PhotoRestorer: Restoration of Old or Damaged Portraits with Deep Learning

Christopher Mendoza-Dávila, David Porta-Montes and Willy Ugarte[a]
Department of Computer Science, Universidad Peruana de Ciencias Aplicadas, Lima, Peru

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Abstract: Several studies have proposed different image restoration techniques, however most of them focus on restoring a single type of damage or, if they restore different types of damage, their results are not very good or have a long execution time, since they have a large margin for improvement. Therefore, we propose the creation of a convolutional neural network (CNN) to classify the type of damage of an image and, accordingly, use pretrained models to restore that type of damage. For the classifier we use the transfer learning technique using the Inception V3 model as the basis of our architecture. To train our classifier, we used the FFHQ dataset, which is a dataset of people's faces, and using masks and functions, added different types of damage to the images. The results show that using a classifier to identify the type of damage in images is a good pre-restore option to reduce execution times and improve restored image results.

1 INTRODUCTION

Photography as we know it today has its beginnings in the late 1830s in France, where Joseph Nicéphore Niépe using a portable camera obscura made the first photograph that did not fade rapidly. Thus, thanks to the camera, different historical moments of humanity could be retained in time. However, despite the fact that the photographs can last several years, this does not imply that they may suffer damage from other sources such as exposure to the environment or poor conservation practices. InstaRestoration[1] mentions that there are different types of damage caused by these sources, such as scratches and cracks, broken parts, missing parts, changes in colors and discoloration. Because of this, today there are countless old, historical or family photos damaged by these bad conservation practices.

While there are different methods of restoring photos today, these methods are not accessible to everyone. Whether for money or lack of knowledge due to, most of the people who own this damaged photographs are non-digital, and the existent methods can be very cumbersome for many people (Ullah et al., 2019; Zhang et al., 2020a; Luo et al., 2021; Jiao et al., 2022; Sun et al., 2022). Consequently, currently there are not many accessible tools that can be used by anyone to restore old photos, which means that many of these photos cannot be restored and are lost over time causing cultural and historical losses.

Among the most used techniques for restoring photographs we have, on the one hand, digital restoration, which consists of digitally scanning the photo to be restored and then using tools such as Adobe Photoshop to restore the photo. This method of restoration requires time and technical knowledge in this type of tools. Thus, the result of the restoration will depend on who is responsible for it. On the other hand, we have restoration using Machine Learning models. These models are trained with thousands of photos to be able to restore a photograph. Although the process of training a model also requires time and knowledge in this field, today there is a wide variety of pre-trained models available for everything from improving quality to restoring cracks and giving color to old photos (Shen et al., 2019; Wan et al., 2023). There are even pre-trained models that are capable of regenerating images of scientific interest, even written characters (Ferreira et al., 2022; Furat et al., 2022; Su et al., 2022; su Jo et al., 2021).

As mentioned, there are different models of restoring images. For example, in (Rao et al., 2023) pro-

[a] https://orcid.org/0000-0002-7510-618X

[1] "How to assess the damage of an old photograph" - InstaRestoration - https://www.instarestoration.com/blog/how-to-assess-the-damage-of-an-old-photograph

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pose a regressive model called MS-GAN to reconstruct images, which is based on a Generative Adversarial Network (GAN) and consists of two phases: The first phase consists of reconstructing the image from the edges and domains of color. The second phase is responsible for improving the quality of the reconstructed image. This technique can achieve high-quality reconstructed images using only the edges and color domains of the image as input. However, there are some negative results with images that contain a lot of details, in this case the difficulty of the reconstruction will increase and therefore the quality of the image will decrease. On the other hand in (Nogales et al., 2021) propose a model called ARQ-GAN to restore images of ancient architectural structures, which is a neural network that locates the parts of the image where information is missing in order to later complete it, adding the missing elements according to their architectural style and the distribution denoting the ruins. The model is capable of restoring these ancient structures contained in the images, however, as in the previous case, it is not capable of accurately restoring parts where the structure is very detailed. Likewise, by not knowing exactly what these ancient structures that are being restored looked like and only basing ourselves on the opinion of experts, it is difficult to know exactly if the restoration is correct.

For those reasons, in our project, we are using machine learning models and different frameworks like Flask and React Native to create a free and easy to use mobile app for photo restoration. One of the techniques to be used are Generative adversarial networks (GAN), a type of algorithm used for unsupervised learning. It consists of the combination of two neural networks in which there is a generator and a discriminator, where, based on a series of samples, the generator tries to create images that make the discriminator believe that they are real (Cheng et al., 2020). With this technique, certain parts of the photographs that have lost quality or are damaged can be reconstructed. On the other hand, if we want to reconstruct missing parts or cracks in the photograph, there is Image Inpainting, which according to (Qin et al., 2021), defines it as the process that is applied to images in order to fill in holes or missing parts (such as cracks) through the analysis of the edges of the missing part. In this project, we are creating an image classificator to detect what process should be applied to the image given by the user and restore that image with just one button, however, internet access will always be needed.

We propose a new approach to restore old or damaged portraits. On one hand, we create a classification model based on a Convolutional Neural Network (CNN) to detect if the photograph either has cracks or is blurred, or both. Thus, according to the classification, different pre-trained and specialized models will be called to restore the type of damage found. Furthermore, to carry out this classifier, it was also necessary to create a dataset of 12,000 images of people's faces, based on the FFHQ dataset, using masks and a Gaussian filter, to simulate damage on the portraits. In addition, a mobile application was built with the models, so people can use them to restore their most precious photos.

To summarize, our main contributions are as follows:

- Implementing a CNN model to classify different types of damage from a portrait.
- A pipeline structure to restore a damaged portrait.
- Building a large dataset of face images with different types of damage.

The rest of this paper is structured as follows. Section 2 presents some related works for image restoration. Section 3 presents the methodology to develop our proposed method. Section 4 shows the experiments and results of the proposed method. Finally, section 5 closes with conclusions and perspectives.

2 RELATED WORKS

In this section, we will see five projects where the authors use some techniques that are going to be used in this paper like GANs and Image Inpainting, these investigations are useful because they work as an inspiration in the development of our project. Thus, in order to reduce the damage not only in photos but in images in general, several recent scientific articles have focused their attention on GANs as a technique to solve this problem.

In (Rao et al., 2023) the authors proposed a novel progressive model for the image reconstruction task, called MS-GAN, which uses an enhanced U-net as a generator. The MS-GAN can achieve high quality and refined reconstructed images using the input of binary sparse edges and color domains. The MS-GAN training process consists of two phases: the generation phase and the refinement phase. The generation phase is to use binary sparse edges and color domains to generate the preliminary images. The refinement phase is to further improve the quality of the preliminary images. The results of the MS-GAN shows that it can achieve high-quality reconstructed images using only the input of binary sparse edges and color domains. However, since every method is not absolute, some representative negative results are presented. For example, when the images to be reconstructed contain many rich details, the difficulty of image reconstruction will increase rapidly and the quality of these reconstructed images will decrease. This approach is similar in one of the cases of our project, which is to improve the image quality. Since our project is the restoration of old or damaged photos, this is an important aspect for us, but it does not cover the full scope of our project.

In (Cao et al., 2020), an attempt is made to restore Chinese Ancient Murals that were damaged by the passage of time and now have some fissures or cracks that do not allow the correct appreciation that it deserves due to its religious, cultural and artistic importance. The authors propose the use of a GAN with improved consistency to repair the missing parts of the mural. In addition, the first layers of the network apply convolutions to extract the characteristics of the mural. As a result, they had a high SSIM score (0.85 in average) compared to other studies, this metric indicates the similarity between the original image and the one generated by the network where a higher score means better quality. Comparing this paper to ours, we have a small similarity in the process, we pretend that the user will take a picture or upload a damaged imaged, and we are going to restore it, but centering in facial restoration instead of murals. Another important difference with our project is that their architecture uses only GANs to restore the mural, and we are proposing a classifier that can determine if an image might need image inpainting and GAN to be applied.

In (Shen et al., 2019), they propose a multitask model, which, unlike a single task model, is capable of optimizing more than one task in parallel learning. This consists of an end-to-end Convolutional Neural Network (CNN) to learn effective features of the blurred face images and then estimate a latent one. Likewise, the different tasks are capable of sharing the weight of the image to be processed for a better result. Talking about metrics, they used the CelebA and Helen dataset to compare it with other state-of-the-art models, the results show that the multitasking model has a higher average PSNR and SSIM than the others (24 and 0.87 respectively), this demonstrates both high quality and similarity of the generated image and the original. Therefore, this model presents an alternative to our project; although it focuses on facial restoration, it is limited to deblurring and does not cover the reconstruction of missing parts as ours. One important difference in architecture is that they have a CNN combined with a GAN to guarantee the deblurr, we propose an image classifier capable of determining if an image should use image inpainting or GAN for facial restoration.

In (Nogales et al., 2021), the contribution of the authors is the ARQGAN network that locates the parts of the image where information is missing in order to later complete it, adding the missing elements according to their architectural style and the distribution denoted by the ruins. The process of this solution is based on two different ways of restoring. In the first, images of the ruins are used to rebuild Greek temples, being the baseline. In the second, a segmented image is used as additional information for the reconstruction of a temple. After applying filters when combining both methods to form the image of a temple, it would be evaluated by the discriminator model, causing the generator to learn from its mistakes. In both cases, the same conclusion was reached: the segmented training was more efficient than the direct one. Although this does not mean that the system is perfect, it still needs to improve in terms of restoring more precise parts of architectural constructions. Although this proposal uses a GAN for restoration, it differs quite a bit from our project, since it is aimed at restoring images of old structures while our project focuses on restoring portraits. Even so, the use of a segmented image to improve the restoration is a very interesting technique that could be used for a possible improvement in our solution.

In (Yuan et al., 2019), the authors propose a framework for image completion based on Patch-GAN that is a type of discriminator for GANs which only penalizes structure at the scale of local image patches. It is composed of a generator, multi-scale discriminators, and an edge processing function, which can extract holistic and structured features from damaged images. Compared to existing methods that only use holistic features, the proposed method learns more details from the given image and achieves more realistic results, especially in restoration of human faces. The process generally consists of three steps. First, one must go through the architecture of the model that aims to receive the masked image and generate the missing context that is consistent with its surroundings while maintaining a high level of realism. They then go through the loss functions, where the reconstruction loss and global guidance loss provide the holistic information of the damaged images to the generator, and the local guidance and edge loss motivate the model to obtain the information of the image structure. Finally, they go through the optimization phase where the goal is to find the best encoding of the masked input, that is, the generator produces the closest image to the one that was originally inserted. The authors conclude that the model is suitable for different types of datasets and obtains the best performance in the restoration of human faces. As a result, the PSNR and SSIM stand out, where they obtained favorable ratings on a wide variety of datasets. This approach is similar to ours for the part of restoring cracks and missing parts of an image. However, we also focus on improving the quality of the images of the user, that is why we use more than one model to restore the portraits.

3 MAIN CONTRIBUTION

3.1 Context

Before we start, it is important to have some definitions in mind. In this section, we will see what we mean when we refer to a Convolutional Neural Network (CNN) that we are going to use as our classifier, Image Inpainting method and Generative Adversarial Network (GAN).

Definition 1 (CNN (Fu, 2021; Wang, 2022))**.** *Is mainly used for image classification methods because it can extract information and features from images and learn from these patterns in order to perform classification tasks based on these found patterns.*

Example 1. *In Figure 1 shows the basic structure of a convolutional neural network (CNN).*

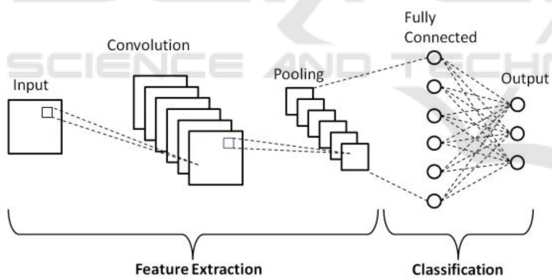

Figure 1: CNN structure by (Tropea and Fedele, 2019).

Definition 2 (Image Inpainting (Yuan et al., 2019; Liang et al., 2021; Fanfani et al., 2021; Chen et al., 2021))**.** *Is an algorithm that receives a damaged image with a missing part as input, then analyzes the edges of the missing part (nearest neighbors) and tries to reconstruct it based on all the analysis performed. This technique has multiple cultural applications, since it can help to reconstruct ancient murals or even images of high historical value (Poornapushpakala et al., 2022; Liu, 2022; Zeng et al., 2020; Cao et al., 2020). In this paper, we will make use of image inpainting to be able to reconstruct cracks or even missing parts of an image, always giving priority to facial restoration.*

Example 2. *In Figure 2 a flowchart about the image inpainting technique is shown.*

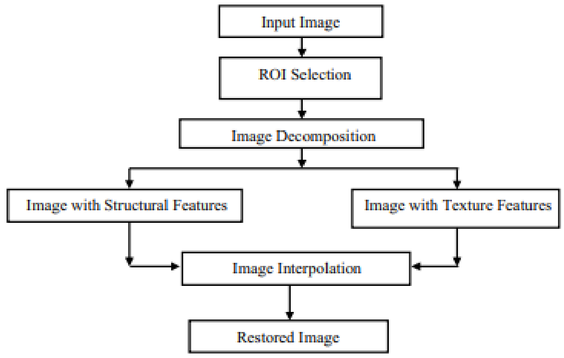

Figure 2: Flowchart of Inpainting technique by (Poornapushpakala et al., 2022).

Definition 3 (GAN (Cao et al., 2020; Fu, 2021; Zhang et al., 2020b))**.** *Is a type of unsupervised neural network that is composed of two networks. The first is a generating network, which is in charge of generating the image from random noise. The second is a discriminator network, which is in charge of evaluating whether the generated image is a real image or a generated one. To do this, the discriminator receives as input data the generated image and the real image and evaluate if the two images are similar or not. The idea here is that the generating network is capable of generating images capable of making the discriminating network believe that the generated image is the real one.*

Example 3. *In Figure 3 shows the basic structure of a generative adversarial network (GAN).*

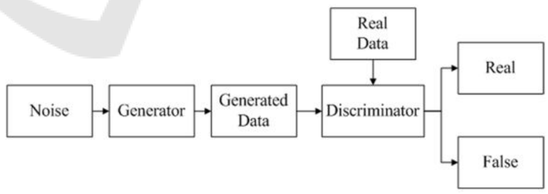

Figure 3: GAN structure by (Cao et al., 2020).

3.2 Method

In this section, the main contributions proposed in this project will be detailed, including the use of pretrained models and the integration with the mobile app.

3.2.1 Classifier Architecture

The main contribution of this research is the classification model. This classifier is in charge of detecting

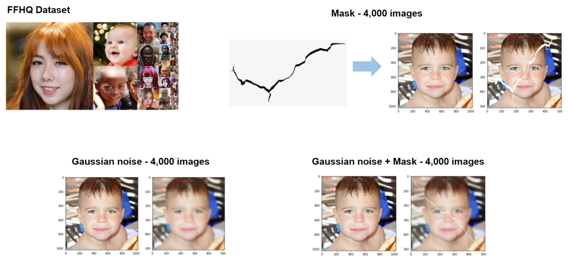

Figure 4: Dataset separation for classifier training.

the type of damage that the input image has, then classifies it into three classes: Blurred, Cracked and both cases. According to the class detected, the application will call the API of a pre-trained model that specializes in restoring that type of damage.

To create our classifier, we used Transfer Learning, a method that allows transferring acquired knowledge from one network to another. The base architecture we used was Inception V3, a type of Convolutional Neural Network (CNN), with pre-trained weights that are useful for image analysis and object detection as shown in Figure 1. We added an input layer to receive a 512x512 image, finally, as an output layer, we have a 1x1x3 value representing the type of damage. This model was exported with the 'h5' extension, so it can be deployed in our backend.

3.2.2 Dataset Building

In order to train a model to classify the type of damage, we developed our own dataset based on an existing one. The Flickr Faces HQ (FFHQ) Dataset consists of 70,000 high-quality PNG images, we randomly selected 12,000 images and separated it in 3 groups. In Figure 4 shows the group separation used to train the image classifier, it should be noted that each group had 4,000 images.

- First group: a Gaussian noise filter was applied to add blur to the image.
- Second group: we applied masks that simulated the cracks and damage
- Third group: a combination of both to simulate a totally damaged image

3.2.3 Model Architecture

In Figure 5, we can see the main process when the user submits an image through the application.

- Upload Image: From the application, the user sends an input image, which can be in PNG or JPG format. This image is sent to our server (backend) and it can be taken from your smartphone camera or can be uploaded from your gallery.

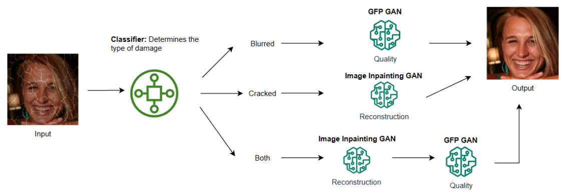

Figure 5: Architecture flow.

- Classifier: The image is classified according to the type of damage found by the classification model. The types of damage can be: Blurred, Cracked and both cases.
- API Call: According to the type of damage found by the classifier, the application will call the API of a trained model specialized in restoring this type of damage. In case is blurred, the app will call the GFP-GAN model, in case is cracked, the app will call the Image Inpainting model and, if the image has both types of damage, the app will call first Image Inpainting and second GFP-GAN.
- Download and Share: After restoring the image, the application allows you to download the image to your smartphone or share it on your social networks.

3.2.4 Architecture of the Application: Backend-Frontend Integration

As we can see in Figure 6, we decided to separate the restoration models with the image classifier (backend) of the application (frontend).

The backend consists of an API that receives an image which will be sent by the user, then it is recognized by the classifier that identifies the type of damage and, depending on the result, it is sent to one or both restoration models. As a result, a JSON object is sent to the frontend with the link of the restored image and the type of damage identified by the classifier.

For the deployment, we used a free plan from Python Anywhere, inside this server we have all our python scripts and the H5 model of the classifier, this server is running all day, every day, for 3 months, the connection with the frontend (app) is through an API call.

The frontend consists of the development of the application, here we have different files using React Native with Expo, the connection with the backend was made with an API call, we choose the Expo SDK because it provides different tools with native Android functionalities such as its camera, gallery and file sharing.

To summarize, we deployed the restoration models and image classifier in a backend server that is connected to the Android application through an API.

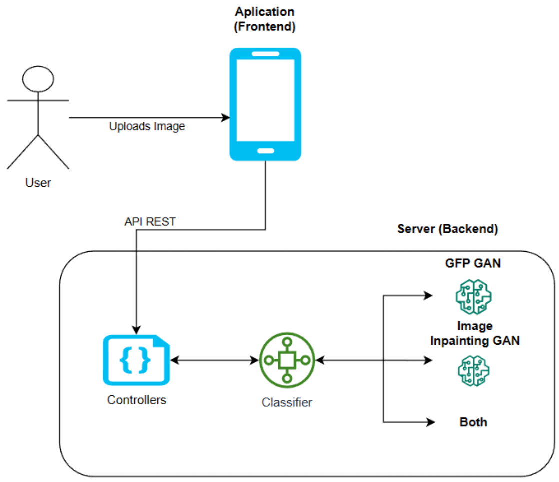

Figure 6: Architecture of the application.

4 EXPERIMENTS

4.1 Experimental Protocol

To develop our project, we divided the development into 4 pieces, the backend where we have the restoration functionality, the server where we deployed our backend, the frontend to create the app and a mobile phone where we put all together.

- Backend: The Python programming language was used in its version 3.10.7, the Flask libraries used for the development of the API server were Pillow for image manipulation, Dotenv for the creation of hidden variables, Keras for the use of our classifier in 'h5' format and Replicate to be able to use the pre-trained models of GFP-GAN and Image Painting.
- Server Deployment: We use the free plan offered by the Python Anywhere website, this platform offers a free plan for up to 3 months; however, this plan does not allow the use of a GPU, so all the processes carried out by the classifier run on the CPU provided by the website; likewise, the platform support team had to be contacted to be able to add the Replicate API to its 'White List' and thus be able to send the links in JSON format to the frontend.
- Frontend: We use React Native 0.71 and React 18.2, this accompanied by the Expo 48 SDK which allows us to use native Android functionalities. Most of the libraries used belong to de Expo SDK and an extra library is Feather to use some vector icons. To export the application, we used the Expo Application Services (EAS), which through command lines is capable of gathering all the files used in the frontend and generating an installer (APK).
- Mobile phone: To test all the functionalities, we used an OnePlus 7 pro with Android 10, to install the APK you have to download the file from our Google Drive Folder or Github because it is not deployed on the Play Store. Having the APK the installation is simple and some permissions to access the files and camera will be asked in order to use the app. It is important to know that this application will run in all Android devices with Android 5 or more.

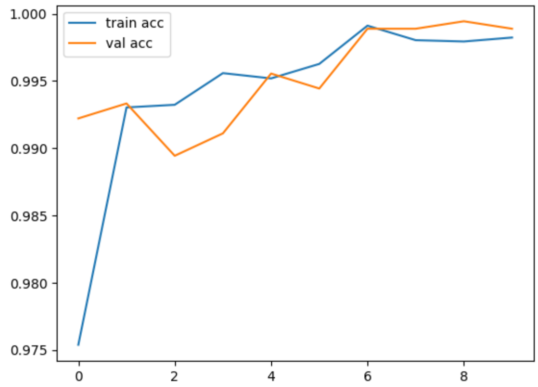

Figure 7: Accuracy of the classification model.

4.2 Results

4.2.1 Classifier Accuracy

To measure the performance of our model, we use the cross-validation technique, which is a technique that helps us compare the accuracy of the model with respect to the training data and the validation data. Figure 7 shows the accuracy of the model throughout the ten training epochs. Thus, it can be seen that the accuracy of the validation data started with a value of 0.99, which is quite a high value. This is mainly because the Transfer Learning technique was used to train the model, this technique uses the structure of a network with already trained weights and is used as the basis for the creation of our own convolutional network. At the end of the training, it is observed that the accuracy had a value of more than 0.995, which indicates a very good performance of the model.

4.2.2 Classifier Labels

It is important that our classifier works correctly, since in this way the application will know which restoration model to call according to the type of damage.

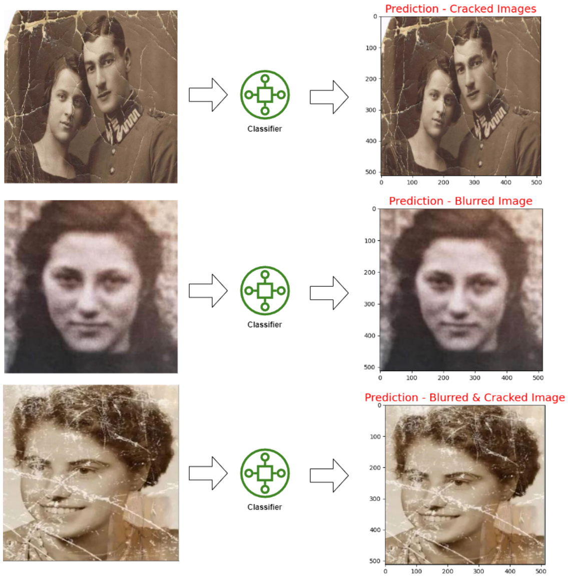

Figure 8: Classification of portraits.

This will help reduce the restore wait time significantly. Thus, in figure 8 some examples of the different classes of our classifier are shown. For a portrait with cracks, our model classifies it as "Cracked Image", for a blurred one it classifies as "Blurred Image" and for one with both types of damage it classifies as "Blurred and Cracked Image".

4.2.3 Execution Time

Regarding the execution time of the restoration models, we have measured both models and the results can be seen in table 1. Thus, it is observed that the GFP-GAN model, which restores blurred images, has an average execution time of 2.59 seconds, a minimum time of 1 second and a maximum time of 8.4 seconds. On the other hand, the Image Inpainting model used to restore cracked images has an average execution time of 55.38 seconds, a minimum time of 32 seconds, and a maximum time of 67.4 seconds.

Table 1: Execution time of restoration models.

	Min	Average	Max
Image Inpainting	32.000	55.380	67.400
GFP-GAN	1.000	2.591	8.400

4.2.4 Quantitative Results

If the image to be restored is classified with both types of damage, the application will call both models for its restoration, that is, both the GFP-GAN model and the Image Inpainting model. In order to know which of the models to use first and obtain the best result, both cases were evaluated using the Peak Signal-to-Noise Ratio (PSNR) metric, which evaluates the degree of distortion or noise of the generated image with respect to the real image. Thus, the higher the PSNR value, the higher the quality of the generated or reconstructed image. Table 2 shows that if we first use the GFP-GAN model and then the Image Inpainting model, a PSNR of 23.16 is obtained, while if we first use the Image Inpainting model and then the GFP-GAN model, a PSNR of 24.02 is obtained.

Table 2: Execution time of restoration models.

	PSNR
Image Inpainting + GFP-GAN	24.016
GFP-GAN + Image Inpainting	23.162

4.3 Discussion

According to the results obtained in figure 7, we can affirm that using the transfer learning technique for image classification is very convenient, since a high accuracy is obtained, which indicates a good result in image classification. This is thanks to the fact that, by using the structure of a model with already trained weights as the base of our model, it is not necessary to train these weights again from scratch. Thus, the amount of time required for training and the amount of data required for this training are also reduced. The use of the classifier also helps to reduce the time needed for restoration, since according to the classification of the image, the application will only call the required model to restore that particular type of damage. Observing figure 1, we can conclude that the Image Inpainting model, which is responsible for restoring cracks, is the one that has a longer execution time with respect to the GFP-GAN model, which is responsible for restoring the blurred images. Likewise, it can be concluded that, if the image has both types of damage, this will be the one that will require a longer execution time for the restoration. In addition to the longer time required to restore an image with both types of damage, it was necessary to know which model to use first to get the best possible results. From the data seen in Figure 2, it can be concluded that the best way to restore an image with both types of damage is to use the Image Inpainting model first and then the GFP-GAN model, since this combination has a higher PSNR. than the opposite combination.

5 CONCLUSIONS AND PERSPECTIVES

In conclusion, the use of a classifier to identify the type of damage of an image and, consequently, calling pre-trained models to restore the damage type found in the image, shows very good results. Knowing what kind of damage the image has avoids having to call overly complex and time-consuming models to restore minor damage to an image. Therefore, it is necessary to train a very good classifier model. Thus, the use of the transfer learning technique has been shown to have very good results in the creation of image classifiers, in addition, requiring less training time and data for it. Since generative models are applied to more domains (Pautrat-Lertora et al., 2022).

Furthermore, it has been shown that when an image has several types of damage, it is necessary to know in what order to use the different models responsible for restoring the different types of damage, since the incorrect order of the use of these models leads to a lower quality in the restored image. Thus, to know which model to use first in case the image has several types of damage, the PSNR and SSIM metrics can be used.

While a classifier is a good first choice for restoring an image based on the type of damage, our classifier only classifies if an image is blurry, has cracks, or both types of damage. Therefore, as future work, more types of damage could be established for the classifier, such as lack of color, missing parts of an image, water damage, among others. Also, you could create a restore model that is capable of restoring all kinds of damage from an image, although this might cause a very high execution time, which might not be very convenient if you plan to use the model in some application for people's daily use, similar to (Ysique-Neciosup et al., 2022; Castillo-Arredondo et al., 2023).

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