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Organization, Extraction, Classification and Prediction of Age in Facial Images using Convolutional Neuronal Network

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***Abstract*—The development of technology and the popularization of AI (artificial intelligence), face recognition has become fundamental by various applications, both in military and economic appearance because it is gradually being introduced into the lives of individuals, exemplifying, in the use of face recognition for unlocking mobile phones. Starting in the 1990s, they began to learn age identification by means of a face photo, it should be said that the recognition of the old face is quite challenging within the environment of the perspective by PC. This article is made in order to be used in marketing, as it could be given differentiated products according to the age of consumers; for this purpose we have used public databases to classify by age the images of faces of both men and women, thanks to a model of Convolutional Neural Network (CNN), with which we obtained an efficiency in the categorization of around 97.86%, we also performed prediction tests in which the silver model obtained an approximate success rate of 87.64%.**

***Keywords*— Convolutional Neural Network, age classification, mathematical model, artificial intelligence, CNN.**

I. Introduction

Facial recognition technology is widely used in different technologies due to the importance and requirement of security and entertainment demanded by people, in addition to recognizing or identifying an individual through an image, video or any audiovisual element of the face [1]. The process of easy recognition requires three important steps, whether these are digital photography, video or capture technology, the face of the individual and a trained and robust software capable of identifying, classifying and extracting more outstanding characteristics of the person[2].

There are various difficulties for physical recognition such as the equality of the twins, obstruction in the face, amorphous faces, etc.[3], technological difficulties such as the quality of the image, the electronic equipment that captures the image, the movement that is being exerted at that moment of the capture, the light of the reflection, etc., and the most important factor that is the software that must be robust, fast and capable of preprocessing, processing, extracting characteristics, identifying and verifying the identity of the captured face[4].

Age recognition is one of the challenges of image processing because there are many methods and algorithm models that aim to perform this process in real time but always have failures and generate error rates, in addition to observing various easy anthropometric variations in all people, that is why it complicates more in image processing, many research papers attribute the creation of age periods for better system accuracy, so far there is no known system in recognizing the age of people accurately and accurately [5].

To date, various classification methods have been developed, for example in [6] where an image classifier by gender is developed, as well as we can also find works such as [7], where the classification of images by apparent age is carried out, using public databases; another way of recognizing the age of a person presented to us in [8] and [9] where in addition to recognizing age they recognize sex, making an analysis of the voice; in [10] they present an analysis of the age estimation applying techniques of support vector machine (SVM), with a multiclass approach; in [4] they propose a method of age estimation in facial images applying convolutional neural networks (CNN) in addition to VGG19 and inception V3; in [5] use a CNN model accompanied by the Local Age Decoding (LAD) model to classify facial images by age; in [11] they present us with a way to detect age-invariant characteristics, in facial images, applying SVM and the modified quadratic discriminant function (MQDF) method; in [12] they propose the methods of Deep Label Distribution Learning Forest (DLDLF) and Deep Regression Forest (DRF), glued to a CNN, to predict the age of inhomogeneous facial images. In [13] they mention that they have developed an algorithm capable of detecting age based on biometric variables of the face. In [14] the age estimate is made by training a CNN with facial images, which show a good performance in the classification.

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The main objective of the research work is the construction of a mathematical model using an algorithm capable of identifying all types of people using deep Convolutional Neural Network (CNN), a set of various databases of facial images was used and based on this train and classify the images by means of age periods.

A convolutional neural network is known as an artificial neural network that is constructed by receptive fields like neurons in the primary visual cortex. Convolutional neural networks are a variation of a multilayer perceptron, meaning that various layers of specialized matrices for training and real-time comparisons are widely used for two-dimensional matrices, artificial vision such as image classification and segmentation [14].

II. Literature Review

In[15], the authors identified that due to SARS-Cov-2, educational centers were forced to close their doors, in addition to this would support by reducing the number of infections in Ecuador, this was thanks to the Central Government of Ecuador through a Resolution of the Emergency Operations Committee due to its decree of the mandatory use of masks as a biosecurity measure, such action has led many centers to identify the correct use of a mask that in many cases is not analyzed correctly. That is why, this thesis proposes to develop a system capable of detecting faces without masks using video frames and analyzed by an artificial intelligence model. To do this, they used 128 analysis neurons for the training of faces with and without a mask all with TensorFlow and Keras, after the system has been trained, it is loaded to a Python script, which first executes faces and then classifies faces without a mask. Obtaining as results, a level of confidence greater than 80% in addition to that it can be applied to Linux desktop environments for the detection of people without masks and all registered faces to be stored in a database. Thus, concluding that, using image processing, systems that require character training and classification can be implemented and applied in various requirements.

In[16], the author mentions that the need for the organization of personal images is important because not always the individual takes photos alone, but people always appear around him and this is given by some event or situation.

Formerly, every image was printed and added in a photo album, but currently there is software that does it, but in many cases, they get an error and appeal to the same face for different people. Therefore, the author proposes the development of an application that uses Artificial Intelligence to allow the user to organize their library of personal images according to the individuals that appear or have been captured around them. The author identified a mathematical model that when he detects the face of the person compares with all the images to identify if it is the same person by means of their characteristics or if they are different, it should be noted that he made a classification by ages being these: 8-16, 17-24, 25-38 and 39-50 years. Obtaining as a result, the chosen models were able to detect 80% of faces in the images and decide which ones belonged to the same person of more than 90% accuracy, these in each age period, indicating that the system was not tested on twins or Asians. Thus, concluding that the system can identify and filter the same faces to assign variables and thus not be confused with other similar faces, because differences will always be found.

In[17], the authors identified that there are currently research works on face recognition, identification of emotions, among others, but there are no studies regarding the estimation of age automatically because it takes into account a training of neural networks and artificial intelligence but not an anthropometric analysis of the face. Therefore, the authors propose a system of identification and classification of a face within a certain age range. To do this, the authors analyzed the theories of craniofacial growth and facial anthropometry, this to identify the most relevant characteristics not only of the positioning of the eyes, nose, mouth, ears but also the shape and structure of the skull and the size of this, this was derived to a selection of anthropometric parameters for the representation of discriminating characteristics for the classification of faces in different age ranges. They used these parameters to generate a classification model using the Weka platform, with SVN, Knn, Naïve Bayes and C4.5 algorithms, where cross-validation was applied to 10 folds in the 4 algorithms. Thus, obtaining a greater accuracy in the Knn algorithm with 7 of these and was 75.28% effective, being the most outstanding compared to the other algorithms.

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Thus concluding, the great usefulness of the anthropometric distances chosen for age recognition in images of faces, in addition to the application in various fields of facial recognition.

III. Methodology

The research work is structured as follows: First of all, the acquisition of the images that is basically the collection of images of faces from various online databases, organization of the images that has as application the ordering of the validations, classification model that is the step by step of the application of the model used and predictions that is the use of the model in the stages of processing of images, these stages can be visualized in Figure 1.

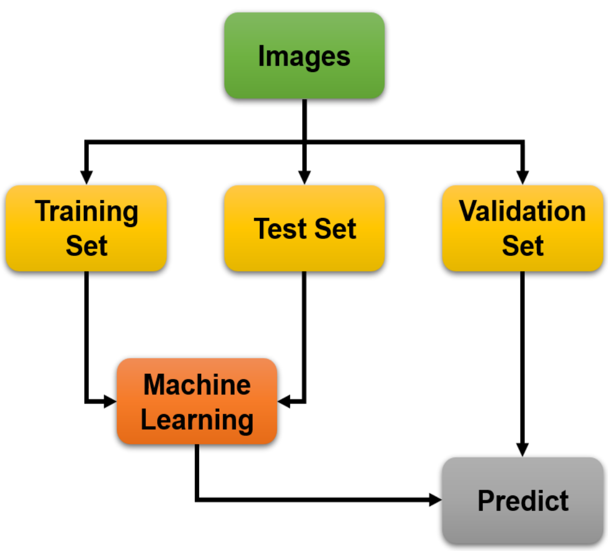

Figure 1. General diagram of the methodology applied.

A. Images Organization

The images of faces have been obtained from 7 public databases such as: age-gender-data, age-prediction, all-age-faces, appa-real, face-age, fg-net and utkface in total 58554 images were obtained divided into 6 categories, which are: from 8 to 15, from 15 to 23, from 23 to 35, from 35 to 44, from 44 to 57, from 57 to more years, this age division is made because the applied ranges cover most of the age of a person, in addition this division covers as much data as possible from the databases obtained; in figure 2 we can see some of the images with which we will work [3].

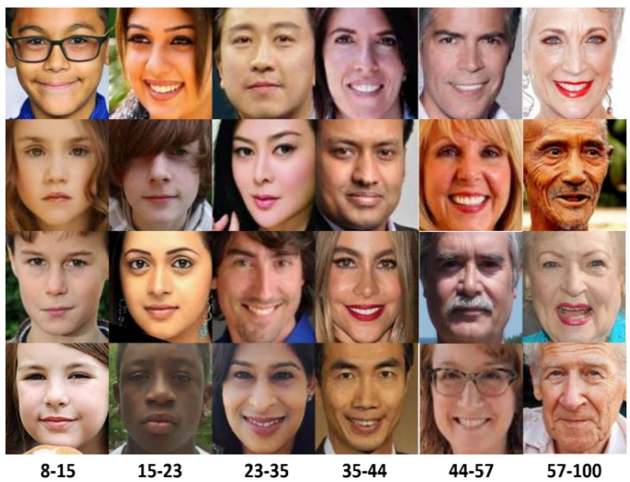

Figure 2. Example of images for age detection.

B. Organization of the images.

After to obtain the images of different databases, were organized in 3 different folders for training, evaluation, and validation, as well as in the previous stage age periods were generated so that artificial intelligence can locate them in each section, so within each folder 6 subfolders were created, as shown in Figure 4, in addition each of them shows the number of images used.

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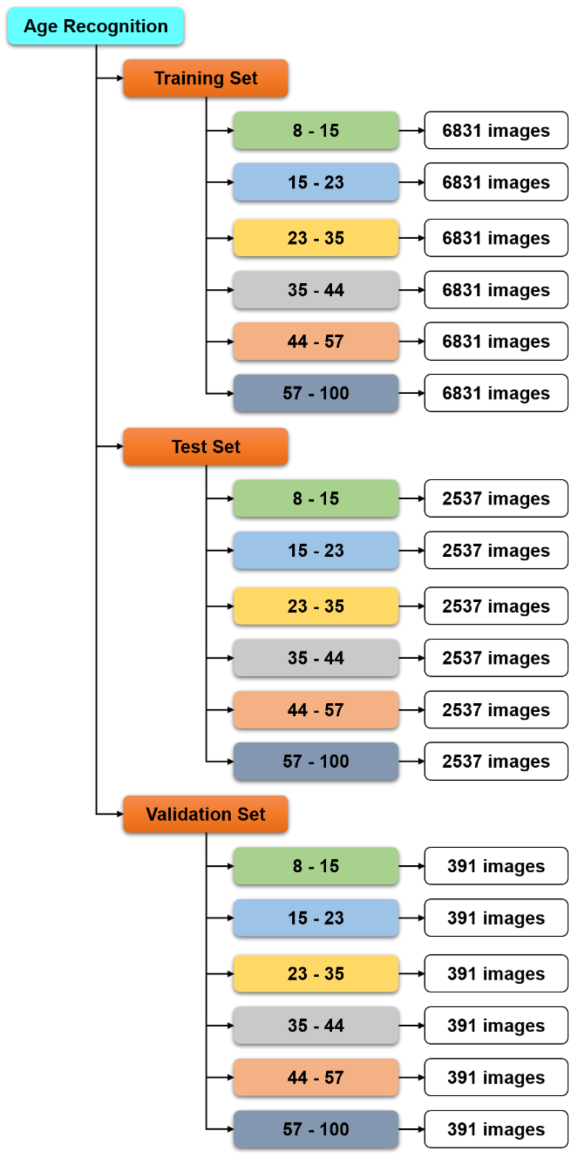

Figure 3. Flowchart of training, evaluation, and validation folders

C. Machine Learning

It was debated among various mathematical models because the most precise is required for the implementation in the research work, it was concluded in the approach of a Convolutional Neuronal Networks (CNN) implemented in Python using keras and TensorFlow [3], this neural network has 6 stages of operation, these are:

- *Stage 1:* Also known as the input stage, which is composed of a 200 x 200 x 3 tensor, these are the dimensions of the images obtained from the databases. [3]
- *Phase 2, 3 and 4:* They are layer composed of: Conv2D, to which a convolutional layer that extracts properties from the images, the convolution helps to blur, focus, identify edges, minimize sound or other operations that have the possibility of contributing to the machine to learn specific properties of an image; the Batch Normalization layer, which by normalizing the inputs of the layers causes neural networks to be faster and more stable; the MaxPooling2D layer, which is a sample-based process, to minimize image magnitudes without losing relevant properties or patterns, as well as minimize computational price; the Dropout layer is a technique used to randomly deactivate a percentage of neurons in each layer, which helps the mathematical model to overfit for each processing. In addition, between layers 4 and 5, an Elatten layer was added, which oversees changing the magnitudes of the tensor, so that the modified or adjusted magnitude is the same as the number of resources contained in the tensor. [3]
- *Phase 5 and 6:* They are layers composed of the Dense, Batch Normalization and Dropout layers. In the end, after phase 6 you have an output layer, which in this situation is the Dense layer, which is a layer fully connected to each of the neurons of the previous layer. [3]

It should be noted that each of the mentioned layers have as activation functionality to Rectified Linear Unit (ReLU), except for the last layer whose activation functionality is the SoftMax functionality, in Figure 4 we have the possibility of seeing the scheme with the layers of the proposed model.

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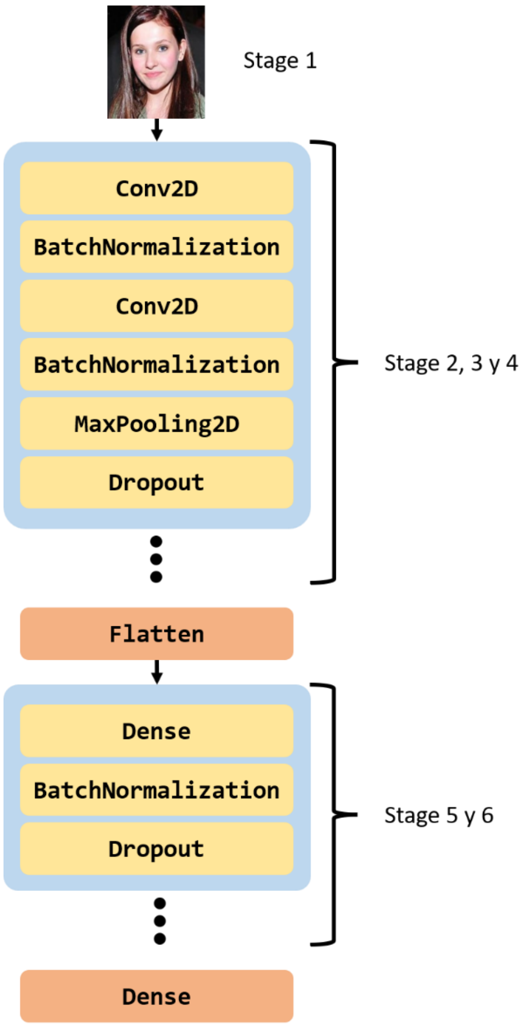

Figure 4. Schematic of the layers contained in the proposed model.

Once the model has been built, it should be compiled, for that we use the categorical_crossentropy functionality as a loss functionality, in addition to this an Adam optimizer was used; When the compiled model is obtained, the training is carried out using the images of the Training folder indicated above, finally the model is saved in the Hierarchical Data Format (HDF), through the h5 expansion.

D. Predictions.

As shown in Figure 5, the mathematical model trained in the previous stages was applied. The process for the possibility of classifying images in age periods begins with the import of libraries required for the algorithm, these are: OpenCV, numpy, etc.; to then build a dictionary, which has included 4 lists corresponding to each class, each list remains composed of the names of each of the images corresponding to the category, and then as the trained mathematical model has already been loaded, a loop is entered infinity, where a class is obtained randomly from the dictionary, with it the list of names of the corresponding images. [3]

Then the existence of data in the list is checked, in order to receive and randomly load the image of the individual's face to a selected name, the prediction proceeds and such result is saved in a list, when there is no data in the list of names of images of the chosen category, this is eliminated, such a process is in an indefinite loop, all this until the lists and categories are empty, the algorithm will be able to go through all the images contained in the folders of validation.

Finally, when the dictionary is empty, the infinite loop stops automatically, saving the data of the predictions and the numpy values, thanks to this a confusion matrix can be created to identify the effectiveness of the predictions, in addition a categorization report is built, to identify the functioning of the implemented mathematical model.

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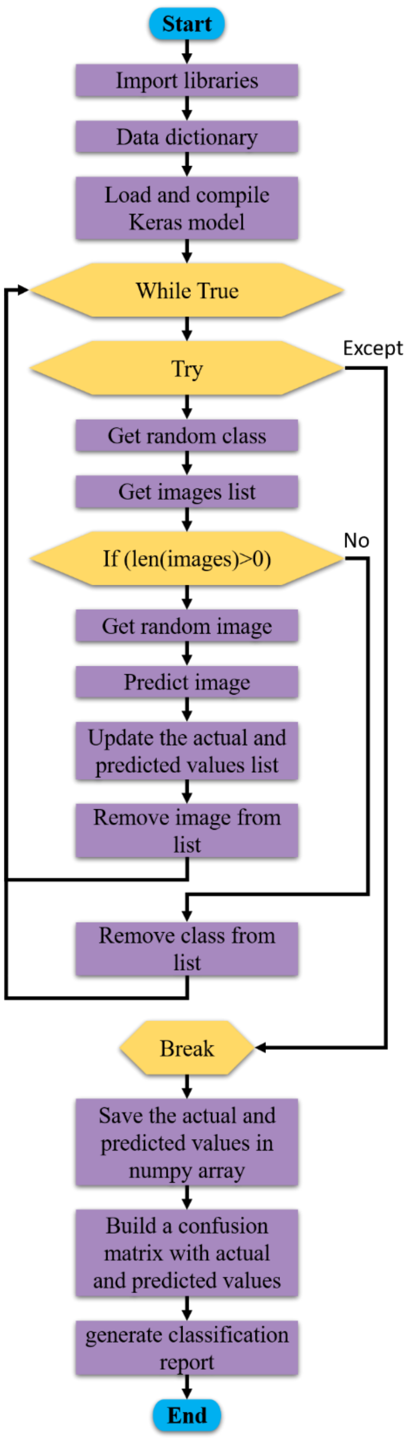

Figure 5. Programming scheme to make predictions.

IV. RESULTS

Finally, when applying the 4 stages, the following results were obtained, thus obtaining a training efficiency greater than 97.86% of the implemented algorithm, in addition to a validation efficiency like 96.48%," Figure 6 shows the graph of the efficiency in training and validation.

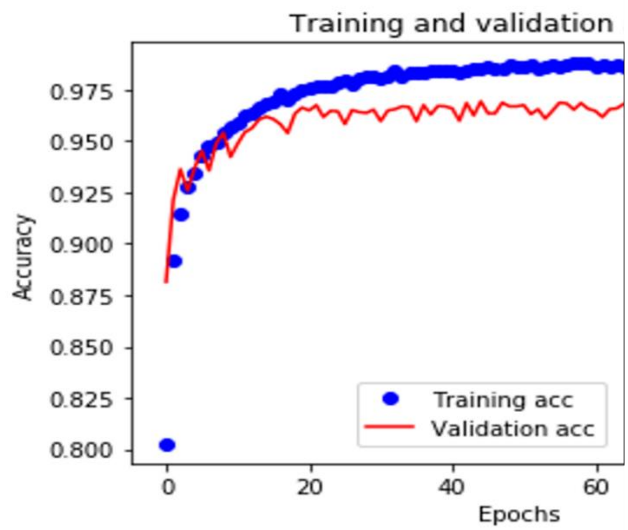

Figure 6. Training and validation accuracy

After identifying the remarkable efficiency of the algorithm in the training and validation, the CNN training is carried out for the identification, extraction of characteristics, prediction and classification of the images of the validation folder, because these are not known by the mathematical model; the results of the process of the mathematical model of the CNN can be seen in Figure 7, where the approximate efficiency is 87.64%, thus indicating the correct prediction of the faces of the individuals in the database collected.

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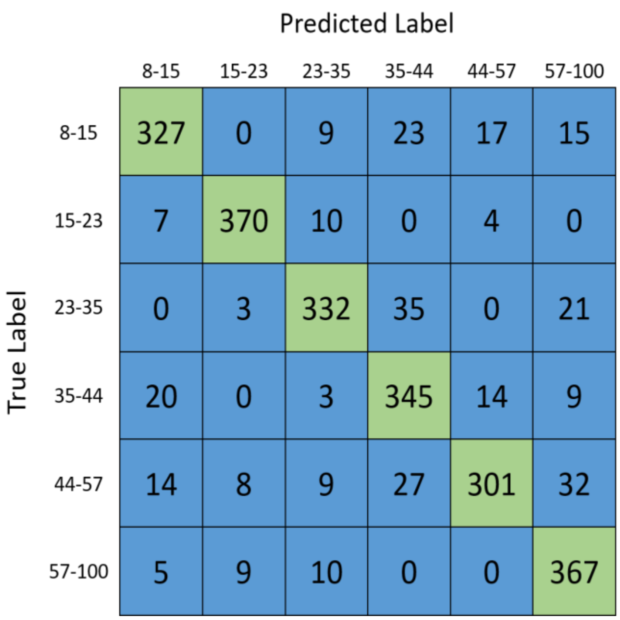

Figure 7. Confusion matrix of the applied mathematical model.

Finally, in addition to the confusion matrix of table I, where you can see the precisions of each of the age periods, also the Recall and F1-Score, where the precision indicates the safety of the true positives, the Recall is an indication of the losses of the positives and the F1-score is the average of both measures. The period of 44 – 57 years of age, obtained an accuracy of 0.90 and a low Recall, thus indicating that such a period is not adequately detected by the mathematical model, being the period that lower Recall has, on the other hand, the period of 15 – 23 years of age, has a good accuracy of 0.95 and a Recall of 0.95 thus indicating that the algorithm detects it well.

TABLE I.
SYSTEM CONFUSION MATRIX

	Precision	Recall	F1 - Score
8 – 15	0.88	0.84	0.86
15 – 23	0.95	0.95	0.95
23 – 35	0.89	0.85	0.87
35 – 44	0.80	0.88	0.84
44 – 57	0.90	0.77	0.83
57 – 100	0.83	0.94	0.88
Macro avg	0.87	0.87	0.87
Weighted avg	0.87	0.87	0.87

V. DISCUSSION

There are multiple research articles, which have performed facial image analyses such as[18], [19],[20], [21] and [2] in these works as well as in many others the images are analyzed, with different methods such as CNN, ordinal method of deep learning, directional age patterns, Kullback-Leibler divergence and antagonistic generative networks; all these methods show very good results, as well as the one obtained in between work; in the reference [4] they obtain an average success rate of approximately 88%, with a CNN model, as well as in the reference[22], where using a machine learning structure they manage to reduce by up to 37.75% the error finally estimated in [23] use large amounts of data to achieve results superior to those shown in this work. the results of our research show that we are on the right track since we have obtained an efficiency in the classification greater than 97.86%, and an efficiency in predictions approximately 87.64%, these values indicate that we are within an acceptable range of efficiency in the classification, however, it is necessary to improve even more, therefore, this work will continue to be developed to obtain greater efficiency in predictions.

VI. CONCLUSIONS

We must bear in mind that this research work presents an artificial intelligence which is capable of sectorize the face of a person in the category of age, this is important because actually, there are electronic systems making this kind of process in a selection type, this is because the age define the entertainment type an among other so it is important the classification

As we have already seen before, we have achieved good results, which we will complement as future work with the increase in the quantity of the images with which we work, in addition to improving their quality also must improve the CNN model used, as well as test new models such as the VGG-16 model and the ResNet-50 model , in order to further optimize the efficiency in the recognition of age images of faces, and thus to provide an efficient algorithm that will help in obtaining better results in marketing campaigns.

As future work, more mathematical models will be used to identify the pressure of the same and thus obtain the most efficient model in the application of collection, extraction of characteristics, evaluation, and classification of the faces.

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