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# Efficiency analysis of the convolutional neural network (cnn)and the tensorflow learning system

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**Summary.** The technology of image identification and machine learning has been applied in various fields such as medicine, in plants, species recognition (snakes)[1][2]. The application of image identification currently in the detection and identification of objects in determining an image momentarily. In this article it is proposed to evaluate the behavior of convolutional neural networks together with tensorflow, with the aim of seeing how the system behaves and whether it is efficient or not before each of the tests that were performed on the System with the different images I know happened, in order to be if it is system shows efficiency numbers or not. In this way we will see the results obtained during each of the tests that were carried out, in this way we will reach the conclusion if the system is efficient or not. After the system has captured images of different species, in this way it improves the identification capacity of the system in an agile way. Implementing these technologies (convolutional neural network (CNN) and the tensorflow learning system), performing the union of these two was obtained a faster system in the results of the recognition of species.

This research has been dedicated to the study of the behavior of the neural network and the tensorflow learning system, which concludes with positive evidence the functioning of the system during the trial period. Minimal failures were found mainly human errors at the time of taking the photographic records such as blur, low quality or the plane in which the animal is found inthe image to be uploaded, in the case of high resolution and quality images no failures were found to large scale. Implying that the neural network and the learning system present a high percentage of assertiveness reflected in the tests carried out.

**Keywords:** Convolutional neural network (CNN), tensorflowlearning system, recognition, canine species

## I. Introduction

Este articulo consiste n un a serie de prueb as of operation of image recognition a starting from a neural network next to the tensorflow learning system. In the first instance, it begins with the test phase, from the loading of test images to the application that consumes the convolutional neural network.

The recognition of patterns from images covers large areas of research, within which are the systems used in neural networks that are used to improve the recognition of species within the application. Therefore, this document proposes an intelligent system of recognition of canine species where the user just entering a photograph of the animal will allow the system to perform the r knowledge and classification according to the traits of different breeds with which the greatest number of similarities were identified. To achieve this the algorithm of the convolutional neural network (CNN) detects the patterns of the animal in the image and through the implementation of Tensorflow as a learning system, will give the classification more close to the species.

Tensorflow is an open source library for machine learning through a range of tasks, developed by Google to build and train neural networks and decipher patterns, this starts with the importance of high-performance libraries for numerical analysis such as Eigen (a high-performance library for C++ and CUDA) and CuDNN (an Nvidia library for deep neural networks) [3] this facilitates operations with arrays and vectors.

In addition, CNN is a type of learning model that processes data that hasn a grid pattern, such as images and this is created so that it learns automatically, since that adapts hierarchies from low to high-level patterns. Neural network system architecture (CNN) is the technology of identifying images through its network architecture.

Faster-RCNN(searches for regions of interest in the image in an agile way), the algorithm handles three layers of operations: feature network, region proposal network (RPN) and detection network. One of the layers is used for classification, the other two are used to find the regions that contain the characteristic pixels of the image, we can see in the one of how the neural network

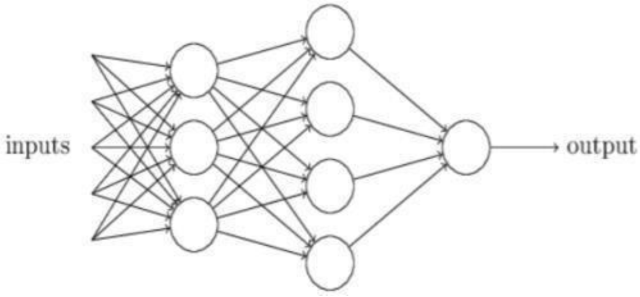


Figure 1.Structure of a simple neural network. [4]

In figure 1 you have to see the layers of a simple neural network, each circle represents a euronal network, this structure consists of three layers that are: an input layer, hidden layers and an output layer. An input layer receives the information, the hidden layers do the process, and the output layers get the final result. Layers communicate between signals, whether they are hidden layers or input and output layers.

Tests were carried out on the library and the convolutional neural network, to demonstrate the operation of the algorithm, when analyzing 120 races it was shown that of 26,936 images 78% of the images analyzed were recognized from a satisfactorily and 22% were not satisfactorily recognized.

To arrive at this statistical information, an extensive analysis was carried out of the results collected in the statistical system in which the data were collected and classified.

Tests that were used were taken from the Stanfor Dogs Dataset page, where 26,936 imageswere contracted, 120 breeds of dogs analyzed which were used as an object of test.

The data collection was done through a statistical system, in which heat maps were made with the data obtained, in this way the data are classified as deficient, insufficient, good, outstanding. Through this data classification it was possible to determine whether the system is effectiveor otherwise deficient. These data went through a statistical analysis, where the data of each of the dog breeds that were analyzed were classified.

In addition, it was possible to reach the conclusions of why the system cannot perform the recognition of an image, what may be the possible causes and how each of the causes that were evidenced can be solved.

### A. Red Neuronal convolucional (CNN)

Now the CNN is a mathematical code construct, which has three layers or known as building blocks which are: convolution, grouping and fully connected layers.

The first two layers mentioned above (convolution and grouping), extract the characteristics of the image, these characteristics what they do is a less redundant data decrease, thus filtering the characteristics of the image that generates a map with the features, then the last layer extracts the final features.

$$x^1 \longrightarrow \boxed{w^1} \longrightarrow x^2 \longrightarrow \cdots \longrightarrow x^{L-1}$$

**Figure 2**. Structure of CNN [5]

In figure 2 we can see the operation of the layers of the CNN, x1 is the input of the image and w1 performs the entire process of the first two layers of the CNN, x2 is the output with the results of the first two layers, in the space check if there are errors in the results obtained.

## II. Materials and methods

To perform the testing process, we use the neural network (CNN) together with tensorflow which is an automatic learning system, the images of

L is a dimensional vector, works with x performing a mass of probability of processing this would become $x^{L-1}$ where this would be the layer that transforms the data. $w^{L-1}$ at this point the entire mathematical part is performed where it sends to the final layer the analysis co rrespondiente of the data, already converted into a map without repeated data.

The process carried out previously is called kernel, this process is done in a repetitive way, through this repetitive process the system learns automatically through an optimization algorithm called "retro programming and gradient descent". In this way it reaches the end of the process where z receives all the data or is called the output layer, this is a hidden layer within the entire system.

Being clear about how CNN works, let's see how it does image recognition by means of code, how is the step by step below this below.

The architecture of the neural network system (CNN) is the technology of identifyingimagesthrough the Faster-RCNN network architecture, since it handles three layers of operations which are: characteristic network, region proposal network (RPN) and discovery network

This system extracts maps from the image through convolutional layers. The proposed region network (RPN) then processes the maps and provides information to ROI (Regions that may contain feature points). In this way ROIhead (responsible for processing ROI responses and RPN proposals) is allowed, at this point the information that has ROI is reviewed and the coordinate correction is made. To finish the detection network takes the inputs of this and RPN generates the classificationof the pet.

In this way we will achieve that the system performs the recognition of species in real time generating a training in the layers of detection of images and RPN that performs the recognition of these. Identifying the **RPN** would be our z in Figure 2, which obtains the final result of the entire process carried out by the neural network between the layers of it.

when the neural network has already been trained, when the neural network has been realized it becomes the Faster-RCNN neural network.

R-CNN (convolutional neural network based on regions), begins to identify more quickly the points of analysis of the images, RCNN begins to quickly and effectively identify the points, the parts Pet keys, also performs the mapping of the images.

### B. Mathematical Explanation of Convolutional Neural Networks (CNN)

Convolution is defined as the product of the integral of two functions displacing a function t (t is a continuous time), and is denoted as follows:

$$F * g \int_{-\infty}^{\infty} f(T)g(t-T)dT$$

**Figure 3**. Mathematical explanation of the convolution of convolutional neural networks [6]

As you can see in figure 3, there is an integral which is solved with the same rules of integration, making that solution we come to the following equation:

$$F * (f * g) = (F(f)) * (F(g))$$

**Figure 4**. Convolution theorem [6]

As can be seen in Figure 3 we can see that the result of the integral in Figure 4 is the convolution theorem or the better known Fourier transform of f, this also applies to Laplace's theorem.

All this triggers in a matrix product, as can be evidenced in Figure 5, where we can observe the convolution operator applied on a filter. To reach the result is

In addition, this system uses a COCO (Common Object in Context) dataset, this helps the system to make a faster recognition of the images. it is called faster neural network - RCNN, it is achieved

you have to multiply each operator by each element of the convolutional filter so that the final result of the matrix is obtained.

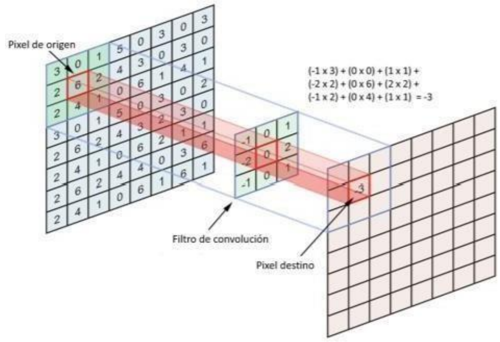

Pixel de origen
(-1 x 3) + (0 x 0) + (1 x 1) +
(-2 x 2) + (0 x 6) + (2 x 2) +
(-1 x 2) + (0 x 4) + (1 x 1) = -3
Filtro de convolución
Pixel destino
-3

**Figure 5**. Convolution theorem [6]

In this way the mathematical structure of convolutional neural networks can be evidenced and the final result can be seen in Figure 6, where we see how the convolutional neural network works in a clear way, where you can evidence in the entrance this image, map of characteristics where the image passes and you begin to review its entire structure, take the data and stop at the convolutions section where you begin to remove the repeated numbers in the records. In the subsample section the recognition is carried out and in the output it gives us as a result the recognition the system gives us the recognition.

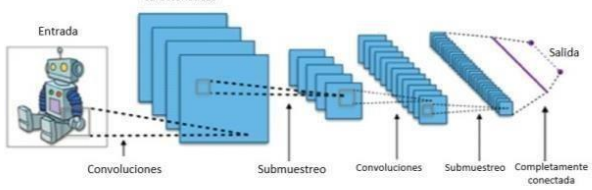


**Figure 6**. Convolutional neural network theorem [6]

### C. Tensorflow a machine learning system

TensorFlow an open source library for machine learning across a range of tasks, developed by Google to build and train neural networks and decipher patterns and

Nvidia fordeep neural networks)[3] this facilitates operations with arrays and vectors.

This library works together with neural networks Able of recognize Patterns it the OPERATION of the AI project, operations that are carried out on the arrays de data or also so-called bookstores are an analogy to statistics inferential, with an extensive database, which in this case is the information of each breed is attempted recognize the pattern of these.

At first the most important is to have the data, a wide and varied library of references that guide the neural network towards an interpretation

Tensorflow uses graphs to create a model on which it works where each node represents anarithmetic operation that generates the tensors, (elements that gives name to this library) are geometric objects that describe relationships between geometric vectors, scalars and other tensioners. That is, they are the objects that the neural network handles to produce valores [7]. Historically, however, tensors have made fewer advances in computer science, traditionally associated more with discrete mathematics and logic. This state of affairs has begun to change significantly with the advent of machine learning. Modern machine learning is based on the manipulation and calculation of tensioners. The simplest example of a tensor is a scalar, a single constant value extracted from the realnumbersis, we call a scalar a tensor of rank 0. If scalars are range 0 tensors, what is a range 1 tensor? A range 1 tensor is a vector; A list of real numbers (a, b). A range 3 tensor would form (N, N, N). An arbitrary element of the tensor would be selected by specifying (i, j, k) as indices[1].

Tensorflow allows the definition of several graphics, but most programs only use the default value one, which is available in this library as tf.get_defaul_graph (). When an operation is

correlations, starts with the import of the libraries that we will need to construir the program, Tensorflow has high performance libraries for numerical analysis such as Eigen (a high performance numerical library for C ++ and CUDA) and cuDNN (a library of

assertive of data patterns, with this set we begin to train the neural network, classifying our data by conditional operators or Boolean logic, this discrete data will be our training dataset.

With supervised learning, the goal is for the bookseller to learn or identify a pattern from a set of data that is used for training, allowing predictions to be made from previously uned observed datasets. In this way, the initial data is used as input to train the convolutional neural network.

creates, is automatically added to the default chart (which is empty at startup), if you want to add custom charts, you must override the default chart within its scope.

To differentiate the training datawith the test data, the cross-validation method or also known as cross-validationis used. It is a technique to evaluate the results of a statistical analysis and to be able to guarantee that they are independent of the partition between the dataset that is used for training and the test set. It is used in environments where the objective is prediction and we want to estimate how accurate the generated model is, this gives an adequate distribution of each class for the best training of them.

Sessions are the second half of the TensorFlow process these execute the operations that are called by the objects and must be built after all the operations have been added to the chart and only then can their operations be executed.

the session constructor takes an optional argument that links it to the part of the graph that it wants to run (if we do not specify the graph, it is used the default chart). A session can only run operations that are on a chart, and this same graph can be executed in different sessions.

To avoid the loss of information TensorFlow offers a type of persistent program of nodes that would be similar depending on the variables. The constructor of a tf. The tf variable receives many when we initialize it. dtype specifies the type of datos that will store the variable (and tells the constructor to convert the entry to that type, generating an error if this is not possible). Trainable is a more interesting Boolean parameter whose default value is True, which tells TensorFlow if the variable should be trained by optimizers (for example, a weight matrix in a neural network).

Once all the variables in a chart have been defined, we need to add the tf.global operation _vari ables_initializer (). This assigns each variable the argument that was passed to its constructor, and it should be the first operation we execute once the execution begins. It is possible to assign a particular value to a variable during runtime as well, by adding tf.assign nodes to the chart. In fact, when we call the tf constructor. Variable, TensorFlow adds three nodes: the variable itself, the assignment operation, and the value tensor
initial. [8]

erminated predet arguments (in fact, it has no other than the default ones), the most relevant of which are possibly initial_value, dtype, and trainable. initial_value receives any tensor-convertible argument and sets it as the desired value for that variable

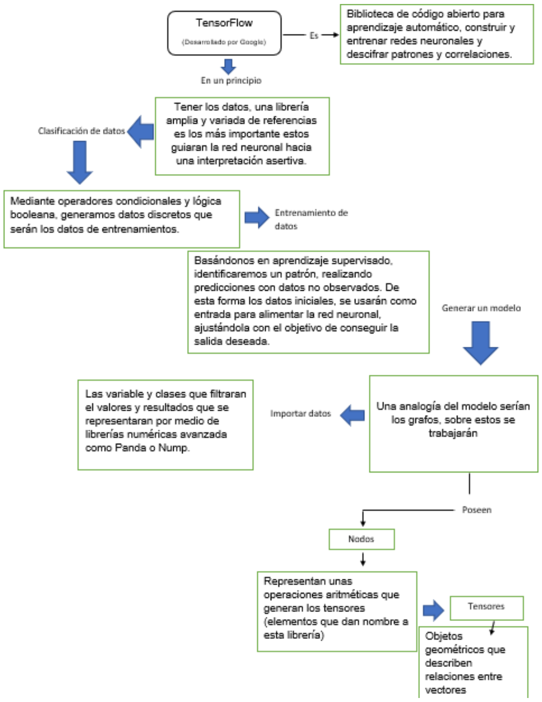
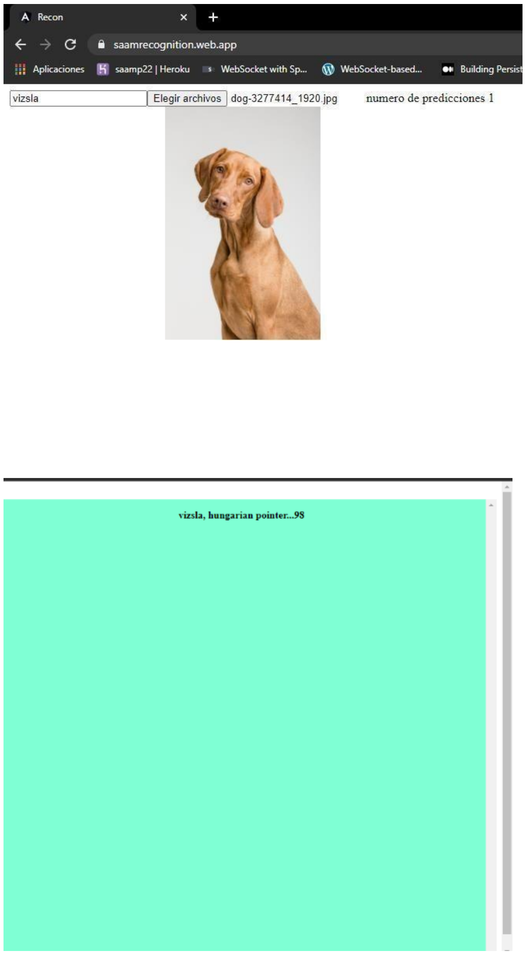

TensorFlow
(Desarrollado por Google)
Es
Biblioteca de código abierto para aprendizaje automático, construir y entrenar redes neuronales y descifrar patrones y correlaciones.
En un principio
Tener los datos, una librería amplia y variada de referencias es los más importante estos guiaran la red neuronal hacia una interpretación asertiva.
Clasificación de datos
Mediante operadores condicionales y lógica booleana, generamos datos discretos que serán los datos de entrenamientos.
Entrenamiento de datos
Basándonos en aprendizaje supervisado, identificaremos un patrón, realizando predicciones con datos no observados. De esta forma los datos iniciales, se usarán como entrada para alimentar la red neuronal, ajustándola con el objetivo de conseguir la salida deseada.
Generar un modelo
Una analogía del modelo serían los grafos, sobre estos se trabajarán
Importar datos
Las variable y clases que filtraran el valores y resultados que se representaran por medio de librerías numéricas avanzada como Panda o Nump.
Poseen
Nodos
Representan unas operaciones aritméticas que generan los tensores (elementos que dan nombre a esta librería)
Tensores
Objetos geométricos que describen relaciones entre vectores

**Figure 7**. How tensorflow works

Taking into account the above, the use of the Tensorflow library was a vital tool to carry out a study regarding its effectiveness in the recognition of canine species and their subsequent breed identified with this learning system.

For this study or test of effectiveness of the library, a sample of 120 breeds with their respective images was taken into account, having a total of 26,936 images analyzed which were analyzed. by designing and deploying a web application to facilitate the data collection process:



vizsla

dog-3277414_1920.jpg

numero de predicciones 1

vizsla, hungarian pointer...98

**Figure 8**. Environment of pruebas of the algorithm (own)

As can be seen in Figure 8, the breed to be analyzed was put inside the text box to later select the image and thus obtain its percentage of recognition which can be seen on the right side.

After that, the data obtained (each cell of Table 1 refers to the percentage of recognition for each image of the breed selected), was inserted into a spreadsheet and at this point the analysis of the recognition of breeds based on certain criteria which will also be taken into account when making the general analysis of the breeds:

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 98 | 98 | 95 | 97 | 99 | 72 | 65 | 67 | 74 | 20 | 99 | 94 |
| 57 | 81 | 89 | 93 | 94 | 97 | 99 | 92 | 97 | 97 | 88 | 9 |
| 0 | 67 | 84 | 97 | 92 | 99 | 97 | 96 | 99 | 99 | 98 | 41 |
| 97 | 95 | 75 | 9 | 94 | 87 | 91 | 97 | 96 | 98 | 99 | 10 |
| 98 | 30 | 94 | 94 | 72 | 0 | 95 | 63 | 99 | 70 | 84 | 44 |
| 9 | 95 | 98 | 12 | 53 | 99 | 0 | 52 | 76 | 7 | 93 | 94 |
| 96 | 69 | 76 | 22 | 13 | 96 | 64 | 99 | 36 | 98 | 15 | 27 |
| 91 | 32 | 87 | 51 | 32 | 91 | 99 | 38 | 0 | 90 | 97 | 69 |
| 92 | 65 | 83 | 61 | 70 | 98 | 79 | 57 | 97 | 22 | 93 | 88 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 56 | 98 | 80 | 98 | 71 | 94 | 23 | 98 | 96 | 97 | 80 | 27 |
| 0 | 78 | 26 | 32 | 100 | 99 | 49 | 0 | 98 | 84 | 99 | 7 |
| 99 | 88 | 70 | 93 | 0 | 96 | 72 | 95 | 92 | 90 | 75 | 32 |
| 0 | 82 | 15 | 75 | 9 | 89 | 98 | 99 | 99 | 72 | 96 | 90 |
| 78 | 93 | 99 | 87 | 56 | 99 | 99 | 98 | 100 | 50 | 85 | 98 |
| 90 | 94 | 0 | 27 | 61 | 86 | 98 | 100 | 82 | 94 | 96 | 83 |
| 20 | 0 | 83 | 4 | 89 | 29 | 98 | 98 | | | | |

**Table 1.** Data obtained inserted in an array in Excel, with heat map (own)

SAMPLE 188

| CRITERIA | RANK | COLOR | TOTAL | % |
|---|---|---|---|---|
| GOOD | 76-100 | 🟩 | 116 | 62% |
| SOBRESALIENTE | 51-75 | 🟩 | 29 | 15% |
| INSUFFICIENT | 26-50 | 🟨 | 16 | 9% |
| DEFICIENT | 0-25 | 🟥 | 27 | 14% |
| TOTAL | | | 188 | 100% |

**Table2.** Criteria for the analysis of the matrix in Figure 8 (own)

As an example, the data of the breed "BLENHEIM SPANIEL" figure 9 and table 2 were taken, which was obtained with the previous procedure and its results were classified by the previous criteria, after which a box diagram was made to evaluate the concentration of data taking into account the values of the matrix shown above:

calculated with another function called "AVERAGE", with the two data obtained above was made calculation of the representative data based on the limits that are set in the following table, for the greater limit is made the sum of the standard deviation to the average limiting that value to 100 since it is the maximum data taken into account and for the lower limit it is subtracts the standard deviation from the average in order to know how far the data are from the average, so we conclude that for the selected breed the most representative data of the sample are between 40% and 100%.

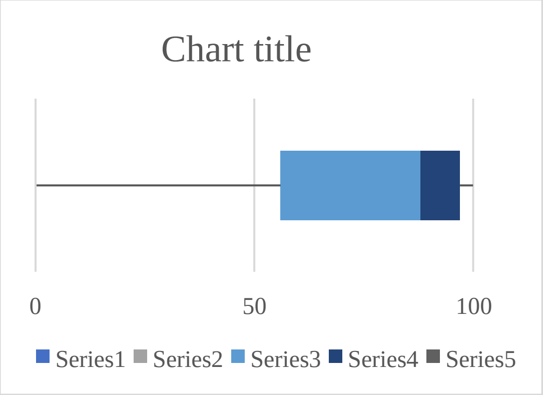


**Figure 9**. Box diagram of the data of the breed "BLENHEM SPANIEL" (own)

In this case herself Used the diagram previous for be able to visually identify the trend of the data, in this case are concentrated between 58% to the 100% being the Previous the data more Significant Influential y Predictive for the recognition of the same breed based on their different images. For table 3, with the breed used as an example, Performed a targeted analysis specifically a the taking of the data significant percentages obtained, where calculation of l is madeto standard deviation by a used function of the worksheet called “DESVEST” y the average of the data the Which one Was

| DESVIACIÓN ESTANDAR | |
|---|---|
| | VALOR |
| PROMEDIO | 72 |
| LIM. MINIMO | 40 |
| LIM. MAXIMO | 100 |
| DESVIACION EST. | 32 |

**Table3**. Data from the diagram of boxes of the breed "BLENHEM SPANIEL" (own)

With the previous procedure, the recognition was carried out for all the breeds one by one so that in this way a general analysis of the performance of the library could be carried out with all the species that were to be evaluated.

Regarding the performance of the race, the evaluation of its effectiveness was made based on 4 criteria with their respective ranks which will be shown below in table number 4:

| CRITERION | MINIMUM % | MAXIMUM % |
|---|---|---|
| DEFICIENT | 0 | 25 |
| INSUFFICIENT | 26 | 50 |
| ACCEPTABLE | 51 | 75 |
| SOBRESALIENTE | 76 | 100 |

**Table 4.** Criteria in which they were evaluated in heat matrix (own)

With the data obtained in the form of Table 4, their data ranges were analyzed taking into account the criterion and classified as follows:

| UNSATISFACTORY RECOGNITION | SATISFACTORY RECOGNITION |
|---|---|
| DEFICIENT +<br>INSUFFICIENT | ACCEPTABLE +<br>OUTSTANDING |

**Table 5.** How the data were classified (own)

### 1. Test results

Continuing with the explanation, the following results were obtained:

| TOTAL RAZAS ANALIZADAS | 120 | |
|---|---|---|
| TOTAL IMÁGENES | 26936 | |
| TOTAL RECONOCIMIENTO SATISFACTORIO | 83 | EN % |
| TOTAL RECONOCIMIENTO INSATISFACTORIO | 37 | EN % |
| TOTAL | 120 | TOTAL |

**Table 6.** results given by the algorithm (own)

Already having the above information and taking into account the evaluation with these criteria by race as a margin of error for the recognition of breeds.

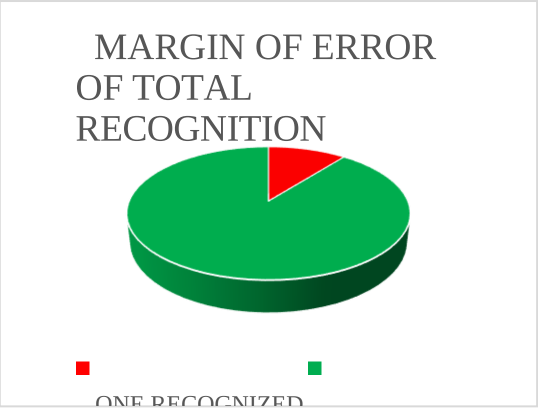


**Figure 11**. Margin of error in total breed recognition (own)

the following result was had between the number of satisfactory and unsatisfactory recognitions for each of them, as we can see in the following figure:

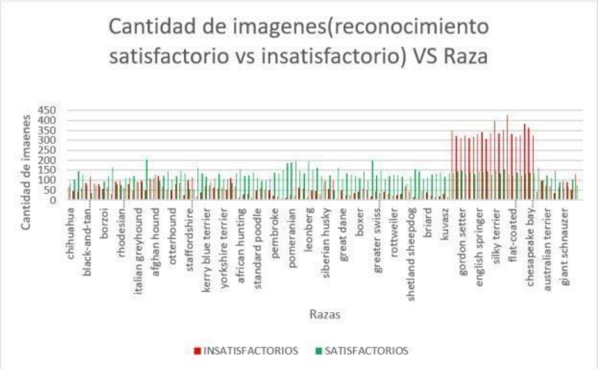


**Figure 10.** Algorithm results (own)

Given the above, we can show that for most breeds the result for satisfactory recognition with the library is higher than the amounts of unsatisfactory recognition except for breeds such as sylky terrier or gordon setter in which a high percentage inverse to what is expected is evidenced where error prevails over valid results.

It was detected that null values were found in the recognition, that is, for some reasons they will be explained later is recognition was 0%, this affects the positive results as can be seen in figure 10, for this reason they were taken

As can be seen in Figure 11, for each breed the null data (results equal to 0%) were subtracted from the amount of data recognized unsatisfactorily which marks a percentage of this margin of errors for each race and by Consequently can be visualized in Figure 12 as follows:

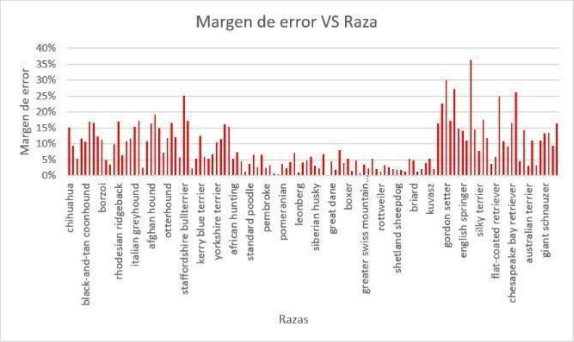


**Figure 12.** Data that did not obtain 0% recognition (own)

In the previous case of null data in the samples, it was decided to take into account only the data that had at least 1% onwards for the study in order to adjust the data and evaluate their respective performance by race from the library in order to reduce the margin of error by improving the test scenario with data that has a minimum % of recognition.

With the above, the respective adjustment was made to all breeds and on this occasion new data were obtainedregarding the values of satisfactory and unsatisfactory recognition in general, which the adjusted data obtained is seen as follows:

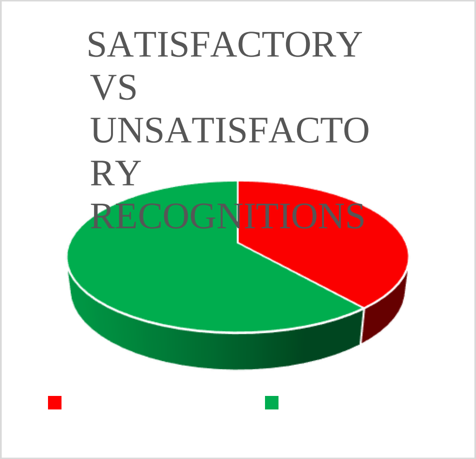
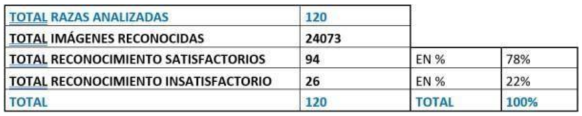


**Figura13.** Representation of the New data (own)

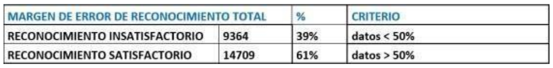
Regarding the number of breeds with satisfactory recognition, a significant improvement could be evidenced, increasing by up to 9% in figure 13 and figure 15 of effectiveness the recognition for the total of the 120 breeds



| | | | |
|---|---|---|---|
| TOTAL RAZAS ANALIZADAS | 120 | | |
| TOTAL IMÁGENES RECONOCIDAS | 24073 | | |
| TOTAL RECONOCIMIENTO SATISFACTORIOS | 94 | EN % | 78% |
| TOTAL RECONOCIMIENTO INSATISFACTORIO | 26 | EN % | 22% |
| TOTAL | 120 | TOTAL | 100% |

**Table 7.** New data (own)

From the above, now the margin of error is taken as all recognitions that are not satisfactory for the recognition of a breed, that is, all inferior results by race that are less than 50% which gives us the following information:



| MARGEN DE ERROR DE RECONOCIMIENTO TOTAL | | % | CRITERIO |
|---|---|---|---|
| RECONOCIMIENTO INSATISFACTORIO | 9364 | 39% | datos < 50% |
| RECONOCIMIENTO SATISFACTORIO | 14709 | 61% | datos > 50% |

**Table 8.** New satisfactory and unsatisfactory data (own)

Giving how one result one improvement pretty much Significant by race respect a the data What demonstrate a percentage of recognition satisfactory much greater than the unsatisfactory Which one Sample in the figure 16 What for the recognition of breeds the bookstore complies with its function of predicting the breed mostly and by Ende, your work is widely viable to do use of the same for the recognition of breeds, continuation herself Show graphically how Stay the data Adjusted Distributed in their Of Categories Unsatisfactory (1% a 50%) y
satisfactory (51% to 100%):

Proposals, taking into account the above, all the data of satisfactory and unsatisfactory recognition by race were reconsidered, which were stipulated as follows:

Unsatisfactory recognitions can be evidenced in Figure 13:

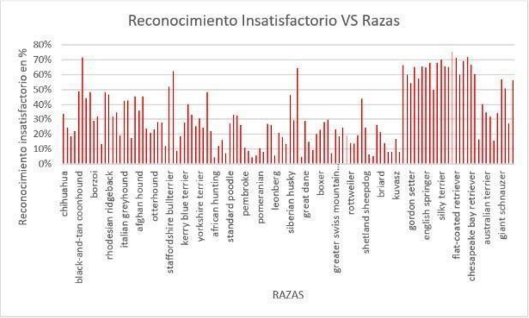


**Figure 14.** New Unsatisfactory Data (own)

Satisfactory recognitions:

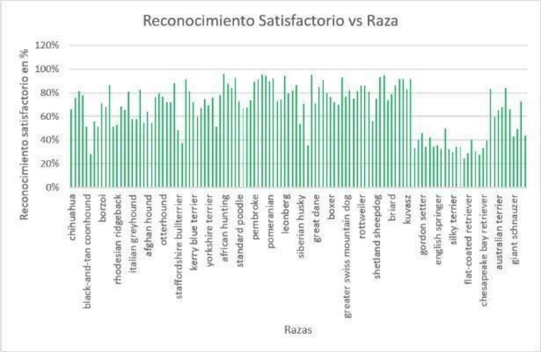


**Figure 15.** New Satisfactory Data (own)

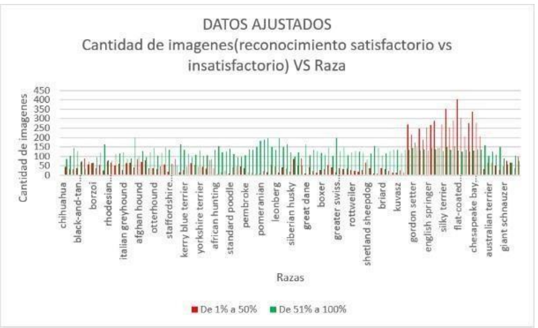
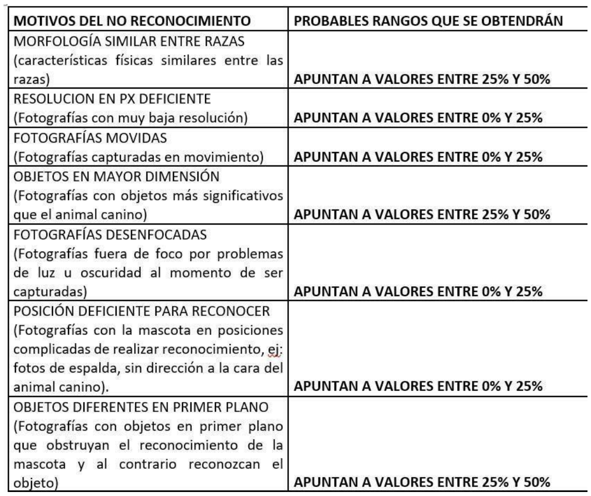


**Figure 16.** Data classified as satisfactory and unsatisfactory (own)

As can be evidenced, the difference between the data that are adjusted compared to those that are not in Figure 16, allow us to see that the performance of the library is widely viable for the recognition of the 120 breeds analyzed, which 94 races of the 120 will be recognized effectively Through the Tensorflow library and the restbefore will have a lower percentage of recognition than expected, on the other hand, for the breeds that were not recognized it was concluded that there are factors that hinder the recognition of pets, cases such as similar morphological characteristics between the same breeds and other problems such as lack of image quality, insufficient resolution in images, objects in the foreground outside the pets, elements in greater dimension than pets, moved or blurred photographs, among others.

## III. Conclusions

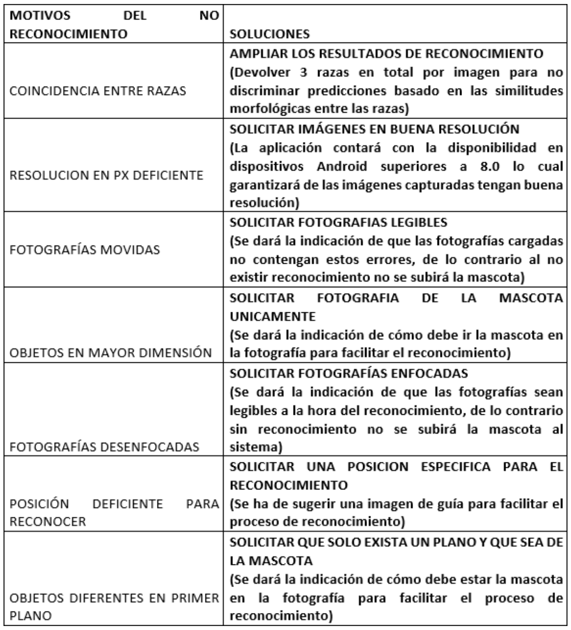
Therefore, an analysis was made of why the predictions yielded 0% or data less than 50% and that obviously affect the performance of the library, then the different cases and their probability that they are insufficient dataor less than 50% are shown by reference to its possible percentage of recognition for each problem when these images with problems are tested in the machine learning system:



| MOTIVOS DEL NO RECONOCIMIENTO | PROBABLES RANGOS QUE SE OBTENDRÁN |
|---|---|
| MORFOLOGÍA SIMILAR ENTRE RAZAS<br>(características físicas similares entre las razas) | APUNTAN A VALORES ENTRE 25% Y 50% |
| RESOLUCION EN PX DEFICIENTE<br>(Fotografías con muy baja resolución) | APUNTAN A VALORES ENTRE 0% Y 25% |
| FOTOGRAFÍAS MOVIDAS<br>(Fotografías capturadas en movimiento) | APUNTAN A VALORES ENTRE 0% Y 25% |
| OBJETOS EN MAYOR DIMENSIÓN<br>(Fotografías con objetos más significativos que el animal canino) | APUNTAN A VALORES ENTRE 25% Y 50% |
| FOTOGRAFÍAS DESENFOCADAS<br>(Fotografías fuera de foco por problemas de luz u oscuridad al momento de ser capturadas) | APUNTAN A VALORES ENTRE 0% Y 25% |
| POSICIÓN DEFICIENTE PARA RECONOCER<br>(Fotografías con la mascota en posiciones complicadas de realizar reconocimiento, ej: fotos de espalda, sin dirección a la cara del animal canino). | APUNTAN A VALORES ENTRE 0% Y 25% |
| OBJETOS DIFERENTES EN PRIMER PLANO<br>(Fotografías con objetos en primer plano que obstruyan el reconocimiento de la mascota y al contrario reconozcan el objeto) | APUNTAN A VALORES ENTRE 25% Y 50% |

**Table 9.** Analysis of why the bookstore gives us 0% in the recognition of races (own)

According to the above analysis we can provide solutions so that the algorithm and the tensorflow machine learning system fully fulfills its operation of recognition of races with respect to their problems:



| MOTIVOS DEL NO RECONOCIMIENTO | SOLUCIONES |
|---|---|
| COINCIDENCIA ENTRE RAZAS | AMPLIAR LOS RESULTADOS DE RECONOCIMIENTO<br>(Devolver 3 razas en total por imagen para no discriminar predicciones basado en las similitudes morfológicas entre las razas) |
| RESOLUCION EN PX DEFICIENTE | SOLICITAR IMÁGENES EN BUENA RESOLUCIÓN<br>(La aplicación contará con la disponibilidad en dispositivos Android superiores a 8.0 lo cual garantizará de las imágenes capturadas tengan buena resolución) |
| FOTOGRAFÍAS MOVIDAS | SOLICITAR FOTOGRAFIAS LEGIBLES<br>(Se dará la indicación de que las fotografías cargadas no contengan estos errores, de lo contrario al no existir reconocimiento no se subirá la mascota) |
| OBJETOS EN MAYOR DIMENSIÓN | SOLICITAR FOTOGRAFIA DE LA MASCOTA UNICAMENTE<br>(Se dará la indicación de cómo debe ir la mascota en la fotografía para facilitar el reconocimiento) |
| FOTOGRAFÍAS DESENFOCADAS | SOLICITAR FOTOGRAFÍAS ENFOCADAS<br>(Se dará la indicación de que las fotografías sean legibles a la hora del reconocimiento, de lo contrario sin reconocimiento no se subirá la mascota al sistema) |
| POSICIÓN DEFICIENTE PARA RECONOCER | SOLICITAR UNA POSICION ESPECIFICA PARA EL RECONOCIMIENTO<br>(Se ha de sugerir una imagen de guía para facilitar el proceso de reconocimiento) |
| OBJETOS DIFERENTES EN PRIMER PLANO | SOLICITAR QUE SOLO EXISTA UN PLANO Y QUE SEA DE LA MASCOTA<br>(Se dará la indicación de cómo debe estar la mascota en la fotografía para facilitar el proceso de reconocimiento) |

**Table 10.** Solutions for the library and algorithm to do the recognition effectively (own)

Finally, it is proposed that the position, definition, resolution of the image be as follows since it is the solution to these problems of recognition by the system:

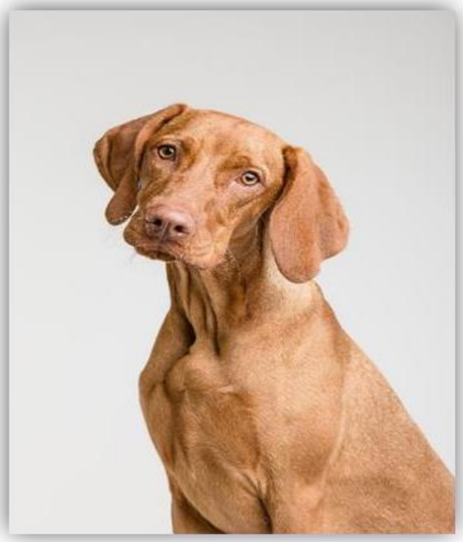


**Figure 17.** How to upload an image for the algorithm and the library to perform the recognition of the race (own)

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