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Article

Intelligent algorithm using convolutional neural networks for facial recognition of people with Autism Spectrum Disorder [ASD]

Algoritmo inteligente utilizando redes neuronales convolucionales para reconocimiento facial de personas con Trastorno del Espectro Autista [TEA]

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Abstract

This article describes the implementation of an algorithm for facial recognition in individuals with ASD. Computational technologies have advanced significantly, benefiting various sectors, including healthcare and education. In the case of ASD, computational techniques and intelligent algorithms can contribute to more accurate and earlier diagnosis, representing a key tool for healthcare professionals and society. Intelligent algorithms play a crucial role in automating complex processes, such as analyzing large volumes of data and making decisions in real time. Their ability to identify patterns and trends allows for more informed and accurate decisions. Therefore, implementing an intelligent algorithm for identifying individuals with ASD allows for more efficient, reliable, and accessible diagnosis.

Goals	Methodology	Contribution
Facial Recognition Reliable Diagnosis	Algorithm Artificial vision Convolutional Neural Networks	Intelligent algorithm for identifying people with ASD.

Autism Spectrum Disorder, facial recognition, computer vision, deep learning

Resumen

El presente artículo describe la implementación de un algoritmo para el reconocimiento facial de personas con TEA. Las tecnologías computacionales han avanzado significativamente, beneficiando diversos sectores, incluidos salud y educación. En el caso del TEA, las técnicas computacionales y algoritmos inteligentes pueden contribuir a un diagnóstico más preciso y temprano, representando una herramienta clave para profesionales de la salud y la sociedad. Los algoritmos inteligentes desempeñan un papel crucial en la automatización de procesos complejos, como el análisis de grandes volúmenes de datos y la toma de decisiones en tiempo real. Su capacidad para identificar patrones y tendencias permite obtener decisiones más informadas y precisas. Por lo que, implementar un algoritmo inteligente para la identificación de personas con TEA permite un diagnóstico más eficiente, confiable y accesible.

Objetivos	Metodología	Contribución
Reconocimiento facial Diagnóstico Confiable	Algoritmo Visión artificial Redes Neuronales Convolucionales	Algoritmo inteligente en la identificación de personas con TEA.

Trastorno del Espectro Autista, reconocimiento facial, visión artificial, aprendizaje profundo

Area: Development of strategic leading-edge technologies and open innovation for social transformation

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1. Introduction

In Mexico, a 2016 study conducted by Autism Speaks and the Mexican Autism Clinic [CLIMA] identified that 1 in every 115 children has autism, occurring more frequently in boys than in girls, and identifying that, for every 5 cases of autism, 4 of them are men and 1 is a woman [Teletón México, 2024].

Today, computational techniques have advanced significantly, providing highly useful technologies that support people in various sectors, from healthcare to education, as well as commerce, industry, research, and more. These technologies not only optimize processes but also have the potential to improve people's quality of life by facilitating their daily activities, increasing their productivity, or even assisting in complex decision-making. In this context, it is essential to leverage these tools to address specific challenges affecting groups of people with particular needs, such as those with ASD.

Due to the diversity of their characteristics and the complexity of their diagnosis, identifying individuals with ASD early and accurately represents a significant challenge for healthcare professionals and society at large. This is where computational techniques, such as artificial intelligence and intelligent algorithms, can play a crucial role. It is important to develop and propose an intelligent algorithm capable of identifying individuals with ASD in an efficient, reliable, and accessible manner.

This type of solution would not only support early diagnosis but could also facilitate the personalization of therapeutic interventions, improve social inclusion, and offer families an additional tool to better understand and address the needs of their loved ones.

The objective is to identify and implement an algorithm to recognize facial features associated with individuals with ASD, with the goal of implementing it in a system that helps identify these individuals. For this important task, machine learning and convolutional neural networks were used for the image selection and classification process.

To evaluate the algorithm, we used the Kaggle dataset with images of people with autism, and a dataset of images of Mexican citizens created for this study.

For the training and testing phases, they were combined into a single dataset, which serves as the training and evaluation corpus for the facial recognition algorithm.

The sections covered in the article are: related works, materials, techniques, algorithm for ASD detection, algorithm models and tests, and results with evaluation metrics.

2. Related works

To develop the project, it was necessary to conduct research to identify how this issue has been addressed in other studies and by various authors from different regions.

The advancement of Machine Learning [ML] and Deep Learning [DL] techniques has allowed them to be widely applied in various fields, including pattern recognition, disease monitoring, sentiment analysis, gender classification, and the identification of facial expressions, among others [Ahmad et al, 2024].

Ahmad et al. [2024] performed autism spectrum disorder detection using facial images: comparing the performance of pre-trained convolutional neural networks. They used the detection of autism spectrum disorders using facial images [Autism Spectrum Disorder – Detection Facial Image ASD-DFI] at early ages.

The methodology they proposed contains 6 pre-trained models of great recognition, these were ResNet34, ResNet50, VGG16, VGG19, AlexNet and MobileNetv2, all of them implemented in Python.

Juárez et al. [2024] developed a computer vision system that uses facial and text recognition to recommend professional profiles.

They used advanced image processing and machine learning techniques to evaluate facial and handwriting characteristics. The results showed an accuracy of 87.5% in facial analysis and 85.93% in text analysis.

Cadena, J.,'s thesis [2021] presents an efficient technique for global face recognition using wavelet transforms and support vector machines [SVMs] on 3D images.

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This work addresses the challenges associated with face recognition in three-dimensional environments, such as variations in facial expression, lighting, and partial occlusions, proposing an innovative approach that improves the accuracy and robustness of the system.

The technique is based on two key components: the wavelet transform, used for extracting relevant features, and SVMs, used for identity classification. The wavelet transform allows the facial surface to be decomposed into multiple scales and frequencies, capturing both global and local information about facial shapes and textures.

These features, represented in the frequency domain, are subsequently classified using SVMs, which separate the different identities by maximizing the margin between classes.

Feng [2023] presents research addressing the early detection of Autism Spectrum Disorder [ASD] in children, using advanced deep learning techniques applied to functional magnetic resonance imaging [fMRI]. Early diagnosis of ASD is crucial for implementing early interventions and improving developmental outcomes in affected children.

The authors developed an algorithm based on a custom Convolutional Neural Network [CNN] specifically designed to analyze resting-state fMRI data. The CNN architecture incorporates convolution, pooling, batch normalization, dropout, and fully connected layers, optimized for interpreting high-dimensional data.

This configuration enables the extraction and learning of hierarchical features from brain images, facilitating the distinction between children with ASD and those with typical development.

3. Materials y Techniques

CNNs have established a strong reputation in the field of image data processing, producing superior results compared to traditional methods. However, they require a large amount of data for the training phase, which is sometimes referred to as data-hungry algorithms, especially training from scratch.

However, transfer learning [TL] has largely solved this problem, where a pre-trained model is retrained to perform a specific task with fewer data samples [Pineda, 2021].

Pre-trained deep learning models provide substantial benefits in artificial intelligence and machine learning. These models allow practitioners to save time and computing resources by providing powerful starting points for numerous tasks, leveraging knowledge from extensive training on large and diverse datasets.

The ability to adapt pre-trained models to specific tasks using limited labeled data is an important feature of transfer learning. It reduces the need for large datasets [Pineda, 2021].

Python was used as the programming language due to its simplicity and variety of specialized libraries, such as OpenCV, TensorFlow, Keras, and Scikit-Learn.

4. Algorithm for ASD detection

Based on related work and the analysis of deep learning techniques, it is proposed to follow the algorithm consisting of the steps presented in figures 1, 2 and 3. Figure 1 presents the first steps that the algorithm will follow; it has two connectives, A and B, which are related to figures 2 and 3 respectively.The descriptive algorithm for training and prediction with the ResNet50 model is described below.

1. Start
2. Evaluate whether a pre-trained model exists [.h5]:

- If the model exists: Proceed to Section B [Image Prediction].
- If the model does not exist: Proceed to Section A [Model Training].

Box 1

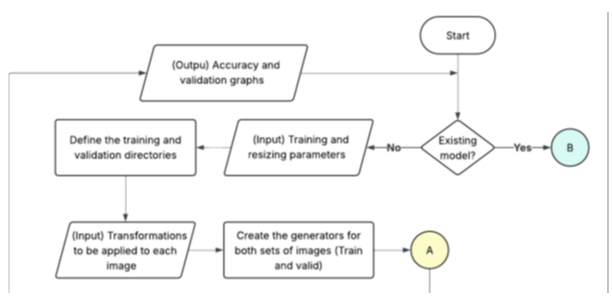

Figure 1
Flowchart of the algorithm
Source: Own elaboration

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Section A: Model training [if no model exists]

Step 1. Parameters and training directories. The input parameters for training and image resizing are defined. In addition, the directories for the training and validation sets are specified. Transformations are applied to each image in the training and validation directories.

Step 2. Create the image generators. The training and validation image sets [Train and Valid] are established. The previously defined transformations are implemented, indicating the directory of the sets and the parameter data to apply them.

Box 2

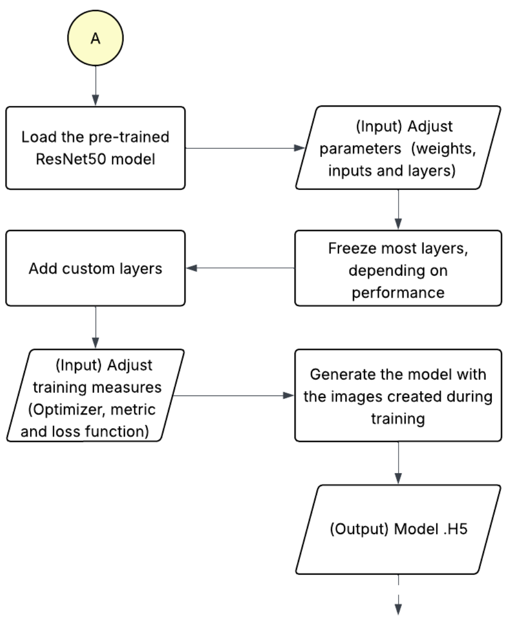

Figure 2
Flowchart of section A of the algorithm
Source: Own elaboration

Step 3. Load the pre-trained ResNet50 model. Import the pre-trained ResNet50 model, defining the input image with the width and height dimensions, using three RGB color channels. Load the pre-trained ResNet model, and fine-tune the model parameters [omit the last layer of input images].

Step 4. Add custom layers. The specific layers for the classification problem are added and the model output is stored in the variable x. The dimensionality of the 3D convolutional output is reduced to a 1D vector. A fully connected dense layer, with 128 neurons, is added to learn to classify, with a relu function that allows learning non-linear patterns, a Dropout of 0.3 is defined to avoid overfitting.

The dense output layer is appended, creating n neurons, one for each category [2 classes], a sigmoid activation function, and the name of the output. The complete model is created using the custom layers that were built previously, considering the ResNet50 model as a base, but using the custom output layer.

Transfer learning is performed by freezing all the layers prior to those chosen, thus ensuring that the training or knowledge that has already been acquired with another dataset is not lost.

Step 5. Freeze pre-trained model layers. Most pre-trained layers are frozen, that is, all layers in the model except those indicated, the last 3 in this algorithm. This is to avoid processing time, i.e., the ResNet50 convolutional layers that will not be modified, since they have already been trained, and thus allow training only the custom layers.

Step 6. Adjust training measures. The loss function is calculated using the categorical_crossentropy function. The Adam optimizer is used for learning, as it adjusts the model's weights to reduce error. It also calculates the model's accuracy, allowing us to identify how many predictions were correct and how many were incorrect.

Step 7. Generate the trained model with the training data. The model is validated using the validation set, and performance metrics are monitored. The first phase is trained with the generated images, performance is evaluated with the validation images, and the weights for fc1, fc2, and output are adjusted. Five epochs are generated. From step 5 up to this point, the model is repeated in two more phases, with the only difference being the time to unfreeze the training layers. Therefore, the changes in phases 2 and 3 are briefly described below.

Step 8. Generate output from the trained model. The trained model is generated in .h5 format. The accuracy and validation data are evaluated to assess model performance.

Section B. Image prediction [if a trained model exists]

Step 1. Check if you only want to classify one image.

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Question: Do you only want to analyze one image?

Yes: Select an image from the gallery, go to Step 2.

- Predict which category it belongs to based on the image data and present it.

No: Identify the path to the folder with multiple images, go to Step 3.

Box 3

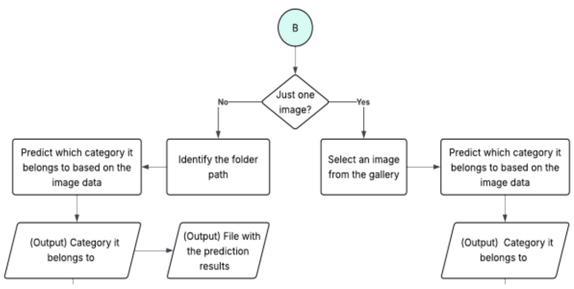

Figure 3
Flowchart of section B of the algorithm.
Source: Own elaboration

Step 2: Prediction for a single image. The image is selected from the gallery. The model predicts which category the image belongs to. The image category is defined. Go to Step 4.

Step 3: Prediction for an image folder. The path to the image folder is selected. The model performs mass predictions on the images and generates a TXT file with the prediction results. Go to Step 4.

Step 4. Finalize the process.

5. Models and tests of the algorithm

This session describes some of the models and parameters that were configured and used for the classification of individuals with ASD. The goal is to test the feasibility of using facial recognition with artificial intelligence techniques, specifically Machine Learning and Convolutional Neural Networks, to identify individuals with ASD and implement it in a system.

To evaluate the proposed model, in pre-training the ResNet model uses the ImageNet dataset [ImageNet, 2020] and in the testing phase the Kaggle dataset is used together with a dataset built for this specific study, the datasets used are freely licensed [Autism dataset, 2024].

The training and testing dataset is composed of four subsets: Consolidate, Test, Training, and Valid. Table 1 presents the detailed data.

Box 4

Table 1
Dataset

No.	Subset	Autism	Non-Autism
1	Consolidate	1523	1521
2	Test	361	
3	Training	1290	1321
11	Valid	70	71

Source: Own elaboration

Table 2 presents the parameters with which the different models with which tests were performed with ResNet were defined.

Box 5

Table 2
Test results

Test	Model generation parameters	Classification percentage	
		Autist	Non-Autist
3	Flatten BatchSize = 32 Epochs = 10 Loss = 'categorical_crossentropy' Optimizer = Adam[LearningRate = .0001] Width & Height shapes = 224 AdicionalLayers = Si	**74.97%**	**25.03%**
		24.08%	**75.92%**
16	Flatten BatchSize = 64 Epochs = 50 Loss = 'categorical_crossentropy' Optimizer = Adam[LearningRate = .0001] Width & Height shapes = 124 AdicionalLayers = Si	**95.24%**	**4.76%**
		38.44%	**61.56%**
23	GlobalAverage BatchSize = 32 Epochs = 5, 7 y 8 Loss = 'categorical_crossentropy' Optimizer = Adam[LearningRate = .0001] Width & Height shapes = 224 AdicionalLayers = No	**95.03%**	**4.97%**
		37.62%	**62.38%**

Source: Own elaboration

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According to the results represented in classification percentages shown in Table 2, the models for tests 16 and 23 are shaded, because of the 25 tests developed. The 2 models that obtained the best classification results, the model for test 16 presents 95.24% correct classification of people who DO have ASD and 61.56% of people classified as NOT having ASD correctly. For model 23, 95.03% correct classification of people who DO have ASD and 62.38% of people classified as NOT having ASD was obtained.

Based on the values in Table 2, it can be seen that the BatchSize in test 16 is greater than in test 23, thus consuming more processing time and resources. Regarding Epoch, test 16 is also greater than test 23, although it can be seen that the latter performs three phases in which some changes are also made.

6. Results with evaluation metrics

Figure 4 presents the evaluation metrics of time represented in seconds [s] for each step, accuracy and loss applied to all models, however, the results correspond to model 23. It can be seen that, when in phase 1 the time is lower, the accuracy has an average value and the loss exceeds the average.

For phase 2 the time increases, the accuracy value increases and the loss decreases, and the same behavior occurs in phase 3, which indicates that the model is learning, this given that the accuracy increases and the loss decreases. Figures 5, 6 and 7 present the accuracy and loss graphs for the 3 phases correspondingly.

Once the model training process is complete, it can be used to classify images of people. This can be done by individual images or by a set of images of people stored in a folder. To achieve this, a system named after the trained model was implemented, allowing it to predict the class to which the model belongs.

Box 6

```
Entrenando Fase 1 [Última capa]...
…
82/82 ━━━━━━━━━━━━━━━━━━━━ 242s 3s/step - accuracy: 0.5495 - loss: 0.7830 - val_accuracy: 0.6525 - val_loss: 0.6537
Epoch 4/5
82/82 ━━━━━━━━━━━━━━━━━━━━ 278s 3s/step - accuracy: 0.5701 - loss: 0.7597 - val_accuracy: 0.6454 - val_loss: 0.6436
Epoch 5/5
82/82 ━━━━━━━━━━━━━━━━━━━━ 271s 3s/step - accuracy: 0.5839 - loss: 0.7245 - val_accuracy: 0.6241 - val_loss: 0.6228

Entrenando Fase 2 [Últimas 2 capas]...
Epoch 1/7
82/82 ━━━━━━━━━━━━━━━━━━━━ 308s 4s/step - accuracy: 0.6015 - loss: 0.7255 - val_accuracy: 0.6809 - val_loss: 0.6524
Epoch 2/7
82/82 ━━━━━━━━━━━━━━━━━━━━ 256s 3s/step - accuracy: 0.6431 - loss: 0.6891 - val_accuracy: 0.6809 - val_loss: 0.6345
…
Epoch 7/7
82/82 ━━━━━━━━━━━━━━━━━━━━ 273s 3s/step - accuracy: 0.6522 - loss: 0.6529 - val_accuracy: 0.5816 - val_loss: 0.6578

Entrenando Fase 3 [Ajuste fino total]...
Epoch 1/8
82/82 ━━━━━━━━━━━━━━━━━━━━ 1170s 14s/step - accuracy: 0.6587 - loss: 0.6171 - val_accuracy: 0.6950 - val_loss: 0.5655

….
82/82 ━━━━━━━━━━━━━━━━━━━━ 1050s 13s/step - accuracy: 0.8633 - loss: 0.3213 -
val_accuracy: 0.6667 - val_loss: 0.7558
Epoch 8/8
82/82 ━━━━━━━━━━━━━━━━━━━━ 998s 12s/step - accuracy: 0.8902 - loss: 0.2823 - val_accuracy: 0.7234 - val_loss: 0.6638
Model: "functional"
```

Figure 4

Model training results.

Source: Own elaboration

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Box 7

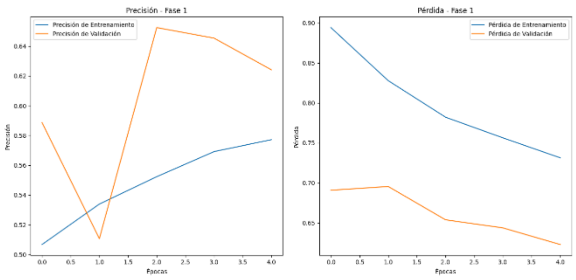

Figure 5
Phase 1 Chart.

Source: Own elaboration

Box 8

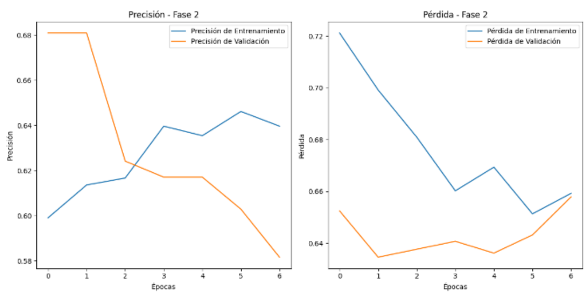

Figure 6
Phase 2 Chart.

Source: Own elaboration

Box 9

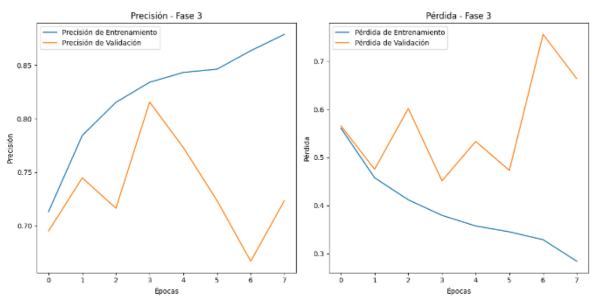

Figure 7
Phase 3 Chart.

Source: Own elaboration

Conclusions

The facial recognition algorithm was developed and implemented using artificial vision techniques, in which the face in the image is detected and convolutional neural networks were used for detection, however, prior to using CNNs, transformations are performed on the images such as rotation, horizontal and vertical flipping, displacement, zooming, in order for the classification model to identify patterns regardless of how the person's face is presented.

The accuracy and specificity metrics were evaluated, yielding the results presented above. This improved on the results of other studies that used the Kaggle dataset, which, like the one used in this study, was used, except that in this study images of Mexican nationals were added. Therefore, it is believed that the algorithm detected and/or strengthened characteristic patterns exhibited by individuals with ASD.

Finally, ASD is a neurodevelopmental condition that manifests itself uniquely in each individual. However, it is important to emphasize that ASD is not associated with specific or distinctive facial characteristics that allow a person with this condition to be identified based solely on their physical appearance. ASD is diagnosed primarily through behaviors, communication patterns, and social skills, not facial features, as these are highly varied and therefore difficult to identify.

Declarations

Conflict of interest

The authors declare no conflicts of interest. They have no known competing financial interests or personal relationships that could have appeared to influence the article reported in this article.

Authors' contribution

Paredes-Xochihua, Maria Petra: Contributed to the project idea, identification of techniques to be applied, development, elaboration, validation testing, and implementation, as well as the creation of the dataset of Mexican nationals.

Sánchez-Juárez, Ivan Rafael: Contributed to the creation of the dataset of Mexican nationals, the development of functional tests, and the evaluation of results.

Pedroza-Méndez, Blanca Estela: Contributed with input into the algorithm, techniques used in the development, evaluation and review of results.

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Abbreviations

APP	Software application designed to run on mobile devices
CNNs	Convolutional Neural Networks
fMRI	Functional Magnetic Resonance Imaging.
ITS	Instituto Tecnologico Superior
RGB	Red, Green, and Blue. RGB color model
TecNM	Tecnológico Nacional de México
ASD	Autism Spectrum Disorder

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Background

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Basics

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