Facial Recognition System for Access Control through the Application of Convolutional Neural Networks

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Abstract

In recent years, biometric systems have been used to provide access control security, to help identify and recognize people. However, today due to the advance of the pandemic some of the biometric systems are considered as sources of transmission and contagion of COVID-19. This situation motivates us to the development of a facial recognition access control system through the Application of Convolutional Neural Networks (CNN) that, by not having physical contact with the devices, safeguards against COVID-19. A pre-trained VGG16 model was used and the new CNN model was trained with the Transfer Learning application. The recognition system was tested using a public database such as celebA, obtaining an accuracy of 84%, this isn't the best possible accuracy as some authors report better results. However, our objective was not to provide the best accuracy with random data, we only need to achieve good accuracy with the company's controlled data, our CNN model achieves an accuracy of 98% in controlled conditions with an average identification time of 80 milliseconds. It has a low implementation cost that allows it to be competitive in low-income countries, like Ecuador, compared to international costs of state-of-the-art systems.

Keywords
Convolutional Neural Network, Transfer Learning, Face Recognition, Artificial Intelligence.

1. Introduction
The late 1990s saw the beginning of the face recognition boom with the Facial Recognition Technology (FERET) program conducted by the U.S. Army Research Laboratory (ARL). The ARL conducted government-supervised testing and evaluation of automated face recognition algorithms. The objective of the tests was to provide an independent method of evaluating the state of the art in automatic face recognition, (Phillips, et al. 1996). Significant progress has been made in recent years thanks to the development made by Lawrence in 1997 (Lawrence, et al. 1997), when he implemented an unsupervised learning method for face recognition based on a Convolutional Neural Network (CNN), leading to multiple applications such as image classification to detect personal protective equipment, tumor detection, emotion recognition, voice recognition, etc. All this processing power is due to Deep Learning, which is a technology for processing data, extracting information, and obtaining predictive models for decision making. CNNs are part of the deep learning algorithms widely used today (Adjabi, et al. 2020; Dean, et al. 2012).

Nowadays, institutions face important security problems when it comes to inspecting the entry of people into their facilities, consequently, they need personnel to be in charge of this control. These personnel makes mistakes that can affect the level of security. Many researchers have focused on analyzing the impact of implementing facial recognition systems to detect intruders in restricted or high-security areas (Ortega, et al. 2020; Owayjan, et al. 2015). Automated access control has become essential in security systems because it not only focuses on controlling building entrances but also helps in the analysis of closed-circuit cameras for work environments and access technologies based on biometric characteristics of people. Biometric technologies have presented a breakthrough in user authentication systems based on the analysis of patterns in different parts of the human body such as iris, fingerprint, hand, gait, face, among others. These technologies have the characteristics of presenting a more efficient and secure access control (Vivas, et al. 2008) compared to the conventional user authentication system, which uses a password or a Radio Frequency Identifier (RFID) card (Huerta, et al. 2017; Rodríguez, et al. 2012).

Currently, facial recognition presents important developments and research with new algorithms and classifiers based on Artificial Intelligence, which allows the identification of people by analyzing the biometric characteristics of their faces (Bargshady, et al. 2020; Kumar, et al. 2019). Major companies such as Apple, Huawei, and Qualcomm have patented a system that allows users to unlock devices using facial recognition (Adjabi, et al. 2020; Changqi, et al. 2019). In Spain, the Galician company Gradiant, developed a facial recognition system applied to an access control system for venues where fairs or events are held, as a security measure and to ensure whether or not a user is authorized to enter a given venue. In Latin America, biometrics has emerged as a need to offer a better service to people. Therefore, this technology has changed its connotation from a tool to catch criminals, to a technology that provides control. The objective is to control personnel access to provide better service, as well as to systematize and simplify the registration process (Huertas Vera, 2015). Another case of temporary implementation occurred at *Empresa Pública Cementera de Chimborazo (EPCE EP)*, as a way of reducing the access time at the time of clocking in and out of the workplace.

Biometric systems play a fundamental role in the organization of companies, its objective is to authenticate the identity of the person to access physical sites or record their work attendance, maintaining security in their facilities. Some access control systems to institutions are based on biometric systems, which are mostly based on fingerprint and handprint reading. This type of system is a source of contagion and spread of many diseases, including COVID-19. Facial recognition meets the parameters of biometric access control that allows maintaining security levels in institutions. The breakthrough in Artificial Intelligent has enabled the development of biometric facial recognition systems to control access to establishments. However, a challenge arises for technology companies: the ethical use of the stored data so that it is not considered a loss of privacy (Siau and Wang, 2020). This paper contributes to the literature showing a practical low-cost use case of CNN application in biometric check in and out at a company guaranteeing safety hygienic measures needed to prevent COVID-19.

2. Materials and Methods

2.1 Biometric Systems

Biometrics is a method based on automating recognition processes based on some of the physical traits of individuals. The strengths and weaknesses of biometric technologies centered in different body characteristics such as the iris, the fingerprint, the hand, the way of walking, the face, among others can be seen in Table 1. These technologies have the characteristics of presenting a customized, efficient, convenient, and secure access control compared to the conventional user authentication system such as using passwords or RFID cards (Dargan and Kumar, 2020).

Table 1. Biometric Technologies Strengths and Weaknesses

	Strengths	Weaknesses
Finger Prints	High precision Low cost Small devices Easy to operate	Low acceptance Poor quality fingerprints (moisture or dirt on the sensor) Improper footprints (burns)
Face Image	Not intrusive Accepted by people Acceptable performance	Operating restrictions (lighting) Privacy issues
Iris	Very distinctive feature High performance	User must cooperate to capture Expensive sensors Performance affected by contact lenses and glasses

	More identifying biometrics No physical contact with sensor	Problems obstructing the iris (eyelashes or eyelid)
Hand geometry	Low system cost Minimal impact from external factors Non-invasive of privacy	Does not provide discrimination Very large sensor Reading error due to rings or mobility limitations Rejection of users for hygiene
Voice	Easy to use Not intrusive Dual functionality	Minimum discriminatory capacity Sensitive to noise factors Limitation of use due to diseases Voice imitation vulnerability

The various face recognition techniques seek to identify a person's face from the mode of acquisition, such as in static images (captured by cameras at an instant in time), in video sequences (images extracted from videos), and finally using sensory data such as 3D or infrared images. However, the person's face is subjected to several uncontrolled factors, which implies that the recognition rate decreases, for example the illumination, the position of the face, its facial expression, face symmetrical, etc. For these reasons, there are some face recognition techniques used to increase the accuracy rate, among the best-known are, geometric features, graph matching, Eigen-faces, Fisher-face, and Neural Networks. Where, the technique of neural networks is the most effective method for face recognition, due to its ability to learn quickly through the extraction of features acquired in the capture of the face, therefore, it is considered as a non-linear network by not reducing the dimensionality and minimizing the dispersion of the acquired samples. One advantage of the neural network is due to the classification time which is less than 0.5 seconds, however, the computational cost for training the neural network takes a few hours when increasing the number of faces to be analyzed (Pandya, et al. 2013). For this reason, CNN-based face recognition techniques are applied in this work to optimize the processing time (Li, et al. 2018; Wen, et al. 2021).

2.2 Data Processing

The analysis of the physiological characteristics of the face is complex because it can vary or change throughout the person's life. Additionally, there are other factors such as the existence of a beard or mustache, or environmental factors such as lighting that could modify the identification of the face. For this research, the following guidelines were established to minimize inconvenience in the image features before being processed: Face Orientation, illumination obstructions and distance.

The face recognition procedure consists of 4 phases: preprocessing, learning, evaluation and prediction, as shown in Figure 1. The preprocessing phase captures the faces of the people that will be used to train in the model and stores the features of each image. This information is used in the learning phase, in which the different files created within the dataset are read. Using a pre-trained CNN model, we apply Transfer Learning to train the new model. The next phase is the evaluation, where new faces are captured to perform image preprocessing and improve the quality, in order to analyze a first response from the system. Finally, in the prediction phase, the CNN identifies, detects, and classifies the face, placing on each image the name of the detected person.

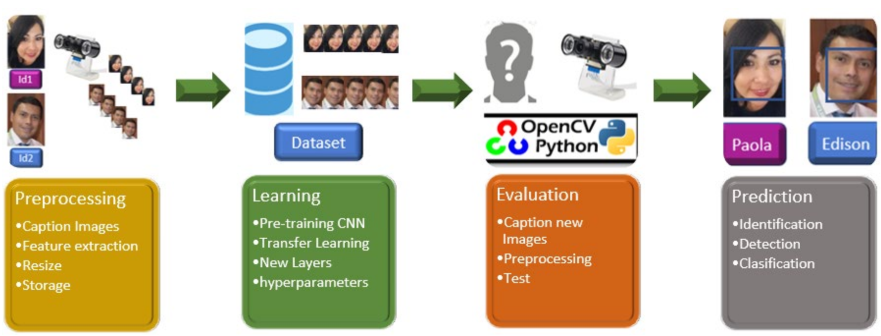

Figure 1. Process for Facial Recognition.

Preprocessing: In this phase the guidelines are established to *capture the images* of the people to be recognized, camera elevation from floor (1 meter) and minimum and maximum distance between camera and person (1 meter to 1,5 meters). This is performed using the OpenCV library and the front face identifier and classifier function, the features or Regions Of Interest (ROI) *are extracted* from the faces with a *resize* of 200x200, to be later *stored* in each of the files. In order to form the database, a storage structure of the images that consists of a matrix directory called Datasets, inside the folder there are three subfolders:

- Train containing the images to be entered into the CNN model for learning.
- Test with the images to perform prediction tests.
- Validation are the images to be compared with the predictions by obtaining the labels of each class with their respective error metrics.

To form the database of the faces to be recognized, several photos must be stored in the Train folder. The greater the number and variety of images, the greater the accuracy for the recognition of people, inside this folder a file is created with the name of the person or user. On the other hand, for the Test folder, you will have 1000 photos, in the same way we must have files with the name of the person. Finally, to perform tests and obtain the metrics of the system we have a Validation folder, with images of the people to be recognized and that were not trained in the CNN network. To include more people or users of the system, the proposed division structure should be followed with the new images.

Learning: Making an analogy of learning between humans and machines, the more varied experiences people have the more they learn, on contrary, computers the more quality data they acquire determines how much they can learn, therefore, the more quality data they have the more experience. With this acquired learning can perform specific tasks such as inspecting faults in industrial systems, drive vehicles, detect diseases, detect faces, etc. Having a large volume of data is a challenge, training the CNN model to have the best accuracy on requires a lot of computational resources (CPU, RAM, GPU, etc) and time. To cope with the above challenge, the best way of training is the following strategy:

- A pre-trained Deep Learning model, dedicated to image recognition that can be VGGFace, ResNetFace, FaceNet and Mobilenet (Niu and Chen, 2018; Szegedy, et al. 2017). Of the four pre-trained Deep Learning models, VGG16 stands out, because it has an architecture that is easy to understand and implement, contains few convolutional layers, its model and trained weights are available within the OpenCV Keras library (Chaudhuri, 2020).
- Applying Transfer Learning, is a method widely used in the field of computer vision, instead of starting the learning process from scratch, we make use of pre-trained models with millions of data that are similar to the problem we want to solve.
- Adding a new Dense Type Layer, of 4096 neurons with Sigmoid activation functions. Finally, a full connected type layer of n neurons is added according to the persons to be identified. These new layers will be placed at the end of the CNN model to recognize the new faces of the generated dataset. In this way, we distinguish already learned features to achieve greater accuracy with smaller datasets, optimizing processing time.
- Configuring the hyperparameters, whose values are set during CNN training and control the learning process. According to the problem to be analyzed, the optimal value of a hyperparameter cannot be known a priori, therefore, generic values that have worked in other experiments or through trial and error are generally resorted to. Therefore, within the model compilation function we set the optimization value to reduce the error made by the Softmax neural network. Then, we have the loss function or cost function, where it tells us the performance value of the network being of type crossentropy. Finally, we have the metric for the performance of the model, in this case of accuracy type. Within the model training function, the hyperparameters to be configured are epoch and batch size. The epoch is the number of times that the algorithm is executed for learning the CNN, this value cannot be chosen randomly because with a smaller amount of epoch the network will not train enough, on the contrary, with a high value the network can fall into overfitting. The value with which the best learning results are obtained is with 50 epochs. On the other hand, we have batch size, being the number of data in each iteration of an epoch, it is very useful because the CNN updates the weights and bias more times, with a batch size of 8 we divide the cycles in iterations with smaller data, optimizing training time and computational memory. With these configurations the training per epoch takes about *1,3* seconds using a GPU in Kaggle.

Evaluation: In order to perform simulation tests of the system, the *captures of new samples* is in real time by means of the function "cv2.VideoCapture(0)" of the OpenCV library, the frames captured by the video are extracted by means of the function "cap. read()", to which it is necessary to perform a *preprocessing* to convert to grayscale in order to reduce the computational load, and finally be entered into the system prediction for the *test*. As it is a single-person facial recognition system, shows that the minimum recommended height range for the installation of the camera is between 1.5 and 2 meters, the distance between the person and the camera should be between one and three meters, the exposure time should be 1 or 2 seconds looking at the camera. These are the ideal conditions for the system to correctly identify the face of each person, which should not contain any element that obstructs or modifies it (caps, glasses, etc.). The system will detect a face and classify it according to the prediction made by the convolutional neural network, and then it will pass another person repeating the same procedure.

Prediction: The prediction corresponds to the final part of the face recognition process, which consists of detecting, identifying and classifying the faces. To perform this procedure the trained model is stored as "modelo_edison.h5" and when executing the function "model.predict ( )" the validation process is activated. If the face of this person was previously trained in the program, the recognizer will make a prediction by placing the name of the person on top of the image. Additionally, by configuring and programming a socket, the access of the recognized person will be validated through a client-server connection between the PC and the raspberry pi. Using the GPIO ports of the reduced board device, a green led will be activated for correctly identified persons and a red led for persons classified as unknown.

The facial recognition program is divided into several blocks, each one fulfilling specific functions, among which we have:

- Face Entry: A block consisting of two phases, the first one is used to capture the faces and store them in the database, and the second one fulfills the function of prediction.
- Facial Recognition Process: With all the information gathered, it enters the CNN model, where the neurons are trained.
- Decision-making: Block used to filter the data depending on the accuracy of the face recognition system. If it recognizes a face, it goes to the labeling with the prediction; otherwise, it goes to the undetected face block.
- Label visualization: Block to visualize the label placed by the CNN on each face that enters the system.
- Access validation: Integration of the facial recognition system with a mechanism to validate access and correct identification of persons.

In order to have a detailed view of the aforementioned blocks, in Figure 2 there is a flow diagram that will follow the data for a better understanding of the designed face recognition system.

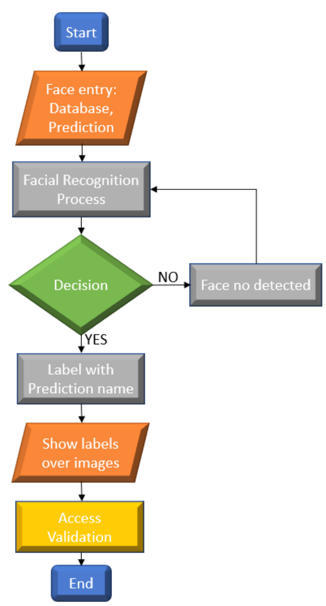

Figure 2. Flow Chart for Testing.

2.3 Confusion Matrix

In the field of machine learning, the confusion matrix or error matrix is a table that accounts for the degree of similarity between true samples and predicted samples. It allows performing a statistical matching analysis, produced by the data obtained from the image classification, to visualize the performance of the CNN. This square matrix is constituted by the same number of rows and columns (MxM) of the elements or classes to be evaluated. The cells corresponding to the diagonal of the confusion matrix represent the True Positives (TP) and True Negatives (TN) of the well-classified classes. The cells outside the main diagonal correspond to the errors produced in the prediction, which can be False Positives (FP), erroneous classes but the model classified them as true, or False Negatives (FN), true classes but the model classified them erroneously (Visa, et al. 2011). A fundamental part of the confusion matrix are its metrics, which help to evaluate the CNN built model:

Accuracy: It is the set of correct predictions of the same class.
Precision: Represents how close the prediction is to a true sample.
Sensitivity: Proportion of positive cases correctly identified.
Specificity: Negative cases that have been correctly classified.

2.4 System Cost Analysis

Many companies offer the latest generation systems based on facial recognition, such as FindFace, BioID sensor fusion, Biometric Systems Inc., Postec Technolog, among others. Also other companies provide specialized biometric devices to perform facial recognition, for example ZK Teco, or Uniview Normally the systems have restrictions on usage by licenses according to the number of users and high costs, devices are expensive.

Consequently, the need arises for creating facial detection and recognition procedures based on low-cost embedded systems. Where the Raspberry Pi or Arduino devices are ones of the best solutions to implement low-cost computer vision and artificial intelligence systems because the data can be processed directly at the source, optimizing response times, without requiring large bandwidths. Also, some research focuses on building low-cost facial recognition embedded systems for deep learning door access control such as the one presented in (Orna, et al. 2020).

Taking these considerations, the estimated cost of our facial recognition access control system is around US $200. Being a precise, reliable, reproducible, and economical device, allowing having an alternative for those who need to implement this type of systems in their companies with budges restrains.

3. Results

Figure 3 shows the predictions achieved by the CNN network when random samples are entered. Each column represents the number of predictions for the classes to be identified, and each row shows the instances of the real class to which they belong. In other words, the number of hits and misses that the trained CNN model has when recognizing new images is displayed.

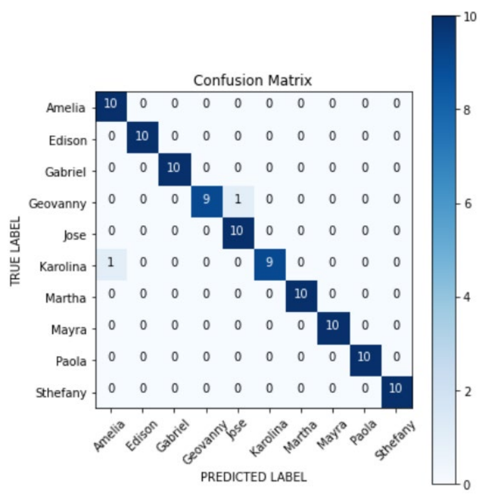

Figure 3. Confusion Matrix Obtained from CNN Trained Model.

The test dataset is made up of 100 images, which are very different from the images entered for the training of the CNN network. With this information in the main diagonal of the confusion matrix, we have the number of hits for each class; on the contrary, everything outside the diagonal corresponds to errors. For example, for the classes "Karolina" and "Geovanny" there are nine hits and one error for each one, while in the other classes there are 10 hits.

The results obtained in the metrics are due to the manner in which the dataset was constructed, the size of the images to be processed and the new layers added to the pre-trained model. The Table 2 shows the comparison of our results with two experiments designed in (Méndez, 2019). In said research, the implemented CNN models are ResNet50 and VGG16, with an image size of 152x152. It should be noted that the number of persons analyzed to identify and train the model corresponds to four, with the following distribution of images Train: 15, Test: three and Validation: two. The added Dense-type neural layers are of 512 and 256, with a Full connected layer of 4 neurons. The accuracy achieved is 92.36% and 84.72% respectively. The model used for this research was VGG16, with an image size of 200x200. The number of persons to be identified is 10, with the following distribution of images Train: 337, Test: 1000 and Validation: 100. The new layers added are Dense with 4096 neurons and full connected with 10 neurons. The accuracy achieved is 98%, improving by 6% and 14% regarding Mendez's work.

Table 2. Comparison with Other Experiments

	Trained Model VGG16	Investigated Models ResNet50 (Méndez Gómez s. f.)	Investigated Models VGG16 (Méndez Gómez s. f.)
Image size	200x200	152x152	152x152
Dataset	Ten people to train Three Hundred thirty-seven images for Train One thousand images for Test One Hundred images for validation	Four people to train Fifteen images for Train Three images for Test Two images for validation	
Layers added	One layer Dense of 4096 One layer Full connected of ten neurons	One layer Dense of five hundred twelve One layer Dense of Two hundred and fifty six One layer Full connected of four neurons	
Precision	98%	92.36%	84.72%

In order to make a validation of the built CNN model, a public dataset celebA (Liu, et al. 2021) of famous faces is used to verify accuracy and compare with other approaches. The celebA is made up of a sample of 200,000 famous people in the world and for each famous person there are 20 facial images, all the images have different poses, lighting, and background conditions. Training our CNN model with 80% of celebA images and using the remaining 20% to test, an accuracy of 84% has been achieved. This isn't the best possible accuracy as some authors report better results, e.g. Chen et al. using multi-task CNN achieved 94,59% (Chen, et al. 2020) or Goel et al. report 91,29% using MCNN, 92,60% using DMTL, and 92,86% using LC-DECAL(Goel, et al. 2019). However, our objective was not to provide the best accuracy with random data, we only need to achieve good accuracy with the company's controlled data. With the dataset up of 10 employees of a micro-company, where each employee has 1500 images with different conditions, our CNN model achieves an accuracy of 98%.

Another considerable factor to be analyzed is the processing time for CNN training. With the distribution of images entered in the VGG16 model, and with a configuration of 50 epochs for training, the computational processing for learning the CNN takes about 1,3 seconds, this using a Kaggle virtual computer dedicated specifically for data science, with 13GB of RAM and access to the NVIDIA TESLA P100 GPU useful for training deep learning models. In contrast, processing on the models investigated, it takes about 45 minutes to train the network, with a computer with 6GB RAM, 2GB GPU. Therefore, the computational processing is optimized, training the CNN network as many times as required to obtain the best accuracy results as obtained in this research.

Figure 4 represents the learning process (y-axis) of the CNN network with respect to each epoch (x-axis). The results shown indicate that as the epochs progress the training accuracy increases and the training loss decreases, which means that the network is gaining knowledge. There is a crossover point at 13 epochs between training loss/accuracy, where the CNN network has achieved considerable learning with respect to the loss, i.e., the network is trained to predict new data. However, it isn´t the highest learning value, which is why it takes more training time to ensure its accuracy. It should be noted that for no reason the training loss should be above the training accuracy, since this would cause an overfitting in the neural network. Therefore, by not witnessing major changes of increase or decrease of the curves, we can understand the behavior of the network and take the decision to stop the training process in 50 epoch reached an accuracy close to one that in percentage terms reflects 98%.

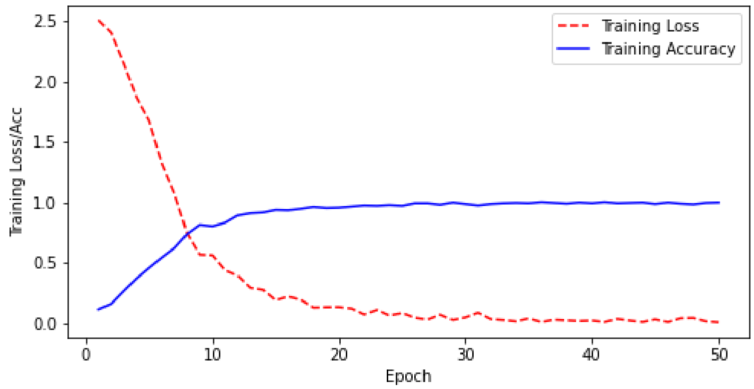

Figure 4. Processing of Training Loss vs Accuracy.

In Figure 5, the training accuracy curve which represents the learning of the trained model is obtained. On the other hand, the validation accuracy curve gives an idea of the generalization of the model. These curves allow analyzing the quality of the CNN model reached, meaning, it evaluates the ability to make new predictions based on images that it has not seen before. If the training accuracy increases while the validation accuracy decreases, it is possible that there is an excessive overfitting that is why there should not be a gap between these two curves. The results in our model, for the training set, match the results of the validation set.

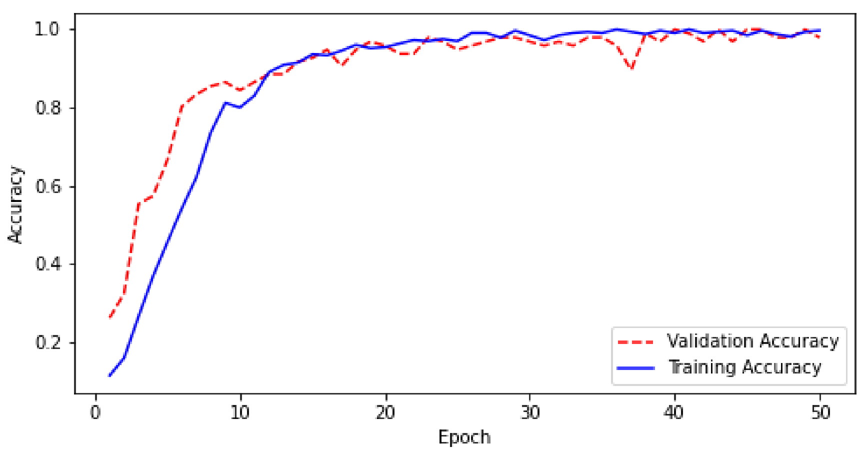

Figure 5. Processing of Accuracy Validation vs Training.

4. Conclusion

In this work, we were able to implement a deep learning model based on convolutional neural networks for face recognition through the application of Transfer Learning. The training time of the CNN was optimized and the data processing time was 13 seconds. The system response was simulated and validated by generating a confusion matrix through the input of untrained faces contained in the test folder. With the results obtained for each class, the system achieves a 98% accuracy with an average identification time of 80 milliseconds. The accuracy obtained corresponds to the number of trained persons, which are 10, with a number of images for Train: 300 and Test: 1000, the accuracy of the system can be improved if we increase the number of images of each employee. The learning curves show that at epoch 13 there is a crossover point between loss and accuracy, indicating that the CNN network has gained knowledge. As the training progresses, overfitting is not diagnosed. Therefore, the number of epochs could be decreased to optimize the training time of the CNN. An access control system was developed with great accuracy, in order to recognize the employees of micro-enterprises, where the lighting environment is controlled. However, for the creation of the dataset, priority was given to having a diversity of images of the faces and with different lighting environments. In addition, by training the model with these conditions it is possible to have high precision for different conditions. Eliminating the use of other biometric systems, like fingerprint, since today, they represent a source of possible contagion of Covid-19. It has a low implementation cost that allows it to be competitive in low-income countries, like Ecuador, market compared to international costs of state-of-the-art systems.

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