Chapter 2 Classification of mature corn cobs using Convolutional Neural Networks

Capítulo 2 Clasificación de mazorcas de maíz maduro mediante Redes Neuronales Convolucionales

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Abstract

The aim of this study is to analyze an algorithm capable of classifying mature corn cobs for the detection of diseases, including Aspergillus, Gibberella and Fusarium fungi, in addition to the common charcoal that these elements may have. The process was carried out through a Convolutional Neural Network associated to a classification algorithm, based on deep learning techniques using MobileNet. This work is divided into two phases, the first one is to determine the performance of the algorithm for a small sample of images and videos analysis and the second one is the extension of the data corpus for the automatic analysis of new samples. It is necessary to mention that this work focuses on the development of the first phase, in which the identification and classification of the cob has had promising results.

Convolutional Neural Network, **MobileNet, Classification Mature corn cob**

Resumen

En el presente trabajo se genera un algoritmo con la capacidad de clasificar mazorca de maíz maduro para la detección de enfermedades, entre los cuales se encuentran Aspergillus, Gibberella, Fusarium y Carbón común que pudieran tener dichos elementos, este proceso se hará mediante una Red Neuronal Convolucional asociada a un algoritmo de clasificación, basadas en técnicas de aprendizaje profundo. Este trabajo se divide en dos fases la primera es determinar el funcionamiento del algoritmo para una muestra pequeña de imágenes y análisis mediante video y la segunda la ampliación del corpus de datos para análisis automático de nuevas muestras. Es preciso mencionar que este trabajo se enfoca en el desarrollo de la primera fase, la cual se basa en el desarrollo y entrenamiento del algoritmo basado en Redes Neuronales Convolucionales haciendo uso de MobileNet para la correcta identificación y clasificación de la mazorca.

Red Neuronal Convolucional, MobileNet, Clasificación de mazorca de maíz maduro

1. Introduction

Image classification in the field of artificial intelligence (AI) is considered by many as one of the most outstanding for the progressive development of this science (Ponce Cruz, P, 2011). The classification techniques of products, species, objects among others have had a great acceptance and more and more research is being done around these case studies, having as main objectives, solve a problem, provide knowledge and tools to different fields of study, as well as provide technological assistance to anyone looking for some kind of solution to a specific task.

In this work, a solution of classification of mature corn cobs is presented to determine the class to which it belongs, these results can be: healthy corn, or diseased corn containing the fungi Aspergillus, Gibberella, Fusarium and Common Charcoal. The classification results will be obtained through the application of Convolutional Neural Networks, in order to make the grouping process more efficient and will be useful to farmers in the northern region of the State of Mexico. It is worth mentioning that currently the classification is carried out by people who know about the identification of corn diseases, and who are usually people over 50 years old, while the younger population does not know how to determine the type of disease and its spread. It should be noted that the state of the art does not mention that there are works fully identified in the analysis of diseased corn and that use artificial intelligence algorithms, since the literature mentions applications that have been used more in the study of fruits, plants, objects and people, so the scope is new in this field.

Regarding the detection and classification of diseases in different plants and fruits (Mora, E. A. H., Huitrón, V. G., Rangel, H. R., & Sosa, L. E. A., 2021), present a work where pests are detected through transfer learning with fine tuning, using the Plant Village dataset, which contains 38 classes, including diseased and healthy leaves. The measures to evaluate the models were precision, sensitivity, F-Score and accuracy, where the results obtained by the VGG16 technique were 90% sensitivity and accuracy. While (Ferreira, U. E. C., & Camacho, J. M. G., 2021), implement a machine learning model with a database of digital images of fruits collected in the field, through the creation of a convolutional neural network (CNN) classifier, training and validating it to identify healthy avocado fruits and fruits infected with scab, this was trained through a hold-out of 80% and validated with the remaining 20%, finally obtaining an accuracy of 87% correct classification.

Likewise (Arévalo, M. D., Ayala, J., & RUIZ CASTILLA, J. S., 2007), they applied a convolutional neural network programmed in Python, using Keras and TensorFlow to classify peaches, obtaining an accuracy of 95.31% in the classification between ripe and immature, when classifying between healthy and damaged, 92.18% was obtained, while when classifying the three categories (damaged, immature and mature), 83.33% accuracy was obtained. On the other hand (Salazar Campos, J. O., 2020), they implement a parameterized model where a correct identification of Hass avocado images was achieved with an accuracy of 87.5%.

There are also applications of the deep learning algorithm in the recognition of people, for example, (Araujo, A., Pérez, J., & Rodríguez, W., 2018), presents a work where, through voice spectrograms analyzed by a Convolutional Neural Network recognizes a person with an accuracy of 93%. On the other hand, a broader application is presented in (Aramendiz, C., et al., 2020), where the development of a mobile application that supports people with visual disabilities is proposed. This application will have the ability to recognize objects from a mobile camera and will provide this information to the person audibly, the information used for recognition is provided to a YOLO convolutional network to have prior knowledge of the objects and capture them in real time. In the same way, the use of convolutional neural networks has been extended to the analysis of sign language, where (Ortiz García, C. D., 2021), where they apply the ResNet50 model for the interpretation and translation of the sign through a webcam.

This work is organized into 5 sections, where the points related to the research topic are treated, organized as follows:

Section 1. Introduction, the focus of the work is presented, and an analysis is made on the fields that have been covered with Convolutional Networks.

Section 2. Theoretical basis, here are presented the fundamental concepts of classification by Convolutional Neural Networks and the development algorithm as well as its architecture.

Section 3. Development, this section shows the steps to follow to carry out the classification of ripe corn cobs.

Section 4. Results, the results obtained based on the experimentation carried out are shown.

Section 5. Conclusions, the conclusion reached based on the results obtained is presented and the future work that is planned to be carried out is shown.

2. Theoretical bases

2.1. Convolutional neural networks

Currently the use of Convolutional Neural Networks (CNN) has practical applications in any field, it is considered as a variation of the Multilayer Perceptron that works with flat or one-dimensional data, while CNN works with two-dimensional data, such is the case of images, voice and video signals mainly.

A convolutional neural network is a network architecture for deep learning that learns directly from data, without the need to extract functions manually. That is, the network takes as input the pixels of an image (Lugo Sanchez, Omar E., et al, 2020). For example, if you have an image of 50×50 pixels in height and width, that is equivalent to 2500 neurons, considering a single color (grayscale), if on the other hand you have a color image, you will need 3 channels (red, green and blue) and then you would have 50x50x3 = 7500 input neurons.

The use of CNNs is highly recognized for three main factors (Convolutional Neutral Networks, 2022):

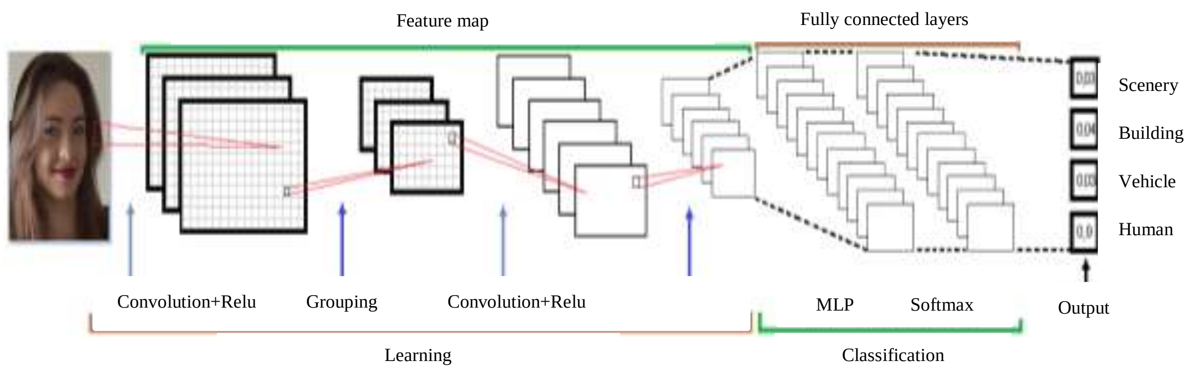
- They learn features directly without having to extract them manually.
- They generate highly accurate recognition results.

– They can retrain themselves for new recognition tasks, allowing them to leverage pre-existing networks.

One of the first works where a CNN is used to classify images of handwritten postal digits is in (LeCun, Y., et al, 1989), obtaining a 99.3% correct classification, but it is not until later years that in 2012 the power of CNNs for image analysis was demonstrated.

The CNN structure is basically composed of 3 different layers, the first is one or more convolutional layers, the second is the clustering layer and the classifier layer, as shown in figure 1. (CNN-RNA Convolutional, 2022).

Figure 1 Layers of a CNN

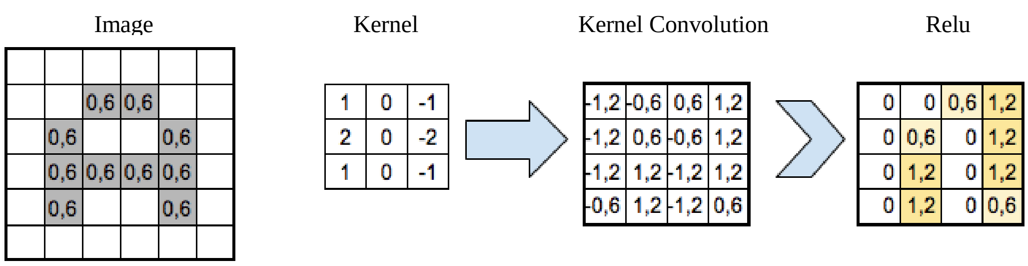


2.1.1. Convolution layer

Here the first convolution layer is not connected to all the pixels of the input image, only to those belonging to its receiving area, in the second layer the neurons are connected to the neurons of the area of the first layer and so on. The purpose of this layer is to extract the features of each image by compressing it to reduce the initial image size.

This layer takes a group of pixels from the input image and makes a scalar product with a kernel, the kernel is the filter responsible for extracting the most important features from the image. The kernel will go through all the inputs and get a new matrix, which will be one of the hidden layers. In case the image is colored, there will be 3 kernels of the same size that will be added to obtain an output figure 2.

Figure 2 Convolution layer



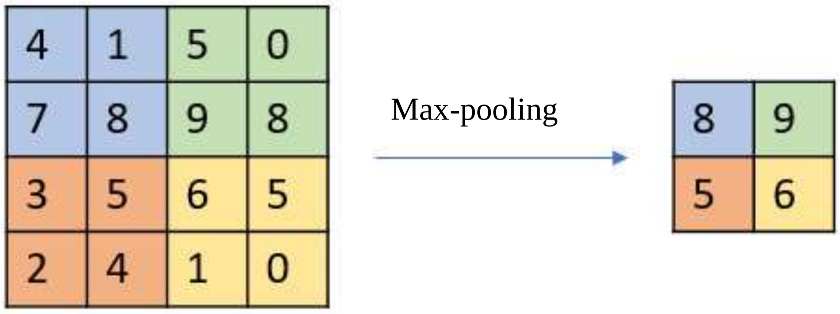
2.1.2 Grouping-pooling layer

This layer is responsible for subsampling the image to reduce the number of parameters and memory usage, in this layer like the previous one the connections are only made to a certain number of neurons of the previous layer, its objective is to obtain the maximum and average values of the sampling window. The pooling layers in a convolutional neural network are used to reduce the size of the activation maps that are being worked on, there are two types of pooling layers in a convolutional neural network which are (Arroyo, D. E., 2019):

– Max-pooling: it is the most common and is responsible for calculating the maximum of the elements. On the other hand, we must bear in mind that this is done for each map of activations of our volume, that is, the depth dimension does not intervene at all in the calculations. As shown in Figure 3.

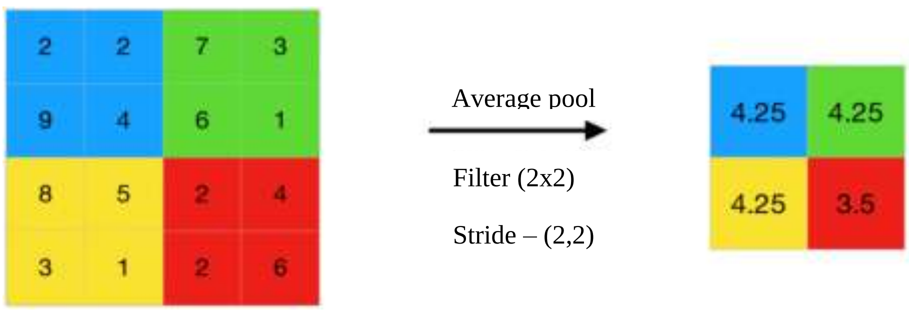
–

Figure 3 Max-pooling



– Average-pooling: It is responsible for calculating the average of the elements that are being studied in a certain image. As shown in Figure 4.

Figure 4 Average-**pooling**

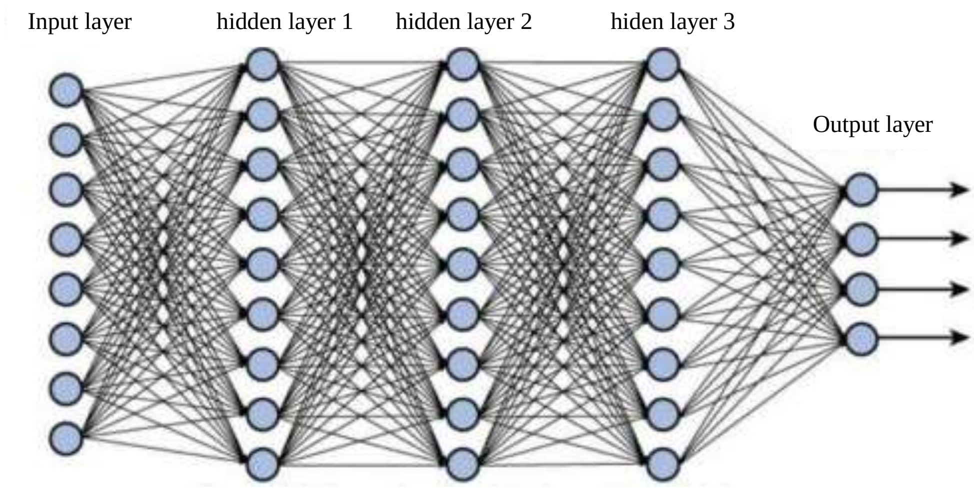


2.1.3. Sorting layer

It combines the features found by the previous layers to classify the image. In this case, unlike the previous layers, the neurons of the previous layer are fully connected to the next layer. It is based on a deep neural network, these have several hidden layers with millions of artificial neurons connected to each other. A number, called a weight, represents the connections between one node and another. The weight is a positive number if one node stimulates another, or negative if one node suppresses another. Nodes with higher weight values have a greater influence on other nodes.

In theory, deep neural networks can map any type of input to any type of output. However, they also need much more training compared to other machine learning methods. They need millions of examples of training data instead of the hundreds or thousands they might need in a simpler network.

Figure 5 Deep Neural Network



2.2. MobileNet

MobileNet is a CNN capable of classifying images, detecting objects and extracting features, based on an architecture of separable elements in depth with factored convolutions that are by dimensions 1 X 1 to optimize latency performances. The factorization of convolutions is called point convolution.

A standard convolutional layer takes as input to feature map $D_F \times D_F \times M$**F** and produces a feature map **G**$D_F \times D_F \times N$ where is the *width and spatial height of a square input feature map* $\boldsymbol{D_F}$ **M** is the input number channels (input depth) **N** *is the channel output number (output depth).* The map of output characteristics for standard convolution assuming stride one and the fill is calculated as (Howard, A. G., et al., 2017):

$$G_{k,l,n} = \sum_{i,j,m} \boldsymbol{K}_{i,j,m,n} \cdot \boldsymbol{F}_{k+i-1,\ l+j-1,m}$$

The mobileNet architecture is based on factoring traditional convolutions into 2 types of layers, a first convolutional layer "depthwise" and a convolutional layer 1x1 "pointwise". This division allows to reduce the computational cost and the size of the model.

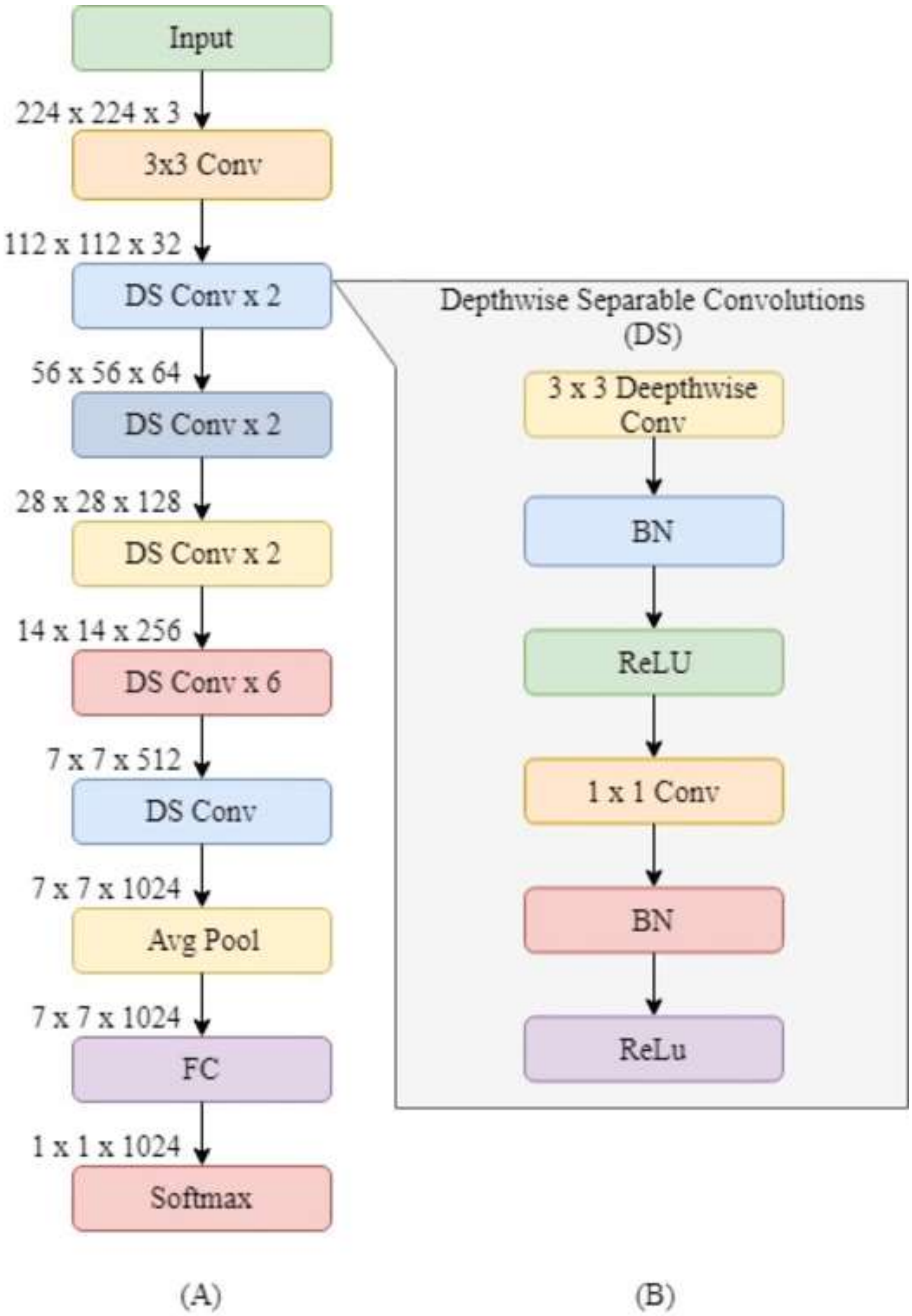
Standard convolutional layers have a computational costbetween 8 and 9 times higher than the computational cost of both "depthwise" and "poinwise" layers. In addition, 2 parameters are added to reduce the size and speed of the neural network. Both parameters allow to reduce even more the size and response time of the neural network:

- The α parameter is a factor that reduces the number of filters/channels applied to each layer by multiplying them α ε 〈0.1〉 .

- The β parameter is a factor that reduces the size of the inputs by multiplying it by ∈ 〈0.1〉 .

The MobileNet architecture is shown below:

Figure 6A) General MobileNet architecture (B) detailed DS explanation obtained from (Phiphitphatphaisit, Sirawan & Surinta, Olarik. 2020)



2.3. K—NN algorithm

One of the algorithms for the classification of large amounts of data is K-NN (k- Nearest Neighbors) or k – close neighbors, conceived by (Fix, E., & Hodges, J. L., 1989), this algorithm is based on the fundamental concepts of deep learning, such as the *dataset* and the *model.* These two fields are within the learning stages, where: the model is built from a set of examples *or data* already classified, the model obtained is represented as a set of classification rules, decision trees, mathematical formula, etc. And in the validation: the estimation of the precision of the model, the model is tested with a set of examples different from the one used for the construction of the model. For each example, its real class is compared with the class predicted by the classifier, the accuracy ratio is the percentage of examples that the model correctly classifies (Berastegui, A. G., & Galar, I. M., 2018).

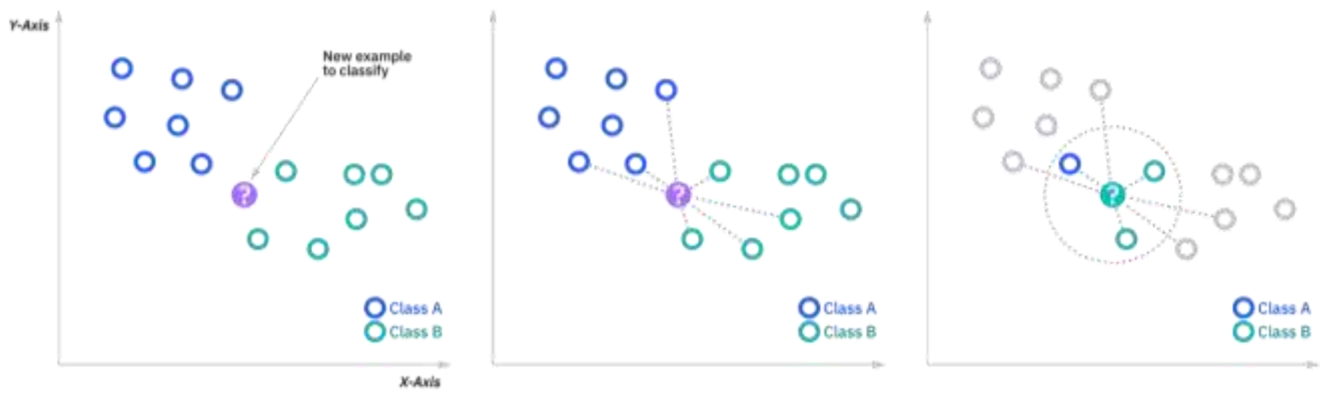
KNN is more of a predictive method than a classification technique, which is relevant, because in order for the algorithm to classify, the most general neighborhood classification rule is based on the assumption that the nearest prototypes have a similar a posteriori probability.

If K_i (X) is the number of samples of the class present in the k closest neighbors to X, this rule can be expressed as:

$$d(X) = w_c \; si \; K_c(X) = \; max_{i=1 \to j} K_i(K)$$

The general model of representation of the algorithm is shown in the following figure:

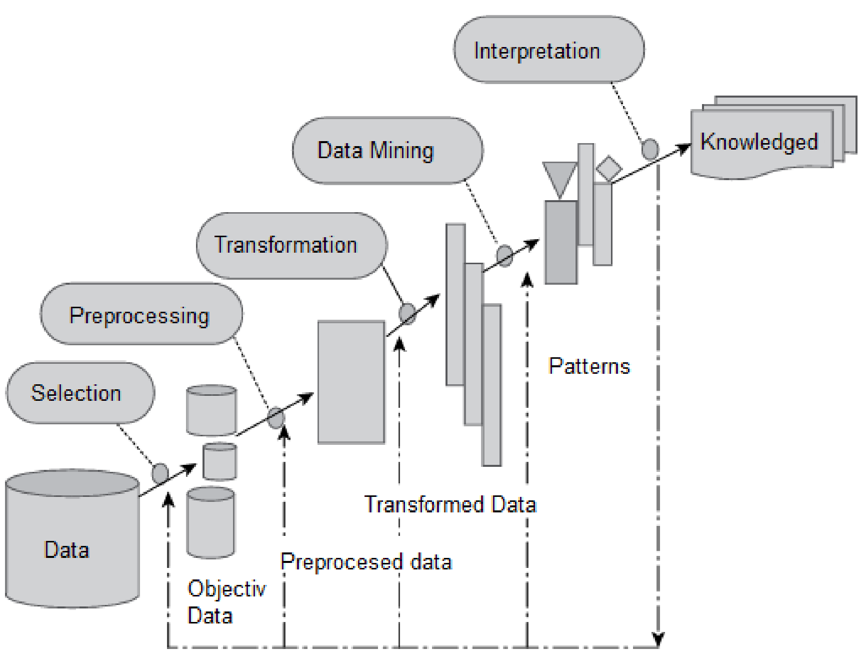
Figure 7 K-NN algorithm obtained from (What is the nearest neighbors k algorithm? | IBM., 2022)



2.4. KDD (Knowledge Discovery in Databases)

The process that is followed to obtain knowledge of a database through the application of data mining algorithms is shown in figure 8, this process is known as KDD for its acronym in English (Knowledge Discovery in Databases), refers to the analysis of large databases through different algorithms to obtain useful information for the organization (Tangarife Morales, 2016).

Figure 8 Stages of the KDD process obtained from (Timarán-Pereira, S. R., et al, 2016)



The description of the stages of the knowledge extraction process according to (Timarán-Pereira, S. R., *et al*, 2016) are:

– Selection: once the relevant and priority knowledge has been identified and the goals of the kdd process defined, from the point of view of the end user, an objective data set is created, selecting the entire dataset or a representative sample of it, on which the discovery process is carried out.

– Pre-processing: data quality is analyzed, basic operations such as noisy data removal are applied, strategies are selected for the handling of unknown data (missing and empty), null data, duplicate data and statistical techniques for its replacement.

– Transformation: useful characteristics are sought to represent the data depending on the goal of the process. Dimension reduction or transformation methods are used to decrease the effective number of variables under consideration or to find invariant representations of the data.

– Data mining: is the search and discovery of unsuspected patterns and interest, applying discovery tasks as classification.

– Interpretation: the discovered patterns are interpreted and the classification is made.

3. Development

In this stage, the application of the KDD process is presented to analyze and classify the cobs by video in real time, considering the training stage of the algorithm based on a deep neural network.

3.1. Selection and pre-processing of data.

In the first instance for this work, it consisted of looking for specimens that will meet the characteristics of a healthy ripe corn cob, in this work only ears with white grain (figure 9) and elements that had an impact on diseases (figure 10, 11, 12, and 13) on the cob were considered, such as: Aspergillus, Gibberella, Fusarium and Common Charcoal, respectively.

To determine to which class the cob belongs, the following aspects should be considered according to (Taba, S., 2004 and Varón de Agudelo, F., & Sarria Villa, G. A., 2007):

– Healthy: does not change the color of the grains and the corn is in good condition. (Figure 9).

– Aspergillus: occurs when infected earswith high moisture content are stored, may contain yellow-green, ivy green or black masses on the grain or on the olote. (Figure 10).

– Gibberella: is more common in cold and humid areas. The first signs of infection are the formation of white mycelia, which descend from the tip of the cob and give a reddish and pink coloration to the infected grains, this type of infection can be poisonous to some species of animals, (see figure 11).

– Fusarium: is the most common disease, causes infected grains to developcottony mold and can be toxic to animals, (see fugure 12).

– Common Charcoal: this disease can be detected in the young plant since the corn is germinating when it is produced in mushroom "huitlacoche" consumed by some people, when it reaches the state of maturation it produces a black color similar to the coal polvo hence its name, (figure 13).

Figure 9 Healthy cob

Figure 10 Cob with Aspergillus

Figure 11 Cob with Gribbrella

Figure 12 Cob with Fusarium

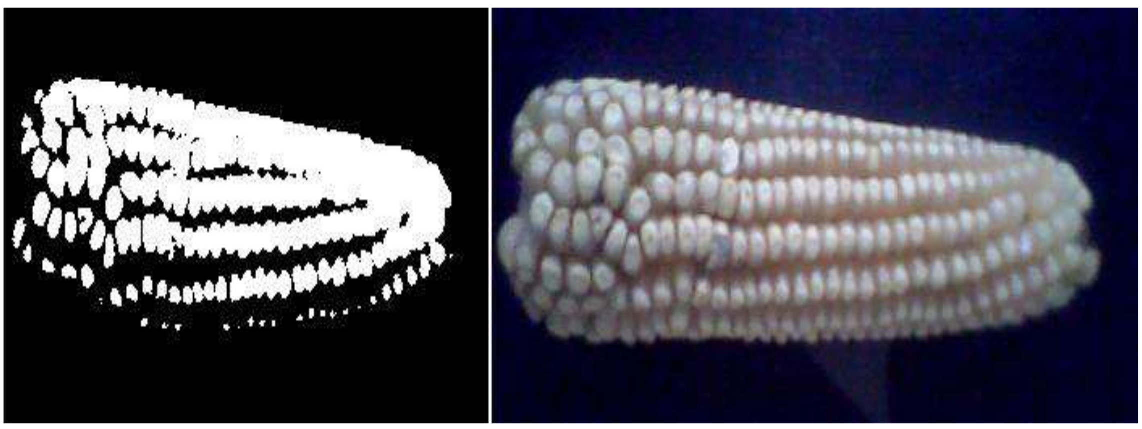
Figure 13 Cob with common charcoal

3.2 Algorithm transformation and implementation

The transformation of the data is carried out once it has been defined how the classifier will operate, for this it has been contemplated that the functions of the classifier both for training and for the evaluation phase are in real time. Since in this way you can take full advantage of the capabilities of Mobile Net.

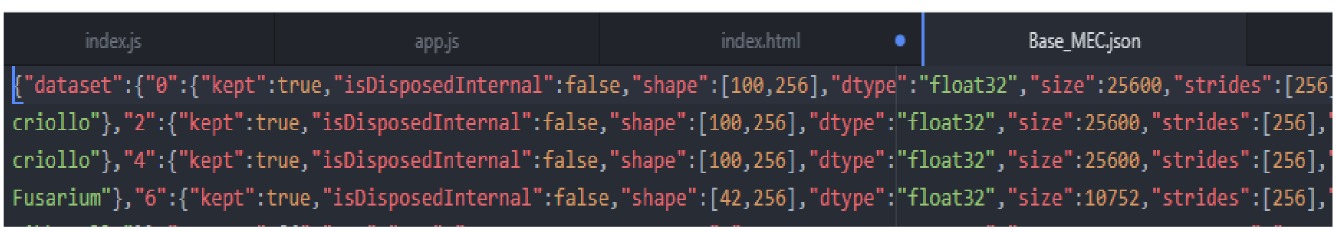
The CreateCaptutre method, is created to make use of the webcam, this will be the way for the classifier to receive the data in real time and thus can also transform them from their original input, and store these elements, in a general basis for knowledge. A white filter (Threshold) will be applied, this is to lighten the information of the images that are being sent to CNN.

Image 14 Transformation using threshould



All the information obtained from the training will be contained in a file called Base_MEC.json, this file will host the transformed data, in a JSON format, which is the way in which ML5 supplies the information to Mobile Net. What Base_MEC.json stores is basically the data set or corpus, which is composed of a valid format for CNN, where it contains the value of the images.

Figure 15 Preview transformed data



3.3 Evaluation of the algorithm

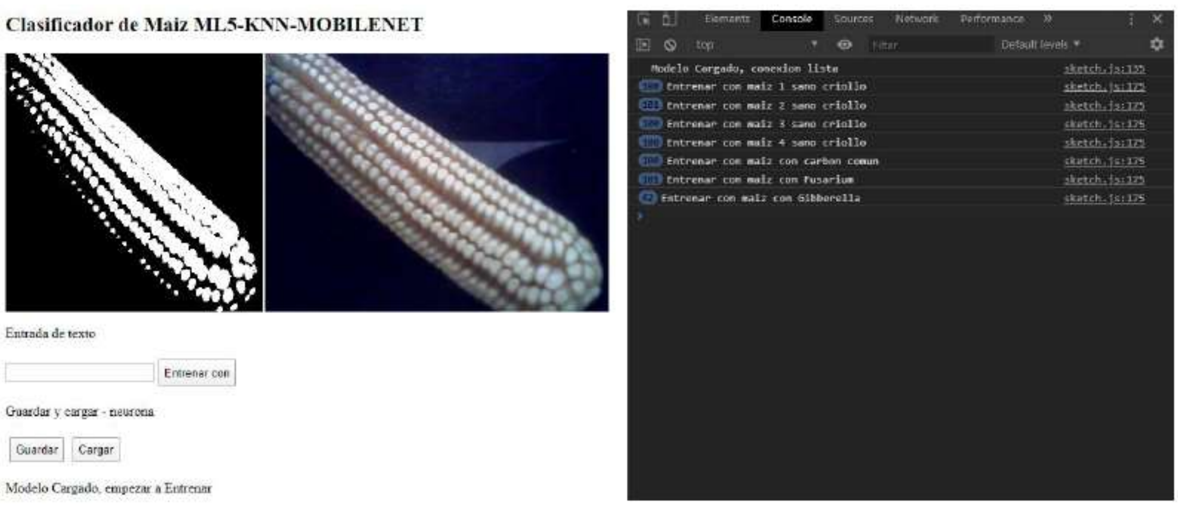
The implementation of a KNN classification algorithm provided by ML5, which is stored in the KNN classifier, will help to form a prediction about the classification processes with the information contained in the data set, to obtain the final results.

Figure 16 Optimal parameters of CNN

```
const ValoresD = {
  version: 1,
  alpha: 0.25,
  topk: 3,
  learningRate: 0.0001,
  hiddenUnits: 100,
  epochs: 60,
  numLabels: 2,
  batchSize: 0.4,
  layer: 'conv_pw_13_relu',
};
```

For the training of the algorithm it is necessary that for each specimen of cob is shown in different positions the button of Train, placed on the text box, the label with which the specimen shown will be designated, repeating this process in all healthy corn cobs and the ears of corn with disease are obtained and the following count that can be visualized in the browser console as shown in the following image.

Figure 17 Classifier interface



In this way, the network training process is carried out in real time and continues to learn from the new samples that are introduced, since the generated data is stored in a database in the MobileNet reading format for the subsequent classification of the new cobs.

4. Results

Based on the implementation and analysis of the results obtained by measuring the accuracy of the algorithm to correctly or incorrectly classify the species introduced in the training and validation of the algorithm, the following table shows two columns, the first corresponds to the analyzed specimen and its white filter and the second corresponds to the labeling assigned to the cob and the level of confidence obtained by the algorithm used.

<table>
<tr><th>Specimens analyzed</th><th>Results</th></tr>
<tr><td>Figure 18 Specimen 1

</td><td>Result: cob 4 healthy creole
Confidence: 100%</td></tr>
<tr><td>Figure 19 Specimen 2

</td><td>Result: cob 2 healthy creole
Confidence: 80%</td></tr>
<tr><td>Figure 20 Specimen 3

</td><td>Result: cob with Gibberella
Confidence: 100%</td></tr>
<tr><td>Figure 201 Specimen 4

</td><td>Result: cob with Fusarium
Confidence: 100%</td></tr>
</table>

<table>
<tr>
<td>

Figure 212 Specimen 5

</td>
<td>Result: cob with common charcoal
Confidence: 100%</td>
</tr>
<tr>
<td>

Figure 223 Specimen 6

</td>
<td>Result: cob with Gibberella
Confidence: 100%</td>
</tr>
</table>

The results obtained, show that the classification is done correctly with the specimens shown, however, the problems presented in the analysis must be taken into account, such as the quality of the camera of which it was used, a more controlled environment to manipulate the levels of luminosity, position of the camera and distance when taking the images in real time, which can affect image quality.

This work has been funded by Tecnológico de Estudios Superiores de Jocotitlán.

5. Conclusions

With the analysis of the ripe corn cobs it was determined that the accuracy of the algorithm is 100% in most cases, however, there are deficiencies in the classification of some specimens, derived from issues of luminosity and the analysis environment, in addition the number of classified images is low, so it is considered to work in a second stage where the number of images is greater to make a More extensive training of the classifier and a greater number of samples are taken for sorting.

zThe process of classification in the ear of mature corn, is an activity with great antecedents, which until recently was done in light or large amounts of elements, manually. To which opens a possibility of extending this work, implementing the same classification system presented, to a device that has the necessary actuators to optimize in its entirety the classification of the ear of mature corn in the area from where the specimens were obtained. Having as consideration and recommendations the following:

- Extend the dataset: Generate a much larger dataset with more instances by varying the characteristics.

- Have better control of environmental variables: contemplate a camera of higher resolution in the quality of the image and take into account variations in luminosity.

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