), Faculdade de Ciências e Tecnologia, Presidente Prudente, Aug. 2014. [Online]. Available: <http://hdl.handle.net/11449/115892>
- [8] X. Xu, W. Liu, and L. Li, "Low resolution face recognition in surveillance systems," *Journal of Computer and Communications*, vol. 02, pp. 70–77, 01 2014. [Online]. Available: <https://doi.org/10.4236/jcc.2014.22013>
- [9] E. Bilgazyev, B. A. Efraty, S. K. Shah, and I. A. Kakadiaris, "Improved face recognition using super-resolution," in *2011 IEEE International Joint Conference on Biometrics, IJCB 2011, Washington, DC, USA, October 11-13, 2011*. IEEE Computer Society, 2011, pp. 1–7. [Online]. Available: <https://doi.org/10.1109/IJCB.2011.6117554>
- [10] S. R. Arashloo and J. Kittler, "Fast pose invariant face recognition using super coupled multiresolution markov random fields on a GPU," *Pattern Recognit. Lett.*, vol. 48, pp. 49–59, 2014. [Online]. Available: <https://doi.org/10.1016/j.patrec.2014.05.017>
- [11] B. K. Gunturk, A. U. Batur, Y. Altunbasak, M. H. H. III, and R. M. Mersereau, "Eigenface-domain super-resolution for face recognition," *IEEE Trans. Image Processing*, vol. 12, no. 5, pp. 597–606, 2003. [Online]. Available: <https://doi.org/10.1109/TIP.2003.811513>
- [12] H. Zhao, O. Gallo, I. Frosio, and J. Kautz, "Loss functions for image restoration with neural networks," *IEEE Trans. Computational Imaging*, vol. 3, no. 1, pp. 47–57, 2017. [Online]. Available: <https://doi.org/10.1109/TCI.2016.2644865>
- [13] M. Davis, S. Popov, and C. Surlea, "Real-time face recognition from surveillance video," in *Intelligent Video Event Analysis and Understanding*, ser. Studies in Computational Intelligence, J. Zhang, L. Shao, L. Zhang, and G. A. Jones, Eds., 2011, vol. 332, pp. 155–194. [Online]. Available: https://doi.org/10.1007/978-3-642-17554-1_8
- [14] "Georgia tech face database." [Online]. Available: http://www.anefian.com/face_reco.htm
- [15] M. T. Jr and A. S. Rosa, "Super-resolução de imagens cbers 2," *XIII Simpósio Brasileiro de Sensoriamento Remoto*, pp. 1197–1204, 2007. [Online]. Available: <http://mart.sid.inpe.br/col/dpi.inpe.br/sbsr@80/2006/11.16.00.47/doc/1197-1204.pdf>
- [16] F. C. et al., "Isr," <https://github.com/idealo/image-super-resolution>, 2018.
- [17] Y. Zhang, Y. Tian, Y. Kong, B. Zhong, and Y. Fu, "Residual dense network for image super-resolution," 2018.
- [18] E. Agustsson and R. Timofte, "Ntire 2017 challenge on single image super-resolution: Dataset and study," in *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, July 2017.