Journal of Theoretical and Applied Information Technology
30th June 2021. Vol.99. No 12

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

# PERFORMANCE EVALUATION OF FOUR LEARNING-BASED AUTOMATIC IDENTIFICATION MODELS FOR PAPAYA FRUIT CLASSIFICATION

[1]JONATHAN VELAZQUEZ, [2]ANDRÉS MARTÍNEZ, [3]FREDY MARTÍNEZ
[1,2,3]Facultad Tecnológica, Universidad Distrital Francisco José de Caldas, Bogotá D.C, Colombia
E-mail: [1]jgvelasqueza@correo.udistrital.edu.co, [2]ansmartinezm@correo.udistrital.edu.co, [3]fhmartinezs@udistrital.edu.co

## ABSTRACT

Colombia is a country with an economy strongly linked to agriculture. Besides, thanks to its geographical characteristics, it has a wide variety of fruit products of great commercial acceptance both domestically and internationally. However, despite its strong economic dependence, this sector has not benefited from adequate technological developments. One of the processes in the production chain that in many cases is still carried out manually is the selection and classification of the fruit. In the specific case of papaya (papaw or pawpaw), this manual sorting strategy does not satisfy the quality of the process in terms of efficiency and performance, triggering the productive stagnation of this sector. This research proposes to support this process using an automatic system through the use of a model based on neural networks. In particular, a performance comparison is made between four neural topologies recognized for their high categorization capacity. The selected topologies include a low depth network and three deep learning structures. The models were trained with a proprietary dataset consisting of three visually identifiable fruit states. As a result, the high performance of the deep convolutional networks, in particular, the ResNet and DenseNet networks, is observed, making them strong candidates for the development of an autonomous embedded system.

**Keywords:** *Automatic sorting, Deep learning, Fruits, Image classification, Neural networks*

## 1. INTRODUCTION

The wide variety of climates and terrains in Colombia allows the growth of a wide diversity of fruits with harvests that extend throughout the year [1]. The country's tropical and uniform climate makes the export of fruits considered exotic an important economic market [2, 3]. This trend has been growing in recent years and is expected to be a strong generator of resources for the country. However, much of the production is carried out by small farming families with little access to technology and with a preponderance of manual labor. This strategy increases production costs per unit, reducing both production efficiency and producer profits [4].

The field of fruit growing requires a constant updating of technology capable of optimizing its production process and thus increase its market niche [5, 6]. Currently, several alternatives are provided to reach the threshold of production, distribution, and quality; the one we will focus on is closely related to the quality of the product, for this, we propose an automated alternative through the use of neural networks. With the use of this tool, an improvement in the fruit classification process is foreseen [7], in addition to ensuring that the product is at an optimal stage for consumption.

The application of taxonomy in fruit harvesting is possible to increase fruit quality and generate growth in demand for these crops [8, 9]. The harvesting process in papaya crops turns out to be a great field of application of this concept since this sector requires an improvement in its quality and growth in demand [10, 11]. Papaya is a fruit whose quality is highly affected by the state of ripeness at the time of harvesting, hence the importance of recognizing the state of ripeness of this fruit. The usual way to classify its current state is the visual recognition of papaya since it is understood that by having a specific texture or color it is possible to determine its ripening stage for its subsequent distribution [12].

This analysis is affected by deficiencies in the person in charge of this task [13]. Inexperience in the worker often leads to the fact that this person is

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

not able to efficiently and accurately recognize the ripening stage of the fruit to be evaluated, classifying it erroneously and affecting the quality of the final product. Not only experience is a determining factor, but in those workers who have it, fatigue is an influential factor in this type of work, affecting the quality of their classification [14]. The accumulated fatigue and the constant repetition of this process can generate visual wear and tear and makes the eyes unable to recognize certain shades of colors, generating in the worker a state of distortion at the time of classification.

The use of an automated ripening classification system, capable of detecting the state of the papaya, is ideal for product improvement [15, 16]. Such information could help to calculate the preservation times of the fruit (passage from the semi-mature or distribution state of the fruit to its decomposed state), and thus ensure that the product is at an optimal stage for consumption, raising quality standards. For the classification system to be able to counteract any problem [17], an automation tool with a solid image classification scheme must be available, since these are based on image processing strategies that use filters to recognize specific parameters in the image, such as shape, colors, symbology, contrast, grayscale, textures, and patterns [18, 19, 20]. Based on these aspects, the use of neural networks proves to be a very effective option [21]. Deep and low-depth neural networks are efficient in training-based classification processes, and they can adapt to changes in the training data [22].

This research is focused on determining the best neural model for the development of an embedded automatic identification system [23, 24]. In this sense, we intend to evaluate the performance of four topologies widely recognized for their capability and performance in image classification tasks [25]. Each of these topologies will be trained and adjusted under the same conditions and dataset, and the performance of each of them will be evaluated to handle the specific identification problem of this fruit [26, 27]. It is expected that the neural models will be able to identify the differences and similarities between images of each state of the fruit, avoiding misidentifications between categories, regardless of particular conditions of the images such as the over position of different fruits, partial occlusion with leaves of the plant, and the difference in contrast and brightness to which each image is exposed, as well as the recognition of some diseases [28, 29, 30].

## 2. PROBLEM STATEMENT

A problem widely encountered in Colombian agricultural production systems is the lack of technological tools in the classification process [31, 32]. This lack of tools combined with low knowledge of fertilizer and pesticide management reduces production capacity, harvest, and fruit quality. Studies have shown that the investment in these tools is amortized in a very short time due to the increase in efficiency, quality, and production [33]. This research presents a preliminary study regarding the most suitable sorting model for use in embedded systems in automatic papaya fruit classification applications. The ultimate goal is to develop a stand-alone system easy to use by farmers either as an application for portable devices (smartphones or tablets), a special purpose stand-alone system, or even on service robots and drones. To this end, the comparative performance of neural topologies with previous positive results on similar classification problems is evaluated.

The selected topologies include a multi-layer perceptron and three convolutional networks. These classification models are trained under similar conditions, i.e., the same dataset and the same optimization and tuning criteria (with appropriate loss and optimization functions in each case). The same criteria and metrics were also used to establish their performance on the problem. The purpose of this stage of the project is to define a topology for the categorization model to be used in a stand-alone fruit sorting system. As such, the dataset used was adjusted to identify the topology with the best capability for this task. Later stages of the research will modify this dataset to develop equipment suitable for commercial use.

At present, there is no similar system in national production schemes. Automatic fruit grading models do exist, but such research work relates to other fruits in different production contexts. As far as this research has been able to identify, there is no classification system like the one proposed in this project, particularly on embedded systems with deep neural networks.

## 3. METHODS

The architectures that will be used in the comparative study are: Perceptron Multi-layer, Residual Neural Network (ResNet [34]), Dense Convolutional Network (DenseNet [35]), and Neural Architecture Search Network (NASNet [36]). These topologies are selected due to their high performance in previous models developed in the research. The architecture selected for each model considered both network performance and the number of parameters and learning capacity. Figure 1 shows the architecture adopted for the multi-layer perceptron network, this figure details some parameters of the model used such as the number of layers, percentage of data used in training and evaluation, as well as the number of epochs and batch size.

Similarly, Figs. 2, 3, and 4 show the details of the architectures for the ResNet, DenseNet, and NASNet convolutional models. For the case of the ResNet network, architecture with a total of 50 deep layers (ResNet50, reduced version of ResNet 152) was chosen. This network has a much higher performance than others such as VGGNet (Visual Geometry Group) in image categorization with a simpler architecture and has shown ample performance in a multitude of applications. The reduced version we use has even lower complexity making it easier to train (shallower convolutional networks learn better than their deeper counterparts) and portability to embedded systems. The residual blocks of this network skip a few layers forward thus reducing the size and the curse of dimensionality problem that causes the network to stop learning. The DenseNet network exploits the same design principles as the ResNet network, i.e., using forward jumps to reduce the curse of dimensionality and allow for greater network depth. We use a 121-layer deep DenseNet network (DenseNet121), the smallest architecture of its kind (169, 201 and 264-layer deep versions exist). Finally, the NASNet topology starts from the principle of segmenting the dataset to find an efficient structural block on a specific classification problem, in particular CIFAR-10, and then using it on the entire dataset. We use the NASNet-Mobile version, a model that is pre-trained with more than one million images in 100 categories. This model, as its name suggests, is optimized for image categorization applications on mobile embedded systems.

This research differs from previous works in this regard in the first place because of the degree of social relevance involved, which is part of the objectives of the project. It is necessary to improve the quality of national agricultural production while strengthening the technological transfer of research centers to the industry. Another distinctive element of this research is its dedicated character, the objective is focused on the development of a low-cost embedded system, a differential characteristic concerning similar projects.

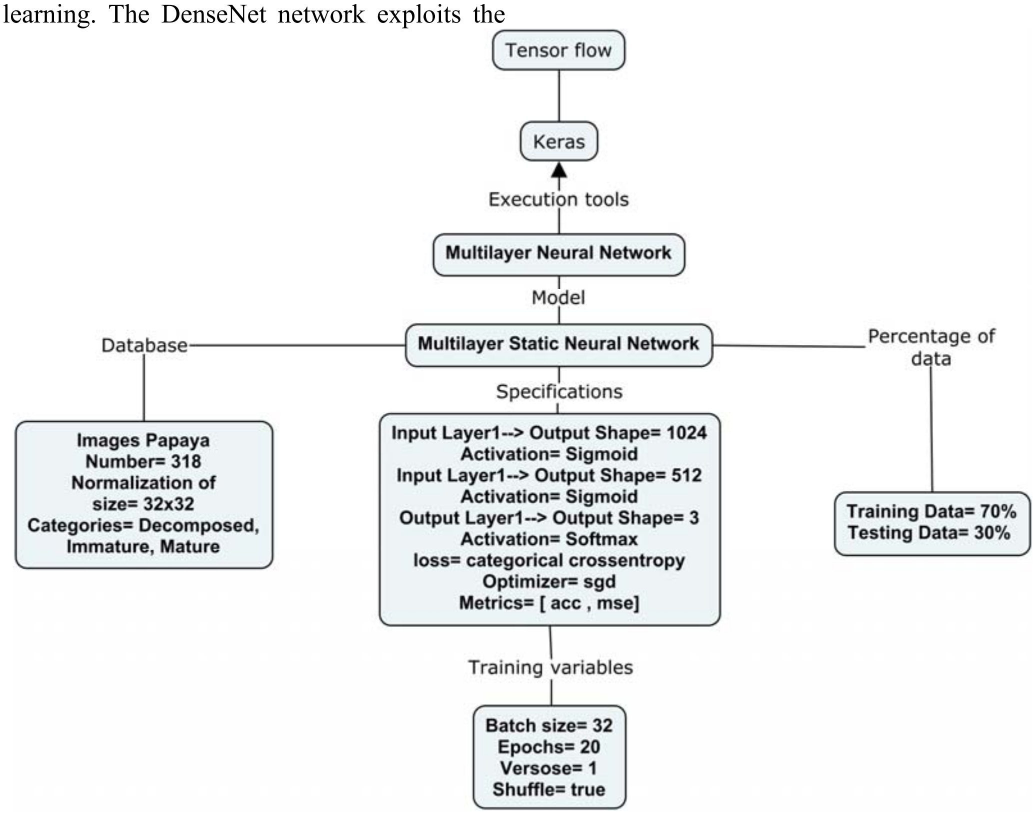


*Figure 1: Architecture Used In The Multi-Layer Perceptron Model*

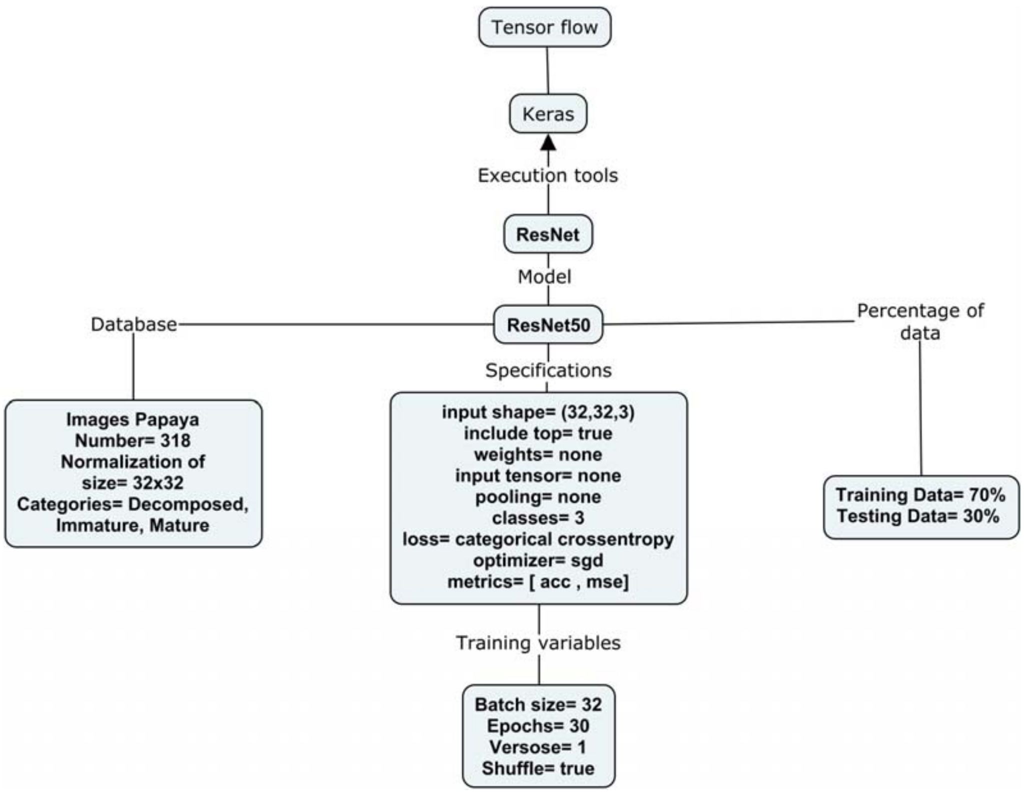


*Figure 2: Architecture Used In The Resnet Model*

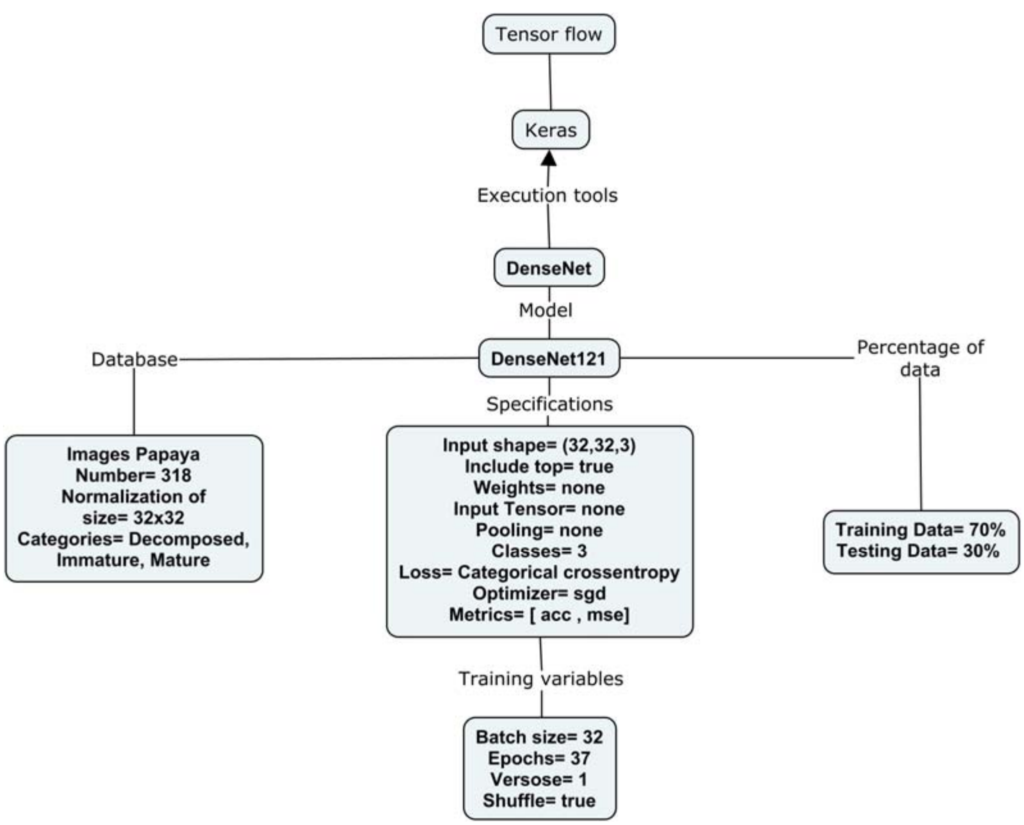


*Figure 3: Architecture Used In The Densenet Model*

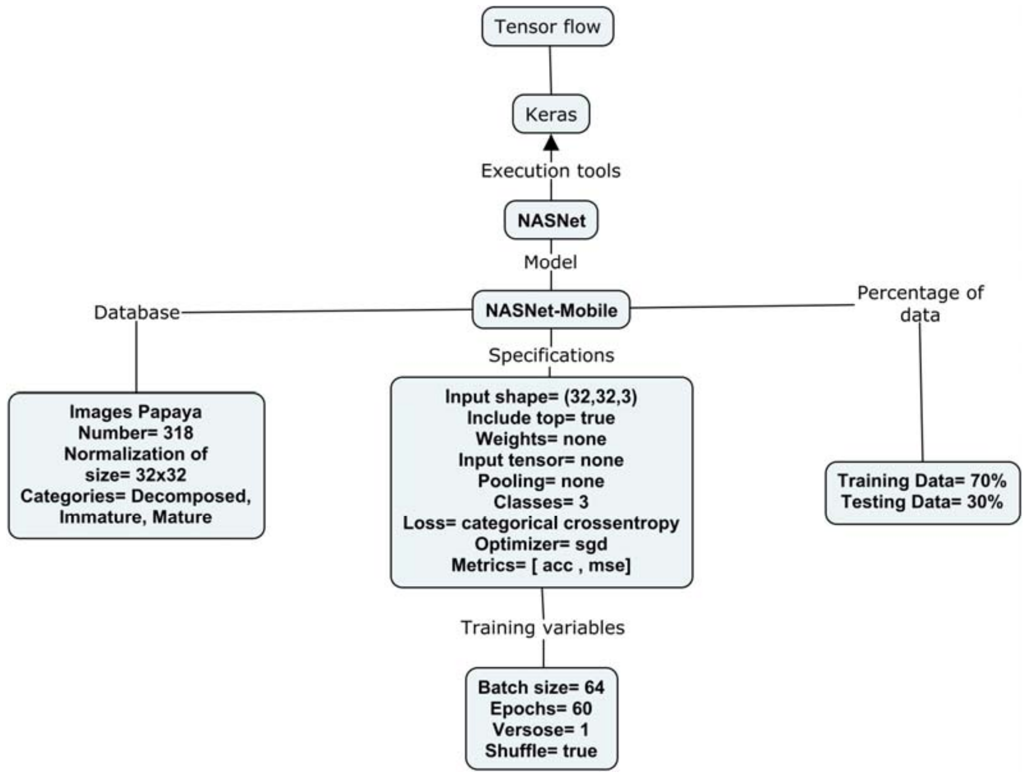


*Figure 4: Architecture Used In The Nasnet Model*

To support the fruit quality classification process, three categories were defined for the neural models: Rotten Fruit (category 0), Immature Fruit (category 1), and Ripe Fruit (category 2). The training database was structured with 106 photographs in each category, for a total of 318 images in the dataset, of which 70% were used for training and 30% for validation (Fig. 5). The selection of training and validation images was random in all cases.

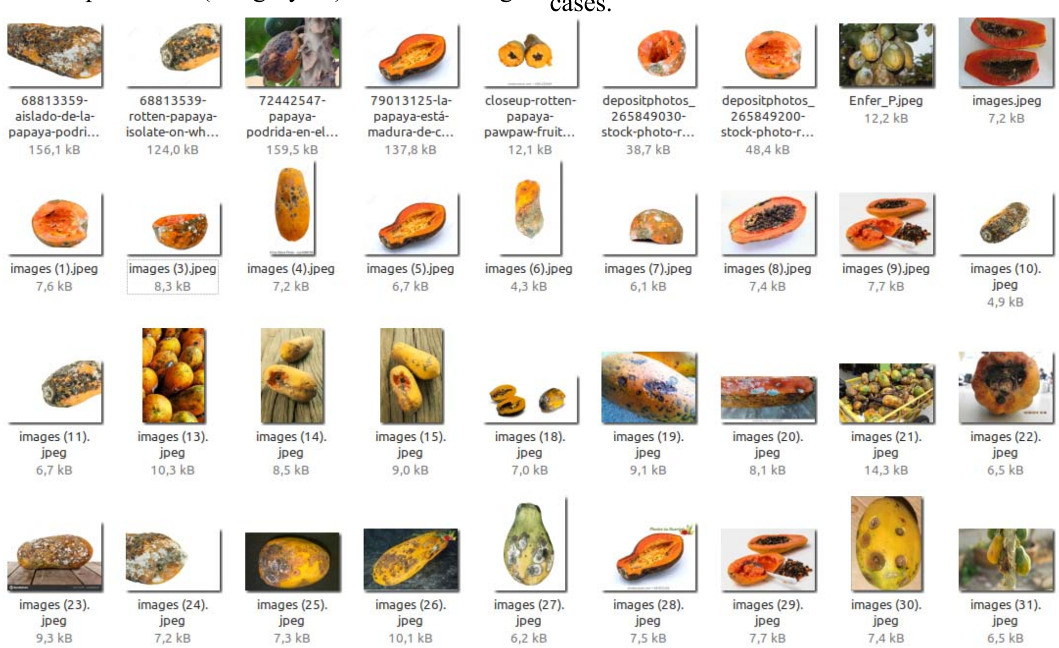


*Figure 5: Sample Of Photographs In Category 0 (Rotten Fruit)*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

## 4. RESULTS

The category classification problem is a classic machine learning problem. The objective is to assign to a pre-established category the unknown samples presented as input to the model. The evaluation of the performance of these models is done by applying metrics that evaluate how well this task is performed. Some of these metrics focus on looking at the number of items that were correctly classified into a category, while others additionally penalize misclassified items within a given category. Classical performance evaluation tools include the confusion matrix and metrics derived from the calculation of this matrix (matrix boxes).

To compare the performance of the four models, the metrics Precision, Recall, and F1-score were calculated using the validation data (Tables 1, 2, 3 and 4). As detailed, these values are unknown to the models and did not affect their training. Precision takes into account the ratio of true positives to all the images assigned to a category, i.e. (equation 1):

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (1)$$

*Table 1: Multilayer Network Classification Report*

| | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| **0** | 0.00 | 0.00 | 0.00 | 32 |
| **1** | 1.00 | 0.49 | 0.65 | 32 |
| **2** | 0.41 | 1.00 | 0.58 | 32 |
| | | | | |
| **Accuracy** | | | 0.52 | 96 |
| **Macro avg** | 0.47 | 0.50 | 0.41 | 96 |
| **Weighted avg** | 0.53 | 0.52 | 0.45 | 96 |

*Table 2: Resnet Network Classification Report*

| | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| **0** | 0.59 | 0.92 | 0.72 | 32 |
| **1** | 0.88 | 0.63 | 0.73 | 32 |
| **2** | 0.96 | 0.83 | 0.89 | 32 |
| | | | | |
| **Accuracy** | | | 0.78 | 96 |
| **Macro avg** | 0.81 | 0.79 | 0.78 | 96 |
| **Weighted avg** | 0.83 | 0.78 | 0.78 | 96 |

*Table 3: Densenet Network Classification Report*

| | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| **0** | 0.76 | 0.88 | 0.81 | 32 |
| **1** | 0.91 | 0.86 | 0.88 | 32 |
| **2** | 0.96 | 0.90 | 0.93 | 32 |
| | | | | |
| **Accuracy** | | | 0.88 | 96 |
| **Macro avg** | 0.88 | 0.88 | 0.88 | 96 |
| **Weighted avg** | 0.89 | 0.88 | 0.88 | 96 |

*Table 4: Nasnet Network Classification Report*

| | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| **0** | 0.31 | 0.60 | 0.41 | 32 |
| **1** | 1.00 | 0.17 | 0.29 | 32 |
| **2** | 0.58 | 0.70 | 0.64 | 32 |
| | | | | |
| **Accuracy** | | | 0.47 | 96 |
| **Macro avg** | 0.63 | 0.49 | 0.45 | 96 |
| **Weighted avg** | 0.67 | 0.47 | 0.44 | 96 |

On the other hand, Recall is more sensitive to the ability to discriminate the elements within a category, this metric is also calculated as the ratio of the true positives within a category but concerning the total number of elements that belong to the category, i.e. (equation 2):

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (2)$$

The third metric used, F1-score, is a function of the Precision and Recall metrics. This weighted value is calculated as follows (equation 3):

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

These metrics can be calculated through the confusion matrix of the model, which we also use for the analysis of results (Fig. 6). The columns of the confusion matrix define the Precision value for each category, taking the diagonal element as the numerator, and the sum of the other elements as the denominator. The rows of the confusion matrix form the Recall values, again the diagonal element forms the numerators of each category, while the sum of the others forms the denominator in each case.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

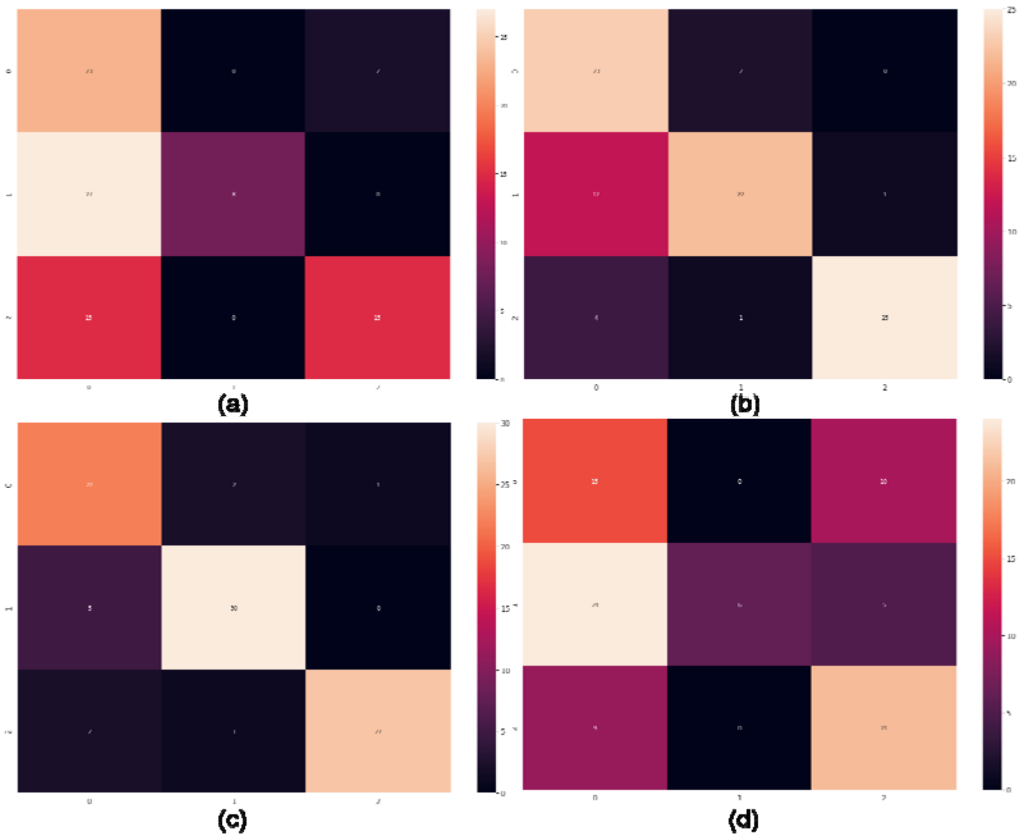


*Figure 6: Confusion Matrix Of The Four Models For The Validation Data. (A) Perceptron Multi-Layer, (B) Resnet, (C) Densenet, And (D) Nasnet*

## 5. DISCUSSION

Precision is the ratio of correctly categorized images belonging to a category to the total number of images categorized within this class. That is, this metric provides information on the number of images within a category that are correctly classified in the category. Concerning the first model (multi-layer perceptron), 100% of correct classification was obtained for category 1, however, category 2 only obtained 41%, and category 0 0%. This means that this model classified most of the images in category 1, including those corresponding to other categories. The performance of this model for this metric is very poor. The performance of the ResNet model is much better since in the three categories it achieves a Precision higher than 50% category 1 achieves 88% and category 2 96%, very good values. Category 0 achieves 59% accuracy, which allows us to qualify the performance of this model as acceptable. The third model, DenseNet, performed even better in this metric. All categories achieved a Precision above 70% (76% for category 0, 91% for category 1, and 96% for category 2), which allows us to qualify the model's performance as very good. The last model, NASNet, while outperforming the multi-layer perceptron, is quite poor (31% for category 0, 100% for category 1, and 58% for category 2).

Recall is a metric that assesses the sensitivity of the model. This metric is calculated as the ratio between the images that belong to a category correctly classified concerning all the images that belong to the category. In other words, this metric indicates what proportion of images in the category have been correctly identified. This metric allows to better assess the performance of the models within each category. It confirms what was suspected from the multi-layer perceptron, that about half of the images included in category 1 do not belong to the category. The metric also confirms the high performance of the ResNet (92% for category 0, 63% for category 1, and 83% for category 2) and DenseNet (88% for category 0, 86% for category 1, and 90% for category 2) models. In the case of the NASNet model, the Recall shows a low performance for category 1 (17%) showing that 100% Accuracy included many erroneous images in this category.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

F1-score is a weighted measure of Accuracy and Recall, so this metric considers both false positives and false negatives. Consequently, again the multi-layer perceptron (0% in category 0) and NASNet (29% in category 1) models perform poorly on this metric, while the ResNet (average value of 78%) and DenseNet (average value of 88%) models perform highly.

For the four models, the confusion matrix was calculated for the validation data (Fig. 6). The best behavior was observed in the ResNet and DenseNet models (Fig. 6(b) and 6(c)), cases for which the diagonal presents the lightest colors (true positives), and the squares above and below it the darkest colors. On the other hand, the multi-layer perceptron has very high false-negative values, and the NASNet model has high false negative and false positive values.

According to the results, the best performance is achieved with the DenseNet model, followed closely by the ResNet model. Either of these two architectures is suitable for the development of the embedded system. According to the computational cost requirements, ResNet is selected as the first alternative. The other two models, the multi-layer perceptron and the NASNet network have very poor performance and are not recommended for use in the application.

## 6. CONCLUSION

This paper documents a performance study of four neural models trained to categorize papaya fruit conditions from images. Preliminary results of such a study prove that the development is not only feasible but can be developed as a low-cost industrial solution. Such a model is required for use in low-cost stand-alone systems for farmer growers. The architectures selected according to previous research work were: Perceptron Multi-layer, Residual Neural Network (ResNet), Dense Convolutional Network (DenseNet), and Neural Architecture Search Network (NASNet). These neural models were trained with a proprietary dataset of 318 images equally distributed in three categories: Decomposed Fruit (category 0), Immature Fruit (category 1), and Ripe Fruit (category 2). For each architecture, the smallest topology in terms of depth layers (in the case of convolutional networks) was selected without neglecting the learning capacity of each model. The images were randomly manipulated in all cases, using 70% of them for training and the remaining 30% for validation. Categorical Crossentropy was used as loss function and Stochastic Gradient Descent as the optimization method. The number of epochs in each training was adjusted according to the behavior of the loss function and in each step for both training and validation data. In the end, an accuracy of 47% was obtained for the validation data in the multi-layer perceptron, 81% in the ResNet model, 88% in the DenseNet model, and 63% in the NASNet model. The performance of the Precision, Recall, and F1-score metrics for each of the categories confirmed the average trends, as well as the confusion matrices for each model. The ResNet model was selected as a design alternative on an embedded platform due to its high performance and smaller comparative size. This architecture has demonstrated high performance with a small footprint suitable for mounting on a small embedded system. The research will continue to evaluate the actual performance of the ResNet and DenseNet topologies on a real embedded prototype (the two topologies will be evaluated on the different target hardware).

## 7. LIMITATIONS AND FUTURE RESEARCH

The final objective of the development is its implementation on a low-cost embedded system. The preliminary results of this study allow the selection of two possible categorization models, with prioritization over the ResNet technology, for possible use as a design strategy for an autonomous embedded fruit identification system. From this point on, the models can be adjusted and the system design can be advanced according to the following approaches.

First, it is necessary to improve the training dataset to increase the capacity of the deep learning model. The dataset used in this study was limited in size to facilitate the evaluation among the four possible structures. Although it is balanced in terms of elements in each category, it is small, which considerably reduces its capacity and performance. The two pre-selected models must undergo a fine-tuning process with a larger dataset, and re-evaluate, based on the results, their generalization ability in each case. The performance of these new models should be re-evaluated with the metrics used, but the ROC Curve should also be included to determine the sensitivity of the model versus the classification specificity for each category in coherence with variations of the discrimination threshold.

It is necessary to define the possible topologies of the embedded systems on which the implementation of the categorization model will be performed and to develop the first performance tests of the real prototype. The performance of the categorization model may be affected by the system on which it is implemented. The characteristics of the image sensor system, the storage elements, and the processing system may affect the performance of the prototype. Handling of the equipment by non-specialized personnel may also affect the behavior of the model. This study should continue to evaluate the actual operation in the field by the personnel involved in fruit culturing to identify shortcomings both in the implementation of the model and in its actual handling.

Image processing support tools should be defined to enhance the performance of the model. In particular, it is necessary to implement a system of identification and isolation of the fruit in the image as a possible strategy to increase the performance of the model. If the fruit is identified in isolation, the categorization model may concentrate its ability to identify elements specific to the fruit, beyond its environment. This tool should be evaluated separately, and if it increases the performance of the model, it should be incorporated as a pre-processing stage of the system.

## 8. ACKNOWLEDGMENT

This work was supported by the Universidad Distrital Francisco José de Caldas, in part through CIDC, and partly by the Facultad Tecnológica. The views expressed in this paper are not necessarily endorsed by Universidad Distrital. The authors thank the research group ARMOS for the evaluation carried out on prototypes of ideas and strategies.

## REFRENCES

[1] D. Varela, M. González, J. González, and J. Hernández. High-throughput analysis of pesticides in minor tropical fruits from colombia. Food Chemistry, 280(1):221–230, 2019.

[2] J. Contreras, L. Calderón, E. Guerra, and B. García. Antioxidant capacity, phenolic content and vitamin c in pulp, peel and seed from 24 exotic fruits from colombia. Food Research International, 44(7):2047–2053, 2011. doi: 10.1016/j.foodres.2010.11.003.

[3] S. Graefe, J. Tapasco, and A. Gonzalez. Resource use and ghg emissions of eight tropical fruit species cultivated in colombia. Fruits, 68(4):303–314, 2013. doi: 10.1051/fruits/2013075.

[4] D. Pivoto, P. Dabdab, E. Talamini, C. Pauletto, V. Dalla, and G. Vargas. Scientific development of smart farming technologies and their application in brazil. Information Processing in Agriculture, 5(1):21–32, 2018. doi: 10.1016/j.inpa.2017.12.002.

[5] T. Wang, H. Zhang, and H. Zhu. Crispr technology is revolutionizing the improvement of tomato and other fruit crops. Horticulture Research, 6(77):1–13, 2019. doi: 10.1038/s41438-019-0159-x.

[6] A. Ali, W. Keat, and M. Wasim. Advances in postharvest technologies to extend the storage life of minimally processed fruits and vegetables. Critical Reviews in Food Science and Nutrition, 58(15):2632–2649, 2018. doi: 10.1080/10408398.2017.1339180.

[7] A. Cifuentes, E. Mendoza, M. Lizcano, A. Santrich, and S. Moreno. Development of a convolutional neural network to recognize patterns in images. Revista I+D en TIC, 10(2):7–17, 2019. ISSN 2216-1570.

[8] C. Guaillazaca and V. Hernandez. Clasificador de productos agrícolas para control de calidad basado en machine learning e industria 4.0. Revista Perspectivas, 2(2):21–28, jul. 2020. doi: 10.47187/perspectivas.vol2iss2.pp21-28.2020.

[9] N.S. Taujuddin, A.I. Mazlan, R. Ibrahim, S. Sari, A.R. Ghani, N. Senan, and W.H. Muda. Detection of plant disease on leaves using blobs detection and statistical analysis. International Journal of Advanced Computer Science and Applications, 11(8):407–411, 2020. doi: 10.14569/IJACSA.2020.0110852.

[10] K. Vikrant, S. Jaivir, C. Suresh, K. Ratnesh, C. Vipul, S. Kavindra, S. Balwant, and K. Pankaj. Post harvest technology of papaya fruits and it's value added products-a review. Progressive Agriculture, 19(2):199–208, 2019.

[11] E. Obledo and J. Cervantes. Laser-induced fluorescence spectral analysis of papaya fruits at different stages of ripening. Applied Optics, 56(6):1753–1756, 2017.

[12] F. Santamaría, F. Mirafuentes, M. J. Zavala, and E. Vázquez. Calidad de frutos de materiales comerciales de papaya roja producidos en yucatán, méxico. Agronomía Costarricense, 39:161–167, 06 2015. ISSN 0377-9424.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[13] X. Zhao, S. Li, H. Su, L. Zhou, and K.J. Loh. Image-based comprehensive maintenance and inspection method for bridges using deep learning. volume 2, 2018. doi: 10.1115/SMASIS2018-8268.

[14] S. Pascuzzi and F. Santoro. Analysis of the almond harvesting and hulling mechanization process: A case study. Agriculture, 7(12):1–9, 2017.

[15] J. Cai, J. Li, B. Liu, and W. Yao. Apple variety recognition based on multiview feature fusion. Revue d'Intelligence Artificielle, 34(3):285–295, 2020. doi: 10.18280/ria.340306.

[16] J. Yasmin, S. Lohumi, M.R. Ahmed, L.M. Kandpal, M.A. Faqeerzada, M.S. Kim, and B.K. Cho. Improvement in purity of healthy tomato seeds using an image-based one-class classification method. Sensors (Switzerland), 20(9), 2020. doi: 10.3390/s20092690.

[17] R. R. Chowdhury, S. A. Preetom, E. A. Mohammed, A. Mohammad, H. A. Sajid, N. Farzana, and W. Abu. Identification and recognition of rice diseases and pests using convolutional neural networks. Biosystems Engineering, 194:112–120, 2020. ISSN 1537-5110.

[18] F. Martínez, F. Martínez, and H. Montiel. Hybrid free-obstacle path planning algorithm using image processing and geometric techniques. ARPN Journal of Engineering and Applied Sciences, 14(18):3135–3139, 2019.

[19] Z K Simbolon, S A Syakry, Mulyadi, and M Syahroni. Separation of the mature level of papaya callina fruit automatically based on color (RGB) uses digital image processing. IOP Conference Series: Materials Science and Engineering, 536:012127, jun 2019. doi: 10.1088/1757-899x/536/1/012127.

[20] S. Schneider, G. W. Taylor, and S. learning object detection methods camera trap data. In 2018 15th Computer and Robot Vision (CRV), 2018. doi: 10.1109/CRV.2018.00052.Kremer. Deep for ecological Conference on pages 321–328.

[21] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. arXiv, 1409.1556:1–14, 2015.

[22] F. Martínez, E. Jacinto, and H. Montiel. Neuronal environmental pattern recognizer: Optical-by-distance lstm model for recognition of navigation patterns in unknown environments. In 4th International Conference Data Mining and Big Data (DMBD 2019), volume 1071, pages 220–227, 2019.

[23] J. Galvis and J. Madrid. Sistema de control difuso para motor de corriente continua sin escobillas (bldc) sobre hardware embebido. Tekhnê, 13(2):43–48, 2016.

[24] A.V. Rendón. Design and evaluation of volume unit (vu) meter from operational amplifiers. Tekhnê, 16(2):31–40, 2019.

[25] J. Suto and S. Oniga. Efficiency investigation from shallow to deep neural network techniques in human activity recognition. Cognitive Systems Research, 54:37–49, 2019. ISSN 1389-0417.

[26] S. Kumari, A. Kumar, and P. Kumar. Maturity status classification of papaya fruits based on machine learning and transfer learning approach. Information Processing in Agriculture, 2020. ISSN 2214-3173. doi: https://doi.org/10.1016/j.inpa.2020.05.003.

[27] C. Quintero, F. Merchán, A. Cornejo, and J. Galán. Uso de redes neuronales convolucionales para el reconocimiento automático de imágenes de macroinvertebrados para el biomonitoreo participativo. KnE Engineering, 3(2):585–596, Feb. 2018. doi: 10.18502/keg.v3i1.1462.

[28] X. Zhao, H. Li, Q. Zhu, M. Huang, Y. Guo, and J. Qin. Automatic sweet pepper detection based on point cloud images using subtractive clustering. International Journal of Agricultural and Biological Engineering, 13(3):154–160, 2020. doi: 10.25165/j.ijabe.20201303.5460.

[29] T. Wang, H. Huang, J. Lin, C. Hu, K. Zeng, and M. Sun. Omnidirectional cnn for visual place recognition and navigation. In 2018 IEEE International Conference on Robotics and Automation (ICRA), pages 2341–2348, May 2018. doi: 10.1109/ICRA.2018.8463173.

[30] B. Shree, R. Brunda, and N. Rani. Fruit Detection from Images and Displaying Its Nutrition Value Using Deep Alex Network: Proceedings of ICSCSP 2018, Volume 2, pages 599–608. 01 2019. ISBN 978-981-13-3392-7. doi: 10.1007/978-981-13-3393-4_61.

[31] L. Melo and A. Orozco. Technical efficiency for colombian small crop and livestock farmers: A stochastic metafrontier approach for different production systems. Journal of Productivity Analysis, 47(16):1–16, 2017. doi: 10.1007/s11123-016-0487-x.

[32] R. Gil, C. Bojacá, and E. Schrevens. Understanding the heterogeneity of smallholder production systems in the andean tropics – the case of colombian tomato growers. NJAS - Wageningen Journal of Life Sciences, 88(1):1–9, 2019. doi: 10.1016/j.njas.2019.02.002.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[33] J. Ramirez, M. Salazar, A. Jarvis, and C. Navarro. A way forward on adaptation to climate change in colombian agriculture: perspectives towards 2050. Climatic Change, 115(1):611–628, 2012. doi: 10.1007/s10584-012-0500-y.

[34] F. Martínez, C. Hernández, and F. Martínez. Evaluation of deep neural network architectures in the identification of bone fissures. TELKOMNIKA Telecommunication, Computing, Electronics and Control, 18(2):807–814, 2020. ISSN 1693-6930. doi: 10.12928/TELKOMNIKA.v18i2.14754.

[35] K. Zhang, Y. Guo, X. Wang, J. Yuan, and Q. Ding. Multiple feature reweight densenet for image classification. IEEE Access, 7:9872–9880, 2019. doi: 10.1109/ACCESS.2018.2890127.

[36] F. Saxen, P. Werner, S. Handrich, E. Othman, L. Dinges, and A. Al-Hamadi. Face attribute detection with mobilenetv2 and nasnet-mobile. In 2019 11th International Symposium on Image and Signal Processing and Analysis (ISPA), pages 176–180, Sep. 2019. doi: 10.1109/ISPA.2019.8868585.