A Deep Neural Network based Detection System for the Visual Diagnosis of the Blackberry

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***Abstract*—Thanks to its geographical and climatic advantages, Colombia has a historically strong fruit-growing tradition. To date, the basis of its food and economic development in a significant part of its territory is based on a wide range of fruits. One of the most important in the central and western regions of the country is the blackberry, which is rooted not only from the economic and food point of view but also culturally. For the departments of Casanare, Santander, and Cundinamarca, this fruit is one of the primary sources of income, rural employment, and food supply and income. However, small and medium farmers cultivate without access to technological production tools and with limited economic capacity. This process suffers from several problems that affect the whole plant, especially the fruit, which is strongly influenced by fungi, extreme ripening processes, or low temperatures. One of the main problems to be dealt with in its cultivation is the spread of pests, which are one of the causes of fruit rot. As a support strategy in producing this fruit, the development of an embedded system for visually diagnosing the fruit using a deep neural network is proposed. The article presents the training, tuning, and performance evaluation of this convolutional network to detect three possible fruit states, ripe, immature, and rotten, to facilitate the harvesting and marketing processes and reduce the impact on the healthy fruit and the quality of the final product. The model is built with a ResNet type network, which is trained with its dataset, which seeks to use images captured in their natural environment with as little manipulation as possible to reduce image analysis. This model achieves an accuracy of 70%, which indicates its high performance and validates its use in a stand-alone embedded system.**

***Keywords*—Automatic sorter; blackberry; deep neural network; fruit handling; image analysis**

I. Introduction

Colombia is a country that has been characterized by its great variety of fruits and fauna [1]. Its diversity and climatic stability, as well as its great cultural variety, have made it possible to define different foods that provide the necessary nutrients with an unparalleled flavor [2]. One of the most known and used fruits in daily life is the blackberry because it has an excellent flavor and an endless number of preparations [3], [4], [5].

Blackberry cultivation is mainly carried out by small family businesses without large investments in technology. These farmers strive to maintain the quality of the fruit [6], however, it is difficult to sustain it in planting with a size of approximately two hectares. Also, the process is further complicated by having to use chemicals to care for the plant, which always has an impact on the quality of the final product [7], [8].

An autonomous artificial sorting system can perform effective segmentation from images of blackberry in its different growth processes. Such a system, easy to use and very low cost, can support the production and commercialization of the fruit in its different stages [9], [10]. This type of system should consider a robust and low-cost portable design [11], [12], [13]. In this sense, the use of an identification algorithm capable of operating in real-time on low-cost embedded hardware is essential [14], [15], [16].

Annually Colombia produces 137,999 tons of blackberry. About 55% of the production stays in Colombia for fresh consumption (supermarkets and marketplaces) and less than 1% is exported [17]. Between 2015 and 2018, 12.8 tons of blackberry were exported, and it is known that the department of Cundinamarca is one of the largest producers, followed by Santander. These have an annual production of 26% and 17% respectively. Blackberry, despite its unique flavor, requires special processes to maintain its quality and avoid premature fermentation. Blackberry production costs are estimated at USD 2,410, which is divided into four main activities: land preparation, planting, harvesting, and inputs. However, for each ton of blackberry it is estimated that the value paid to the farmer is USD 400, which means that for every 14 million, a gross profit of USD 1,542 is obtained [18], [19].

Blackberry exports in Colombia are less than 1% [20]. However, this is one of the crops that generates the highest permanent income due to the domestic market [21]. Twenty percent of the product remains in the agro-industry for the production of juices, and jams, among others, while the remaining 55% remains for fresh consumption. This indicates that about 75% of the production remains for domestic trade, and is distributed in the largest distribution centers of agricultural products in the country. For example, Corabastos in the Colombian capital handles 36% of production, followed by the city of Bucaramanga with 20% in 2019. Its economic importance is reflected in the domestic market due to its great demand, and this, in turn, generates jobs and economic resources for the Colombian population. Therefore, it is estimated that 1,900 new hectares of blackberry crops are established annually. These crops can be affected by pests, which can end up destroying the entire crop if they are not properly cared for or do not have the necessary resources [22].

Since blackberry is a perishable food that grows in the field, and its characteristic of food for pests such as flies, thrips, mites, and even the so-called fruit worms [23], it is essential to perform a quick and efficient characterization of the affected fruit to reduce possible damage and losses. These pests cause the fruit to be damaged, and this in turn is spreading throughout the crop, i.e., will produce losses to the farmer. For this reason, they implement various chemicals to eradicate them, which means that the blackberry has a large amount of them. An automatic grading system capable of being used by the farmers would increase their production capacity and product quality [24], [25].

The blackberry is a product with broad social roots that benefits the Colombian population from a nutritional and economic point of view. The blackberry industry provides employment in economically depressed areas, and at the same time has great nutritional value. Although it is not a product that brings income to the country as an export product, it is very important for the domestic economy in many regions of the country. It is a product that should be consumed fresh because it has a characteristic of rapid fermentation that considerably reduces its quality. Also, to maintain the quality of the crops, certain chemicals are used to eradicate pests, therefore it is necessary to invest in technology to facilitate and reduce production costs while ensuring the quality of the fruit [26], [27]. An automatic recognition system allows keeping control of the fruit throughout the production and commercialization process, which provides added value to the process and reduces costs [28].

In current fruit production processes, there is no equipment or tools similar to the one proposed in this research [29]. Previously, fruit inspection systems for harvesting have been implemented with shallow success, particularly for using traditional image processing strategies for sorting, which is very unreliable in actual field applications.

The paper is structured as follows. Section II describes the problem under study and the possible profile of the required solution. Section III presents the methodological development followed for the solution, giving details of each section of the system, from the input dataset and its manipulation to the desired output categories, including the architecture designed for the model. Section IV summarizes and discusses the results achieved by the model, using metrics and discussing their scope. Finally, Section V concludes our paper by highlighting the strategies used and the most important findings.

II. Problem Statement

The objective of this research is to develop an autonomous classification model based on images to determine the conditions of blackberry fruit throughout the harvesting and marketing process. It is intended to use this model for the construction of a low-cost embedded system that is easy to use with farmers. With this system, the farmers will be able to identify in time the problems of the fruit in their harvest, reducing negative effects on production. The handling of this fruit must comply with certain processes that guarantee its quality, i.e., avoid the proliferation of pests and diseases that attack the crop, as well as maintain its growing conditions. Changes in these processes often affect the plant from the root to the fruit, potentially lowering the volume of the harvest. When one plant gets infected, the damage quickly spreads to other plants, generating large losses for growers. These crop problems are not only due to the misuse of insecticides or soil, but the weather plays an important role. Low temperatures produce frosts that influence the weakening of the plant and therefore facilitate the incorporation of pests and diseases.

Pests and diseases are not the only problems that cause damage and losses in this crop, an extreme ripening of the blackberry causes fermentation, making it impossible to consume. Blackberry is consumed fresh, inadequate handling and storage processes affect the quality of the fruit, an effect that also spreads rapidly throughout the product.

As a solution strategy, we propose an image categorization model based on a convolutional network. We propose the use of a ResNet (Residual Neural Network) trained and tuned with a proprietary dataset to identify three fruit states: ripe fruit (category 0), unripe fruit (category 1), and rotten fruit (category 2). This architecture is chosen due to its high performance in similar problems, and its small size which facilitates its use in a low-cost embedded system. The aim is that such a system can identify possible problems in the fruit early, before spreading and infecting the whole crop (harvest). The general model of the proposed system is shown in Fig. 1.

III. Methods

In the preliminary performance tests, the ResNet model obtained the highest average and category performance. The ResNet version of 50 layers deep (ResNet-50) was implemented, seeking the smallest possible size for the model. The great advantage of this model is that it reduces the depth by sending information forward, skipping layers, and improving at the same time the learning capacity [30]. The coding of the model was performed in Python 3.8.5 with support for numpy 1.19.2, scikit-learn 0.23.2, scipy 1.5.2, OpenCV 4.4.2, and matplotlib 3.3.2.

One of the essential features of our categorization model is that it must be able to produce results with images captured in real environments, such as those that a farmer could capture with his cell phone. In this way, the system would be easy to manipulate in real environments, and the categorization model would produce reliable results. To test this argument, we built our dataset from images supplied mainly by local farmers and experts in fruit handling. In addition, this database was supplemented with public images of fruit conditions. The images were not manipulated to extract or remove information from them, but the leading actor was always the fruit.

The training of the convolutional model was performed according to the following characteristics:

- **Dataset**. We built our balanced dataset with 100 images in each category (300 images in total, Fig. 2). The images in each category correspond to states identified by fruit condition experts. According to the performance of the system, this dataset can be increased if this increases the categorization performance. The possibility of continuous updating of the database and online training is proposed.
- **Manipulation of the Dataset**. The image processing was done with OpenCV. The images were randomly

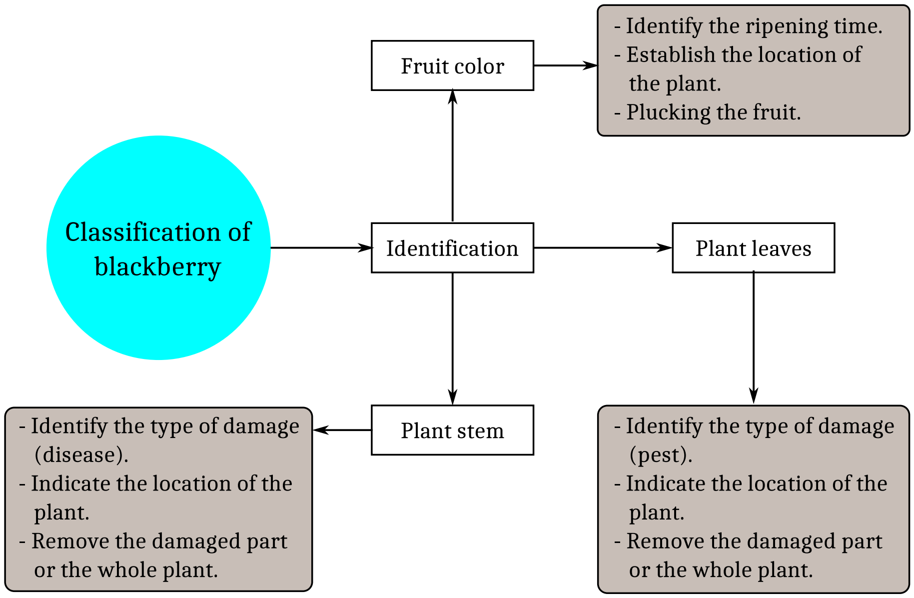

Fig. 1. General Diagram of the Classification and Control Scheme of the Blackberry Plant.

shuffled and scaled to a size of $32'times32$ pixels to reduce the complexity of the code. This size is conditional on the performance of the model, but in initial tests, it showed a high capacity to retain features while considerably reducing the processing power required on the embedded hardware. The images were processed in RGB matrices and normalized to the working values of the convolutional network.

- **Training and Validation**. To build the model, training is performed with 70% of the dataset (random selection of images), while the remaining 30% is used for validation. The optimization is performed with the Stochastic Gradient Descent (SGD) function, and the loss calculation is performed with the Categorical Crossentropy function. The training was performed over 30 epochs, and at each step, the accuracy and Mean Squared Deviation (MSD) error values produced for both training and validation data were controlled. The number of epochs was defined according to the learning capacity of the model, avoiding over-fitting.

- **Model Assessment**. The performance of the model was evaluated using three metrics: Precision, Recall, and F1-score. These metrics were calculated for the validation images in each category of the model, as well as its average behavior. The convolution matrix was also used to identify problems related to false positives and false negatives.

We use a ResNet-50 model looking for architecture with high performance, but at the same time suitable for propagation on embedded hardware (Fig. 3). This deep network is inspired by cells of the pyramid of the cerebral cortex to form equivalent functional blocks. This functionality is achieved using jumping connections to send information forward layers of the structure. It is thanks to these jumps that this deep model manages to avoid gradients that fade away during training, which is what gives it its high performance. This structure makes sense when all the intermediate layers are linear or are superimposed on the nonlinear layer, otherwise, the re-use of weights in the forward layers would not make sense. The ResNet-50 model has five stages, each with a convolution and identity block. Each convolution block contains three convolution layers, as does each identity block. With this structure, the model has a little more than 23 million parameters to be adjusted.

IV. Results and Discussion

The capacity and performance of the model were evaluated throughout the training with both training and validation data. Accuracy (Fig. 4) and the behavior of the loss function (Fig. 5) were calculated throughout each epoch. The Accuracy of a classification model indicates the number of correct predictions for the total number of input images. In Fig. 4 the red curve shows the Accuracy behavior for the training data, while the green curve shows the same metric for the validation data. The Accuracy of the training data remains always high, while the behavior of the validation data remains very poor, at least until epoch 13, from which the performance of the validation data increases according to the model fit.

Fig. 5 shows similar behavior. The red curve again shows the behavior for the training data, while the green curve shows the error produced by the validation images. Although in both cases there is error reduction, the initial model had a good performance for the training data, and the most marked reduction in error is observed in the validation data. Without wishing to cause training bias, the model was tuned to produce better behavior for unknown images. Again, the reduction in error becomes more marked from epoch 13 onwards.

The confusion matrix of the model allows to observe graphically the overall performance, as well as in each category, and allows for calculating the Precision, Recall, and F1-score metrics (Fig. 5). The matrix uses a heat grading that assigns

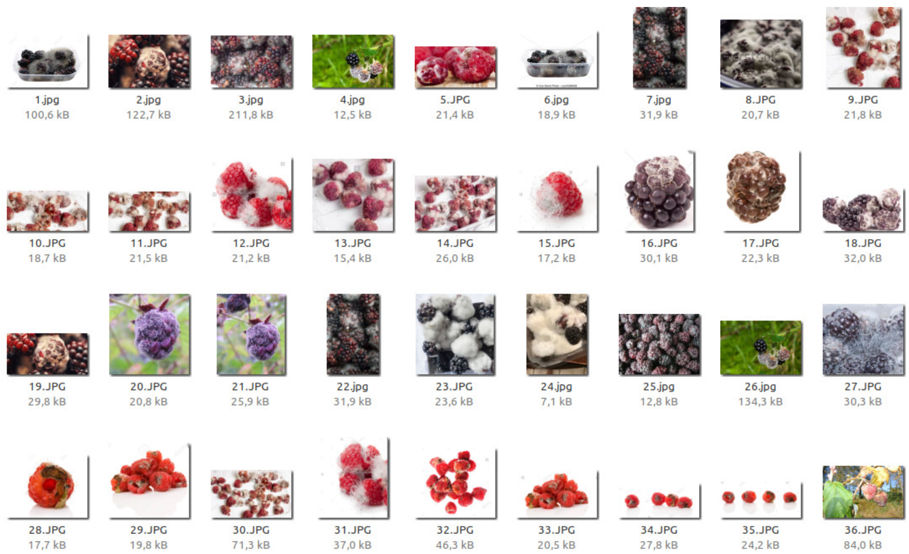

Fig. 2. Sample Dataset used in Category 2 (Rotten Fruit).

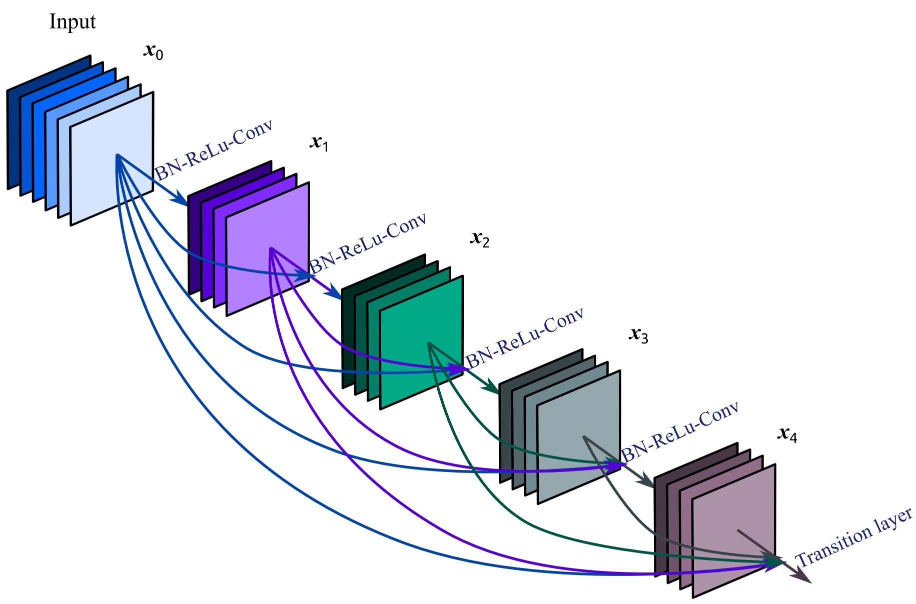

Fig. 3. ResNet-50 CNN Architecture.

light colors to high values, and dark colors to low values. The main diagonal in Fig. 6 with light colors, and the dark colors above and below it, show high categorization performance. Specifically, it is seen that in the ripe fruit category, 21 of the images are correctly classified, with very low percentages of false positives and false negatives. In the category of immature fruit, it is seen that it had more difficulties in the classification, since it only classified 18 of these, and in the category of rotten fruit it had the best performance since it was able to correctly classify 27 of the images.

We also calculated the Precision, Recall, and F1-score metrics for the model using the validation data (Table I). The accuracy of the model indicates how good the model is at placing the correct images in a given category, i.e., how many of those placed in a category belong to it. Our model obtained an accuracy of over 68% in all categories and an average value of 76%. Although not perfect, the values are more than good for the proposed development. On the other hand, the Recall shows how many of the positive ratings in each category belong to that category. In category 1, as indicated in the confusion matrix, we have a relatively low value (51%), but the values for the other categories exceed 84%, which speaks very well of the model. The average value for Recall is 75%. Finally, F1-score corresponds to a weighted average of the first two metrics, so it combines their qualities. The model obtained a value per category of over 75% and an overall average value of 73%.

This categorization model is being evaluated on the

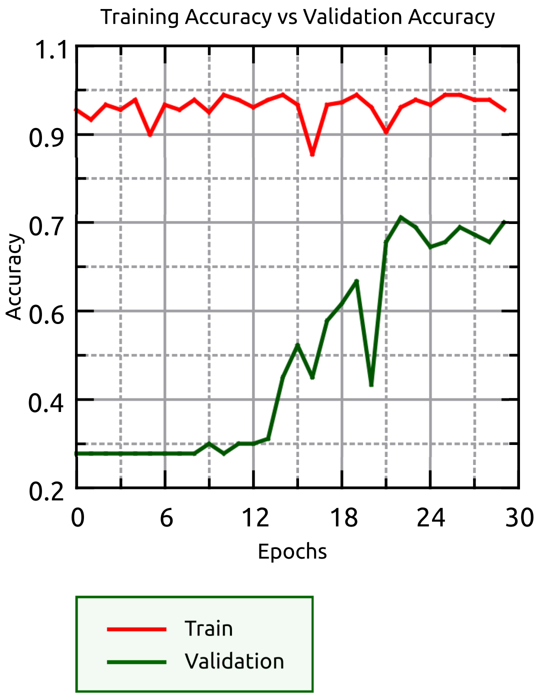

Fig. 4. Accuracy for Training and Validation Data throughout the Training Process.

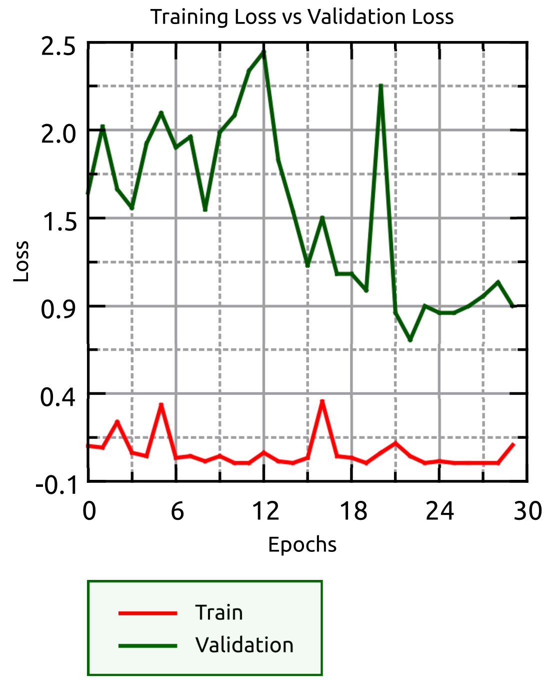

Fig. 5. Loss for Training and Validation Data throughout the Training Process.

TABLE I. SUMMARY OF THE BEHAVIOR OF THE MODEL METRICS

	Prescision	Recall	F1-score	Support
0	0.68	0.84	0.75	25
1	0.90	0.51	0.65	35
2	0.69	0.90	0.78	30
Accuracy			0.73	90
Macro avg	0.76	0.75	0.73	90
Weighted avg	0.77	0.73	0.72	90

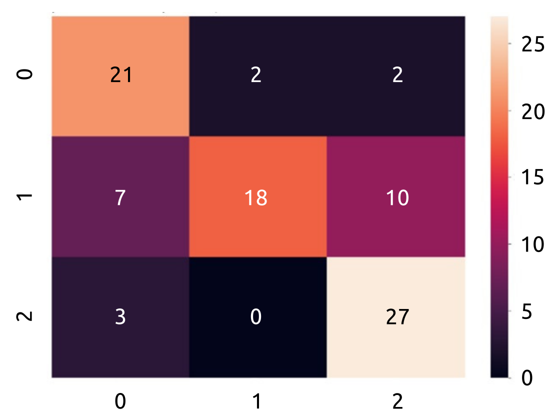

Fig. 6. Model Confusion Matrix.

DragonBoard™ 410C development board from Arrow Development Tools. This system is powered by a 64-bit ARM®Cortex™ A53 Quad-core processor and 1 GB of RAM. The system has been configured with Debian Linux, and in initial testing has demonstrated high real-time performance. Further evaluation will be conducted in the future development of this research.

Compared to traditional strategies for the identification and categorization of fruits, our proposal presents excellent advantages for implementation in real systems, not only because of the high performance reported by the model but also because of the possibility of working with images with minimal or no previous processing, which allows farmers to manipulate the tool and produce reliable results immediately directly. This advantage is further enhanced by the lack of the need for complex, high-cost hardware, which allows the development of prototypes on small embedded systems.

V. CONCLUSION

This paper presents an image categorization model of blackberry fruit as a strategy for the construction of an autonomous identification system to support the process of cultivation and marketing of the fruit. The ResNet-50 convolutional neural network was selected for the development of the model due to its high performance and small size. This network was trained, tuned, and validated with a proprietary dataset separated into three categories coinciding with the state of the fruit. The code was developed in Python with Keras and TensorFlow support, and a model with good performance suitable for embedded applications was generated. During training, the Categorical Crossentropy function was used as a loss function, and the Stochastic Gradient Descent function was used as an optimizer. The evaluation of the model was performed with the Precision, Recall, and F1-score metrics, as well as the confusion matrix of the model. According to the results with the validation data (Precision of 76%, Recall of 75%, and F1-score of 73%) the model has adequate performance for the development of the prototype, also, the behavior throughout the training allows intuiting that it is still possible to increase the learning and performance of the model. It is expected that the system can be used to perform on-site fruit sorting, allowing the early identification of rotten fruit, reducing damage at harvest, and handling the product. Future directions of the project are oriented to allow real-time updating of the database and evaluation of the system on hardware prototype.

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