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Design of a Sugarcane Diseases Recognition System Based on GoogLeNet for a Web Application

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***Abstract*—Sugarcane diseases in Peru occur due to the agricultural community's lack of understanding of these, which means a slow response to the application of methods of control and eradication of these diseases; thus, causing economic losses and underproduction. Due to the aforementioned, a web application for sugarcane diseases recognition is proposed. The five types of sugarcane diseases that will be recognized using this system are: Pineapple Sett Rot, Ring Spot, Mosaic, Brown Rust and Leaf Scorch. This system was developed using GoogLeNet, which is a 22 layers convolutional neural network (CNN), and also the Matlab software and its App Designer extensions (for the web application creation); additionally, Matlab Web App Server was used to host the application on the web. The pre-trained neural network developed in Matlab based on the GoogLeNet architecture allowed the creation and configuration of the training parameters (supervised learning) that were evaluated, and it was considered convenient to split the data between training, validation and testing (70%, 20% and 10%, respectively). A total of 250 images composed of 50 images for each disease were used. The web application was designed in App Designer which provided us with a set of tools and a programming interface for the insertion of the trained CNN, with a validation percentage of 94.67% obtained by varying the number of epochs, reaching a maximum of 6000 iterations. Finally, the web application supported by the Matlab Web App Server was generated and tests were performed on a local network, resulting in a web application capable of identifying images within the established guidelines, with an accuracy rate of 96%.**

***Keywords*—Sugarcane Diseases Recognition, GoogLeNet, Convolutional Neural Network (CNN),Matlab, Precision Agriculture.**

I. Introduction

Peru is one of the main sugarcane producers in Latin America. Thanks to the climatic conditions and the quality of its soils, its coastal region is home to the largest sugarcane production in the country.

According to the quarterly bulletin "Commodity Observatory - Sugar (July - September)" of the Ministry of Agrarian Development and Irrigation [1] the country is ranked 23rd in the world and it will produce around 1.3 million tons for the 2021/2022 period; Peru is also the country with the best production yield per hectare with 121.8 t/ha (tons per hectare). Behind all thesefigures, there is a complex production activity that includes manufacturing and basic processes such as agriculture. The majority of farmers engaged in the planting of sugarcane located in the regions of Lambayeque, La Libertad, Ancash, Lima and Arequipa experience every year an inclement weather, the arrival of pests and diseases that put at risk the proper growth of crops [1]. Various diseases caused by fungal, bacterial, viral and pest agents put farmers, who hope to generate profitability, in trouble [2].

The strategies implemented by the National Agrarian Health Service of Peru (SENASA), such as pest control using biological controllers, are of great help to small producers [3], but they are still insufficient. From this arises the need to implement accessible technological alternatives for precision agriculture in the country in order to provide support to small producers for the detection and elimination of diseases in sugarcane crops. As such, the implementation and usage of these technologies is necessary to guarantee a good harvest for the benefit of farmers and their collaborators, considering also that their economic livelihoods hinge on this activity. Sugar production supports price fluidity and stability at the national level in some countries. Recently, some of them were affected by a global sugar supply deficit caused by the low production of the leaders such as Brazil and China [4, 5].

II. Literature Review

There are many applications of precision agriculture focused on sugarcane around the world.

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In Pakistan, a study proposed a web page system where farmers can register and send the images of the plants with or without diseases, where they are later downloaded and analyzed by a specialist with the help of a desktop application that is responsible for isolating the particular characteristics of the diseases [6]. Once all the studies have been carried out by the specialist, the results are sent to the farmers. Similarly, the authors of an Iranian study implemented a system for predicting the final growth of sugarcane plants, using non-traditional methods such as Extreme Learning Machine (ELM), having as input variables such as maximum temperature, evaporation, insolation, rainfall, humidity, irrigation and electrical conductivity of the crops [7]. In addition, they highlighted the main characteristics of the ELM model, such as fast learning (a single layer) and lower training errors.

On the other hand, regarding technological trends for imaging, it has been indicated that out of 119 articles reviewed, the following technologies were used: proximal (ground vehicles) in a total of 50 articles, satellite in 45, Unmanned Aerial Vehicles (UAV) in 8 and multiscale in 16 [8]. The levels of abstraction used are divided into low (data acquisition, data processing), medium (feature extraction) and high (classifier assembly and regression models). In the foregoing study it has been concluded that it is of utmost importance to study the levels of complementarity between the data acquisition methods, the levels of abstraction and the variables to be considered according to the type of application. Finally, it is also mentioned that the processing of information for precision agriculture purposes is a complex process due to the large amount of data and variations that all kinds of crops undergo during their growing stages. Another research work has taken the analysis and compilation of processing models and imaging methods for the prediction of productivity and phytosanitary status of sugarcane [9]. It was found that out of 107 different projects, 52 of them were developed for sugarcane mapping, 11 for crop growth, 14 for health monitoring and 30 for yield estimation. From that major study, it was concluded, first, the use of satellite images is more reliable and cost-effective, because it allows obtaining a greater number of samples, performing a more efficient mapping; however, its use is for vast sowings due to its decametric resolution, which depends a lot on weather conditions. To remedy this deficiency, it is necessary to use other satellites. Second, they highlighted the use of UAV for monitoring small areas, but their application is limited due to the cost they generate when flying over larger areas.

Another study stated that the method of image acquisition from the census of the field, detection by satellite images and others are not so accurate because satellite images can only have a total view of the field and not of independent parts of the field, and they cannot operate on cloudy days [10]. For this reason, the authors of that study opted for a weed classification system with color detection of the different plants in the sugarcane fields with images taken from an UAV.

Based on the studies carried out by [11, 12]it can be seen that the tendency of vegetation analysis is carried out by means of normalized coloration indices (NDVI, NDRE, GNDVI and WDRVI). In addition, for studies of large areas in production estimates and phytosanitary status, the acquisition of images provided by satellites is selected [11, 12, 13].

In view of the above, our present research aims to design an intelligent system for the identification of sugarcane diseases by means of GoogLeNet and Matlabfor a web application, which will help in the control and elimination of sugarcane diseases. Initially, information was gathered on sugarcane diseases and the training images were classified. The algorithms for training the CNN and the web application were developed in Matlab. Finally, the CNN success rate in the recognition of these diseases was evaluated.

III. Methodology

The modelling of the sugarcane diseases identification system is divided into 4 stages: image acquisition, training parameters, CNN and the database (Figure1).

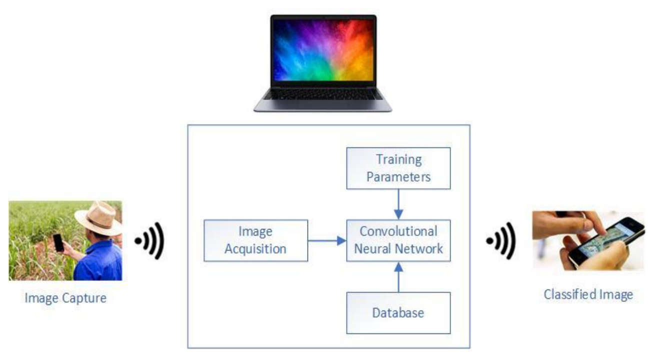

Figure 1. Block diagram of the sugarcane diseases recognition system.

A. Image Acquisition

Images from the sugarcane fields will be acquired with a smartphone camera. The selected fields of sugarcane should have among their crop, five sugarcane diseases: Pineapple Sett Rot, Ring Spot, Mosaic, Brown Rust and Leaf Scorch. The device must have at least standard features such as: Android 8 operating system or higher and a camera resolution of 8 megapixels or higher. Mobile devices need to have internet access so that the farmer can process his images via the web. In this process, a significant number of images that the farmer considers necessary to get to know what disease is the one that is afflicting his crops will be used. It is recommended that the images are focused correctly on the leaves, stems and do not include external agents such as soil or other plants.

B. Training Parameters

Being a CNN, the learning will be supervised, therefore the training parameters are focused on the characteristics of the data (volume of data and object of study). TrainingOptions() which is a function to structure the general attributes of learning from GoogLeNet will be used.

C. GoogLeNet (CNN)

GoogLeNet is a convolutional neural network that has 22 layers of depth and for its use, it is necessary to scale the images to a resolution of 224x224 pixels [14]. This CNN is composed of three fundamental sections: convolutions, inception modules and output modules [15].

*1) Convolutions:*These are performed throughout the GoogLeNet architecture and are always accompanied with max-pooling layers [15]. They handle feature extraction by using small and large filters depending on the position of the layers, initial and posterior respectively [16].

*2)Inception modules:*These are responsible for reducing the density of connections between neurons and number of layers based on feature detection [15], lightening the computational load [17].

*3)Output modules:*They include procedures to turn off 40% of the neurons and enable the image classification function. They also have built-in auxiliary classifiers that compensate for the non-existence of the gradient [15]. Within the three main sections presented, neurons are set as ReLu units (they will be activated as long as the values entered are positive). Besides taking into account that there is a loss due to cross entropy, typical of image classifiers.

D. Database

To achieve satisfactory results in the recognition rate of sugarcane diseases in crops, it is necessary to have a large database. Having a large number of reference images improves processing, comparison and final detection of specific patterns (pests, weeds and diseases) [18]. For the development of this research, a database with 250 images (50 for each disease) was generated by gathering images from publicly available sources on the Internet.

1)Training and testing database: It has been indicated [19] that dividing the amount of data for training and validation aims to find a better configuration of the data distribution, achieving better interpretation and stability in the results. It has been indicated that allocating 80% for training and 20% for testing results gives greater stability in the test of the loss curve. Nevertheless, using 70% and 30% for the aforementionedpurposes results in a better interpretation.

E. CNN Programming and Configuration

Based on the system's main block diagram, the programming sequence and functions are formulated as shown in Figure 2.

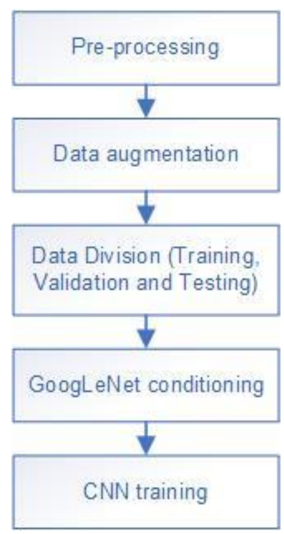

Figure 2. Matlab programming and configuration sequence.

1) Pre-processing: To condition the images to the GoogLeNet scale (224 x 224 pixels), the function to use is AugmentedImageDatastore() which is capable of transforming the features of the data batch, by means of rotations, reflection and resizing (scaling or cropping) [20].

*2) Data augmentation:*To get a large amount of data for training, validation and testing, we proceeded to add rotations and reflections to the existing images, to achieve a more robust system. Agreeing with [18], collecting good quality images is difficult, so generating others by adding noise, overlap and brightness is a viable process. Based on the above, the function and arguments that were used for the data increment is ImageDataAugmenter(), which allows generating more data by means of rotation, reflection or resizing processes, altering existing images and generating new ones with other characteristics to be used by the system. Within this function, the RandRotation argument defines the rotation interval, whereas the RandYReflection argument allows to activate the reflection with respect to the Y-axis.

*3) Division of the database into training:*The total information will be divided into 70%, 20% and 10% between training, validation and testing, respectively. For this, the SplitEachLabel (Data, …) function was used [20]. This allows the total number of images to be divided into groups, depending on the exact percentage or quantity allocation for each storage variable.

4) GoogLeNet Conditioning: As GoogLeNet is a pre-trained CNN, it has a number of procedures for modifying some of its layers, among the main ones are fullyConnectedLayer and ClassificationLayer[20]. FullyConnectedLayer() is a function that connects a layer and multiplies it, specifying the size of the output. The WeightLearnRateFactor argument of this function receives the factor by which the global learning rate will be multiplied, thus obtaining the learning rate per layer, whereas the BiasLearnRateFactor argument is a multiplication that calculates the learning rate of the biases of each layer. The ClassificationLayer() function is responsible for estimates of losses due to data processing in the classification.

*5) CNN Training:*The training of the CNN in Matlab will be achieved from the structuring of the main function TrainingOptions() [20]. Within this function the Sgdm argument enables the stochastic gradient descent optimizer, in charge of measuring the change of the variables with respect to each other. The argument MiniBatchSize sets the number of mini-batches with which the data block will be processed. MaxEpochs sets the number of epochs to be performed with the data. InitialLearnRate receives the learning rate that the system achieves. Shuflle sets the shuffle type. ValidationData sets the validation data during training.

ValidationFrequency is the validation frequency in number of iterations. Verbose is in charge of displaying the training progress. Plots, Training-progress is in charge of showing the graphs of losses and precisions of the minilotswhile the training is being carried out.

F. Programming Structure of the Web Application

After the development of the programming structure for the CNN training, the web application based on the Matlab App Designer development environment and supported by the Matlab Web App Server, which will host the application, was developed. The structure used for the development of this section is shown in Figure 3.

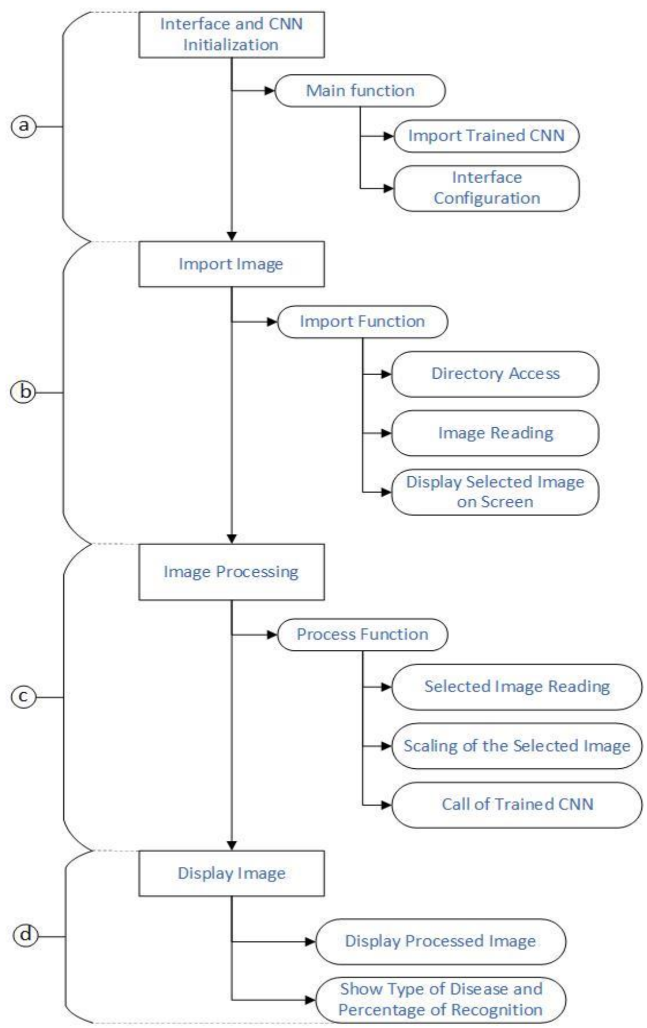

Figure 3. Programming sequence for the creation of the web application in App Designer -Matlab.

1) Interface and CNN initialization: Figure 3 (segment a) shows how the previously trained CNN is imported and hosted within the web application code. Also, the graphical interface is configured and initialized.

*2) Importing image:*Figure 3 (segment b) indicates how the importing of images into the application is developed based on the access to the directories of the computer or mobile device that has internet access.

*3) Image processing:*Once the selected image is available, processing begins, for which the input data is scaled and the trained CNN is called (Figure 3, segment c).

4) Displaying image: Finally, the processed image with the quantitative and qualitative information of the disease detected by the CNN will be shown in textual form (Figure 3, segment d).

After the integration and sequence of the processes previously mentioned, the first results were obtained for the sugarcane disease recognition system. The graphical interface generated is shown in Figure 4.

Figure 4. Graphical interface produced with App Designer – Matlab.

IV. Results And Discussion

The results of the classification algorithm system are based on the accuracy to classify an image and to determine which sugarcane disease are identified. To develop this algorithm, we need a sugarcane diseases image dataset which contains 5 sugarcane diseases: Ring Spot, Pineapple Sett Rot, Mosaic, Brown Rust and Leaf Scorch. The image dataset collected contains 250 images made up of 50 images per disease.

There are some image classification algorithms on sugarcane diseases like Probabilistic Neural Network (PNN) used by [21] with an 89% recognition rate for Ring Spot disease. Moreover, [22] and [23] use Deep Neural Network (DNN) and Convolution Neural Network, You Only Look Once (CNN YOLO) with 83.3% and 95.9% of accuracy, respectively.

The image classification algorithm for our study is based on GoogleNet and developed in Matlab. The accuracy test and validation test for this algorithm are 96% and 94.67%, respectively. The image dataset was divided in training, validation and test dataset, which are divide in 70%, 20% and 10%, respectively. In Figure 5, we show the training and validation accuracy results of the algorithm from Matlab. To reduce the loss function (cross entropy for classification), we use the optimization algorithm named Stochastic Gradient Descendent with Momentum (SGDM). The loss function defines how well the machines learning is occurring.

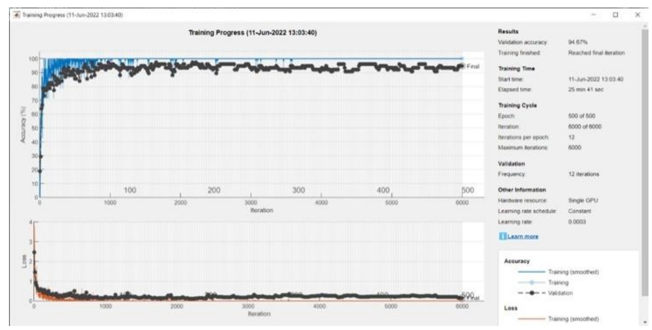

Figure 5. Training progress of the CNN.

Figure 6 shows the test accuracy results. For that, the confusion matrix was used. The confusion matrix is an evaluation metric used in machine learning algorithms to determinate the quality of a model [24].

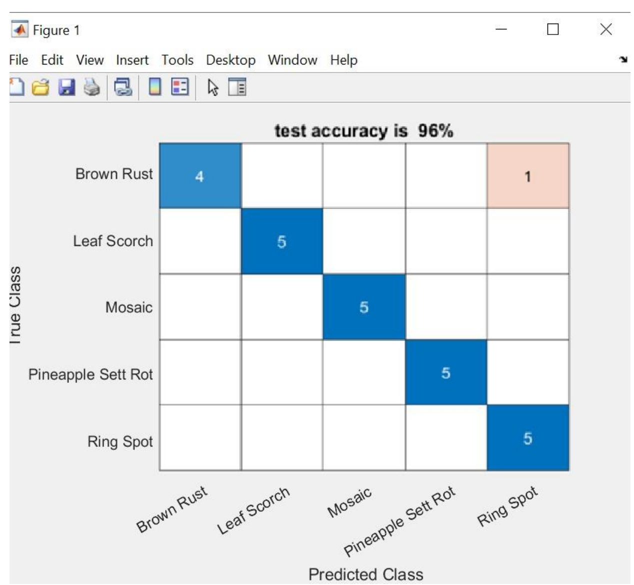

Figure 6. Test accuracy for the test dataset.

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For multiple classes models, the measurement equations are less than for binary classification models. So, we use ACC (Accuracy), which is the rate of correctly predicting the positives and the negative values of the desired outputs classes. The accuracy equation is as follows [25]:

$$ACC = \frac{tr(E\epsilon)}{N}, \qquad (1)$$

In equation $1E\epsilon$ denotes the confusion matrix, *tr* indicates the trace operations (sum of elements in the main diagonal of confusion matrix) and N is the number of dataset. So, the accuracy for this test is 96% and the total error is 4%. The total error is defined by: (1-*ACC*). This result is not deceiving because our image dataset classes are balanced.

Other parameters which have an impact on accuracy are the quality and the background noise in the image from the dataset. For that, there are many authors who mentioned about the reason of having image datasets without interferences like the operators' hands, soil, shadow, leaves, stems and spikes [18, 21, 26]. [9] concludes that the recognizing in training algorithms depends on the image quality. An optimal image dataset is difficult to find because, in the case of sugarcane diseases the need of an image classification label by an agricultural expert is preferable. Furthermore, to generate a robust model, the images in the dataset should have little noise. The images from real environments are not conditioned to an environment where the leaf or stem of sugarcane does not have noise in a sugarcane crop.

In Figure 7, we show Ring Spot disease images with background noise, and its results in Table I. As it can be seen, the main characteristic of this disease is the ring spot on sugarcane leaf caused by Leptosphaeria Sacchari. The corresponding percentages to the Ring Spot class are high on these 3 images. We selected these 3 images because of the variety in the background noise they have. Figure 7 (a) and 7 (b) have little noise (leaves and soil), that is the reason why they have high percentages. In Figure 7 (c), the percentage that indicates that the disease belongs to the Ring Spot class decreases. This is very likely caused by the background noise (other sugarcane leaves and the sky), which fills more than 50% of the image.

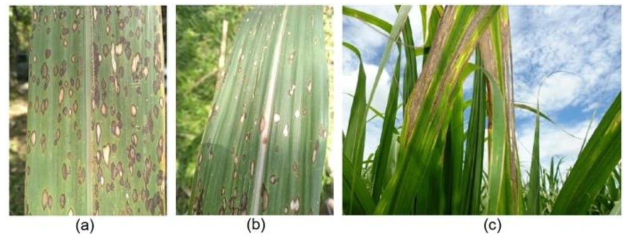

Figure 7. Ring Spot disease images.

TABLE I
ACCURACY RESULTS FOR RING SPOT

	Figure 7 (a)	**Figure 7 (b)**	**Figure 7 (c)**
Disease Output	Ring Spot	Ring Spot	Ring Spot
Class Recognition	99.97%	100%	76.93%

In Figure 8, we show the test images for the Pineapple Sett Rot disease and their results in Table II. This disease is caused by Ceratocystis Paradoxa, product of cold dry or wet soil conditions. The corresponding percentages of Pineapple Sett Rot class are high in the 3 images shown. This is quite likely because the sugarcane stem of this disease has a particular color and, in this regard, the CNN algorithm is based on a convolution operation which can extract morphologic characteristics and colors from input images [27].

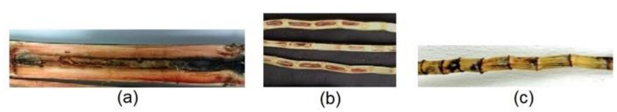

Figure 8. Pineapple Sett Rot disease images.

TABLE II
ACCURACY RESULTS FOR PINEAPPLE SETT ROT

	Figure 8 (a)	**Figure 8 (b)**	**Figure 8 (c)**
Disease Output	Pineapple Sett Rot	Pineapple Sett Rot	Pineapple Sett Rot
Class Recognition	99.99%	99.99%	99.99%

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In Figure 9, we show the image tests for the Mosaic Virus disease and their results in Table III. This disease is caused by sugarcane Mosaic Virus from the Potyvirus family. The symptoms are a mosaic leaf pattern and stripes on the young stalk [28]. The corresponding percentages to the Mosaic Virus class are high on those 3 images shown in Figure 9. The model based on CNN recognizes morphologic characteristics, texture and coloration and takes as a patron these to classify the images. That is the reason why the background noise does not affect the corresponding classification percentages.

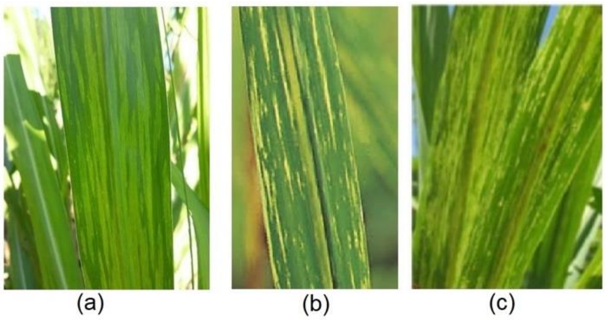

Figure 9. Mosaic Virus disease images.

TABLE III
ACCURACY RESULTS FOR MOSAIC VIRUS

	Figure 9 (a)	Figure 9 (b)	Figure 9 (c)
Disease Output	Mosaic	Mosaic	Mosaic
Class Recognition	99.99%	99.91%	100%

In Figure 10, we show the test images for Brown Rust disease and their results in Table IV. This disease is caused by Puccinia Melanocephala, product of cool nights or warm sunny days. The corresponding percentages to Brown Rust class are high on the 3 images samples. The pattern of this disease is the brown coloration on the leaves. [23] mentions the necessity of having color characteristics and texture to recognize the brown rust. In spite of noises in the images, the model classifies correctly the images for the Brown Rust disease.

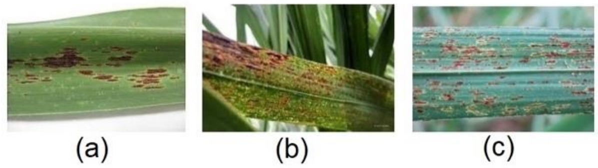

Figure 10. Brown Rust disease images.

TABLE IV
ACCURACY RESULTS FOR BROWN RUST

	Figure 10 (a)	Figure 10 (b)	Figure 10 (c)
Disease Output	Brown Rust	Brown Rust	Brown Rust
Class Recognition	96.41%	100%	99.99%

In Figure 11, we show the test images for the Leaf Scorch disease. This disease is caused by StagonosporaSacchari, product of rain and warm conditions. The classification model takes the morphologic characteristic and its coloration. The corresponding percentages to Lead Scorch class are high in the 3 images presented in Table V.

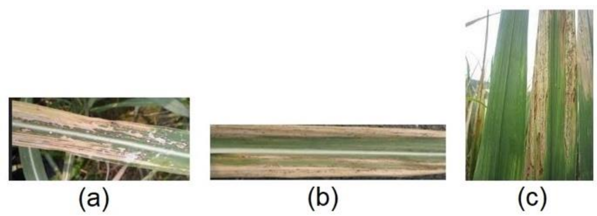

Figure 11. Leaf Scorch disease images.

TABLE V
ACCURACY RESULTS FOR LEAF SCORCH

	Figure 10 (a)	Figure 10 (b)	Figure 10 (c)
Disease Output	Leaf Scorch	Leaf Scorch	Leaf Scorch
Class Recognition	99.99%	99.99%	99.80%

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Finally, we generated a Graphic User Interface (GUI) developed on Matlab App Designer with the purpose that sugarcane farmers can use this model on the Internet. Figure 12 shows the web application interface, where users can load the image (of which the disease would like to be known), then start model (by clicking on the "Process" button) and the model provides the sugarcane disease with its associated percentage of classification. In Figure 13 and example of the output of the web application is shown; the Brown Rust disease is identified at a 100%.

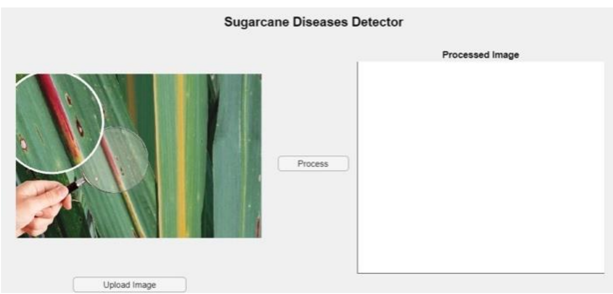

Figure 12. Web application GUI.

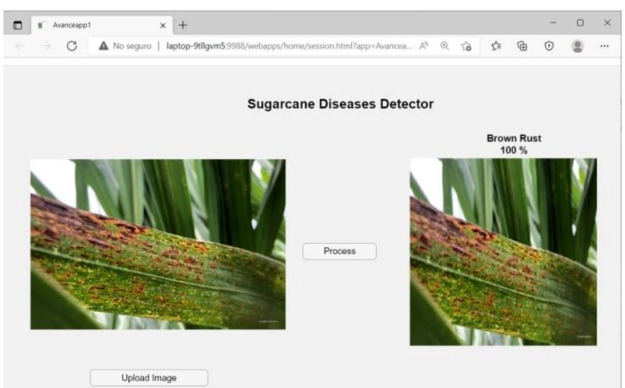

Figure 13. Testing of the web application for sugarcane diseases recognition.

The classification model was set up on local server, and it can eventually be made public; we have not done so due to a limitation with the security on our local server. However, Matlab can solve this problem with a dedicated server, the Matlab Web Server.

V. Conclusion

This research study developed a web application on Matlab to identify sugarcane diseases. The results demonstrate the high model accuracy (96%), compared with other studies.

The model was developed using GoogLeNet and our image dataset was made up of 250 images with little noise, this to make robust the model. To increase the accuracy percentage in any classification system based on CNN, we should have had a bigger image dataset and further reduce the loss function in every iteration, because this shows how well the model is learning.

As the designed system presented in this work is a recognition system for precision agriculture, it is of the utmost importance to have a larger database and images certified or validated by professionals or reliable sources dedicated to the field of agricultural engineering. Thus, as a future work, it is suggested to increase the number of images in the dataset;it is suggested to add more diseases for training and recognition. Furthermore, a mobile application for Android and iOS devices could be developed to register farmers and provide them with more information on control and caring methods for certain diseases.Finally, calculations of the composition and preparation of agricultural fungicides and pesticides depending on the disease to be treated can be included.

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