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Classification of emotions on images through convolutional neural networks as a method of preventing secondary alexithymia

Clasificación de emociones en imágenes mediante redes neuronales convolucionales como método de prevención de la alexitimia secundaria

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Abstract

Alexithymia can be defined as the inability to verbalize affective states. One of its main causes lies in the lack of learning of emotions during childhood and can prevail until adulthood. Its identification at an early age can solve problems such as depression and cutting that, in severe cases, can lead to suicide. The present investigation shows the implementation of two convolutional neural networks for the classification of emotions through images.

Convolutional neural network, Classification of emotions, Secondary alexithymia

Resumen

La alexitimia puede ser definida como la incapacidad de verbalizar estados afectivos. Una de sus principales causas radica en la falta de aprendizaje de las emociones durante la infancia y puede prevalecer hasta la edad adulta. Su identificación a temprana edad puede solventar problemas como la depresión y el cutting que, en casos severos, pueden llevar al suicidio. La presente investigación muestra la implementación de dos modelos de redes neuronales convolucionales para la clasificación de emociones a través de imágenes.

Red neuronal convolucional, Clasificación de emociones, Alexitimia secundaria

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Introduction

Alexithymia can be defined as the inability to identify, recognize, name or describe one's emotions or feelings, with particular difficulty in finding words to describe them (Alonso-Fernández, 2011). There are two types of alexithymia: primary alexithymia, which occurs due to biological issues; and secondary alexithymia, which is usually attributed to traumatic and psychological factors.

The prevention of secondary alexithymia in early stages can contribute to avoid problems such as: cutting, depression and, in severe degrees, suicide (Alonso-Fernández, 2011).

To achieve the prevention of this emotional communication deficit, it is essential to carry out an adequate detection. For this purpose, there are different tests that involve the classification of emotions through images by the patient. Performing these tests using digital methods is desirable to provide greater confidence to people, in addition to seeking a high degree of efficiency in the process.

The present research implements two convolutional neural network models in order to perform automatic classification of emotions through images as a support tool for prevention of secondary alexithymia.

Literature review

Emotion classification is a research problem that has been worked on constantly for at least two decades; however, it is still relevant because human expressions are complex and variable. Some of the most current contributions to the state of the art are shared below.

In (Jain, 2018), a deep neural network model is presented in a hybrid method of convolutions and recurrent neural networks for facial expression recognition. Such a network is applied to JAFE and MMI databases, which have as emotions: anger, sadness, surprise, joy, disgust, fear and neutral. Its best results are up to 94.91% correct.

Meanwhile, in (Mehendale, 2020), they propose a novel technique called "facial emotion recognition using convolutional neural networks" (FERC). FERC is based on a two-part convolutional neural network (CNN): the first part removes the image background and the second part concentrates on extracting the facial feature vector. The supervised data they used was obtained from the stored database of 10,000 images (154 people). Their results were 96% accuracy.

On the other hand, in (Pranav,2020), they propose a Deep Convolutional Neural Network (DCNN) model that classifies 5 different human facial emotions. The model is trained, tested and validated using the manually collected image dataset. Its results are 78.04% correct.

Similarly, in (Ferreira, 2018), they propose a new end-to-end neural network architecture along with a well-designed loss function based on the strong prior knowledge that facial expressions are the result of movements of some facial muscles and components. As a test dataset they use the CK+ database, which includes 1308 images with different emotions (80% training and 20% test). Their results are 93.64% correct.

On the other hand, in (Saravanan, 2019), classify images of human faces into one of the seven basic emotions. They experimented with several different models, including decision trees and neural networks, before arriving at a final convolutional neural network (CNN) model. As results, they obtained a 60% accuracy rate using the FER-2013 database.

Finally, in (Hung, 2019), a neural network was implemented for basic emotion classification. They used a test set from various databases, including FER-2013. Their best results are 84.59% correct, achieving one of the best classifications in the state of the art when using this database.

Methodology

Two convolutional neural network models were proposed for the development of this research. In both cases, the phases that the methodology went through were: reading the input data, creating the input vector (image and label), normalizing the data, creating the data sets, creating the models, training, and, finally, validation.

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Model 1

The first model of the convolutional neural network (CNN) consists of: a convolutional layer of 32 neurons with linear activation, a LeakyReLU activation function with a parameter of alpha = 0.1, a MaxPooling2D (2x2) function, a Dropout function of 0.5, a Flatten function, a Dense layer of 32 neurons with linear activation, a Dense layer of 32 neurons with linear activation, a LeakyReLU activation function with parameter alpha = 0.1, a Dropout function of 0.5 and finally a Dense layer with Softmax activation..

Model 2

The second model of the convolutional neural network (CNN) consists of: a convolutional layer of 32 neurons with relu activation, a MaxPooling2D function (2x2), a convolutional layer of 64 neurons with relu activation, a MaxPooling2D function (2x2), a convolutional layer of 128 neurons with relu activation, a MaxPooling2D function, a Dropout function of 0.5, a Flatten function, a Dense layer with relu activation, a Dense function with softmax activation

Database

The database used was the "Learn facial expressions from an image", FER-2013, consisting of 48x48 pixel grayscale images of faces. The database is labeled in seven categories: 0=angry, 1=disgust, 2=fear, 3=happy, 4=sad, 5=surprise, 6=neutral. The training set consists of 28,709 examples and the public test set consists of 3,589 examples. An example of this database can be seen in Figure 1.

Figure 1 Sample of the FER-2013 dataset used for emotion classification during this research

Tests and results

For the tests, 10 runs of each proposed model were performed, in all cases for 100 epochs. For the first model, the average accuracy was 60.89%, although the validation of the model obtained 49.98% accuracy. The results of the model can be seen in Figure 2 and Figure 3. For the second model, better results were obtained, with 74.90% accuracy, although the validation of the model obtained 55.42%. The results of the model can be seen in Figure 4 and Figure 5.

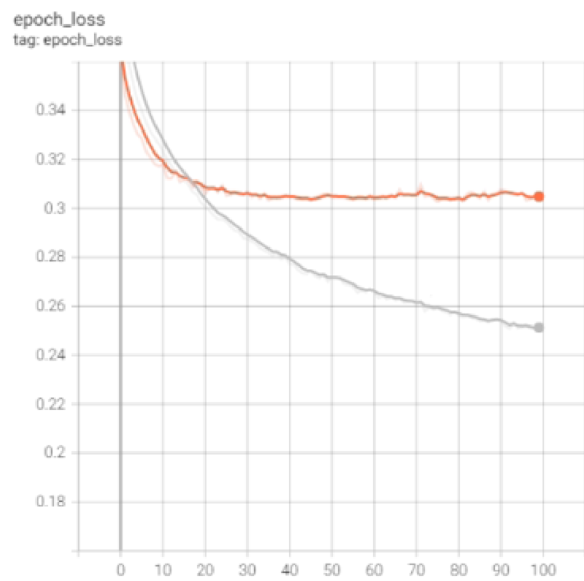

Figure 2 Loss versus number of epochs behavior of the first proposed model for image classification, both validation and hit

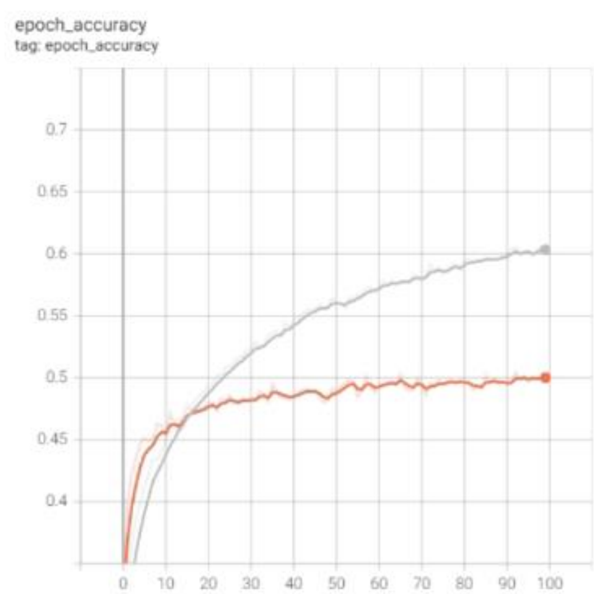

Figure 3 Hit versus number of epochs behavior of the first proposed model for image classification, both validation and hit

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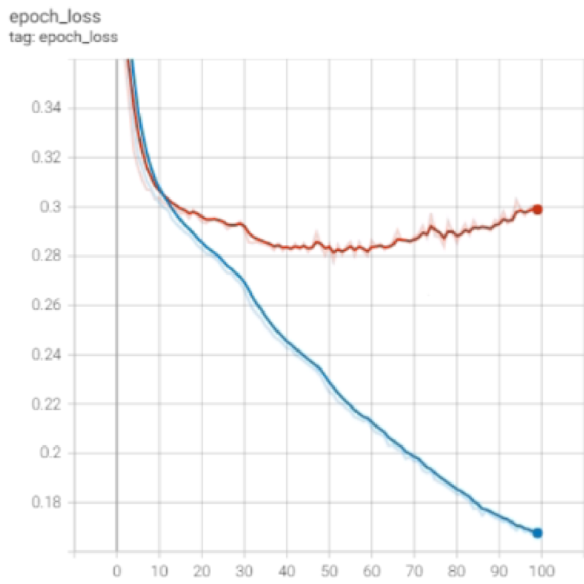

Figure 4 Loss versus number of epochs behavior of the second proposed model for image classification, both validation and hit

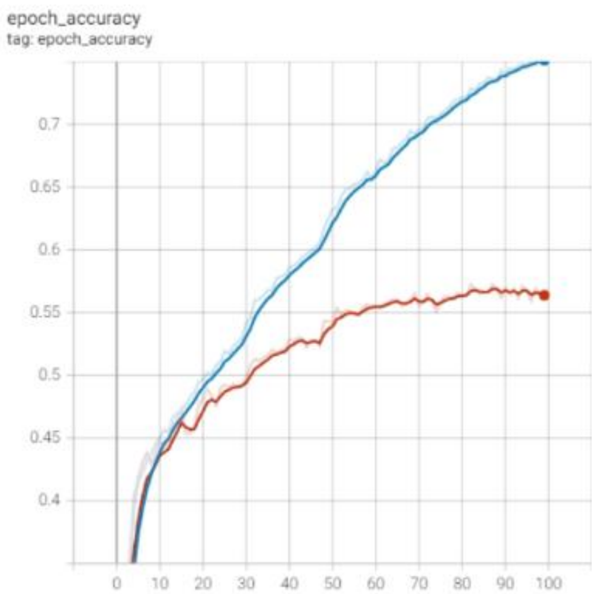

Figure 5 Behavior of hit versus number of epochs of the second proposed model for image classification, both validation and hit

Conclusions

Although we obtained good results compared to what was found in the state of the art by using the FER-2013 database, surpassing research such as that of (Saravanan, 2019), it would be important, as future work, to increase the data of the test set through other more images, since in (Hung, 2019) better results were achieved by implementing this alternative, therefore we conclude with a work that will contribute to the state of the art in this research topic where we will continue working to improve the results and obtain a better tool to be able to meet the objective.

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