MULTILAYER PERCEPTRON NEURAL NETWORK FOR THE PREDICTION OF THE RIPENING STAGES OF FRUITS AND VEGETABLES

Hernández-Aguirre J.A., Arzola-Flores J.A., Vidal-Robles E., Saviñon-Flores M.F., Maldonado-García A., Guarneros-Bejarano G., Rojas-Rodríguez J.F., Hernández Santiago A.A.

Meritorious Autonomous University of Puebla

Puebla, C.P. 71590, Mexico; e-mail: ximikad09@mail.ru

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Abstract. We propose the implementation of Machine Learning techniques for the classification of fruits and their ripening days using photographs of them. As a supervised learning method, a multilayer perceptron neural network was used. The results obtained from the neural network were compared with the K-nearest neighbors method through a Bayesian t-test, finding that the neural network is a better classifier of the type of fruit. Finally, Hierarchical Clustering was used to determine the ripening days of the fruits. The results obtained show that it is possible to generalize the neural network to improve its precision by increasing the variety of fruits and the size of the database.

Key words: *neural network, ripening stages, prediction.*

INTRODUCTION

Currently, due to the food demands of society and environmental problems, the supply of food to places increasingly distant from the place of production has become increasingly important [1,2], so producers have been in need to implement technological tools to guarantee the correct distribution of products [3], that is to say, they have had to achieve essential improvements in their logistics processes to ensure that their products arrive quickly at their destination and with the quality expected by the consumer. To guarantee the quality of their products, producers have currently implemented sensing mechanisms that allow products to be monitored during transport, and they have used sensors for temperature, humidity, color, the concentration of gases, etc., however, in most of the Sometimes, they are usually expensive and therefore inaccessible to producers [3, 4]. Thanks to the development of Artificial Intelligence (AI), it has been possible to equip computers with a learning capacity through the acquisition of experience; that is, it is possible to include computational algorithms from a series of data to endow them with the ability to recognize patterns [5]. Within the AI, there is a branch of Machine Learning, which is divided into supervised learning and unsupervised learning time [6, 7]. The first is to give it a series of data with its characteristics and label. In such a way, the algorithm through different evaluation techniques learns patterns so that later, it can be used to predict the label, only knowing the characteristics of the base of data. Supervised learning, in turn, is divided into classification and regression [7]. The classification is used when the variable to be predicted is categorical, while the regression is used when the variable to be predicted is numerical [6, 7]. On the other hand, unsupervised learning, as its name says, does not require knowing the label of the characteristics of the database, so it is used to determine if the data has some pattern of behavior or to perform a reduction in dimensions of the database [7]. At this point, it is possible to distinguish the immense possibility of solutions that the AI gives us for the problem of determining the quality of food products during transport, so it is possible to use a supervised learning algorithm to classify the different stages of ripening and quality of fruits and vegetables, for example using the data obtained through a humidity, color sensor, etc., or only through a photograph, so in this work, the implementation of a multilayer perceptron neural network is proposed [8] and combined with the convolutional neural network (CNN) SquezeeNet [9, 10] to classify first, between two types of fruits, apples and bananas and later, to carry out the classification of the stage of maturation in days using only photographs.

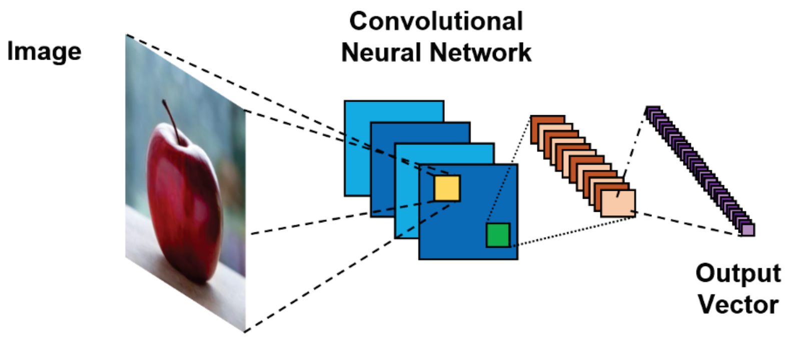

Figure 1. Schematic representation of embedded images on CNN SquezeeNet. A vector of dimension 1000 is obtained from each image

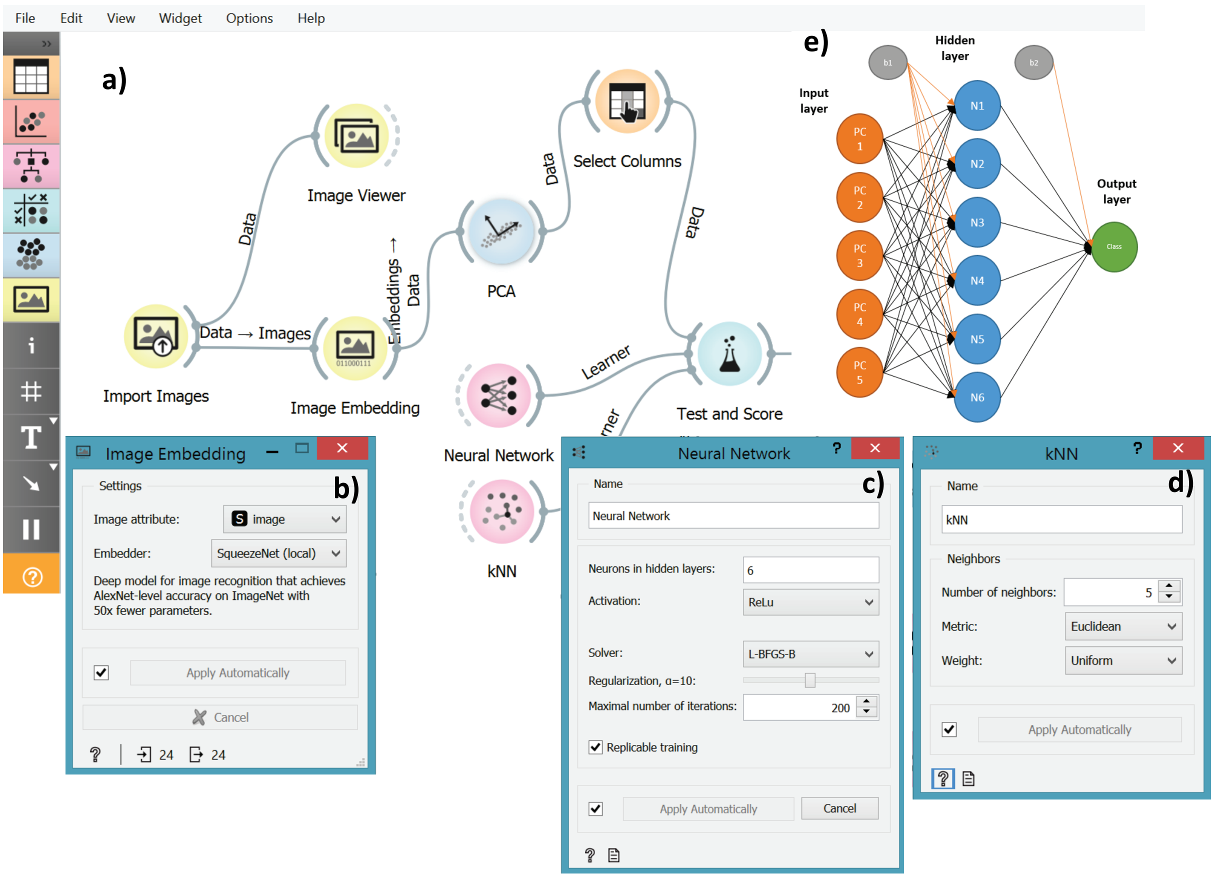

Figure 2. Orange interface for image processing, a) typical orange workflow, which is a visual toolbox with widgets that allows you to perform a large number of calculations, b) window that shows the “Image embedding” widget, in which the CNN SqueezeNet to embed the images, c) a window that shows the “Neural Network” widget for tuning the hyperparameters of the MLP, d) a window that shows the kNN widget for tuning hyperparameters of the k-Nearest Neighbors supervised learning model, and lastly e) achitecture of MLP

METHODOLOGY

To carry out this study, photographs of bananas and apples at different ripening stages were obtained using a standard cell phone camera (Samsung Galaxy J6, 13 MP camera, LED flash, f / 19). Once the images were obtained, the images were embedded using the transfer learning technique, which is an AI technique used to classify the images [10, 11]. Transfer learning consists of pre-training CNN with a large number of images to provide you with a certain degree of learning or experience. Later, this learning can be used to classify images of another very different problem. CNN SquezeeNet has been pre-trained with the ImageNet database [9, 10]. This CNN is used as an extractor of characteristics or descriptors (vectorize the images), obtaining a vector of dimension 1000 for each image (Fig. 1). Once the descriptors were obtained, a principal component analysis (PCA) was applied to extract the five principal components (PC), which explain 90% of the total variance (Fig. 2) [12]. Subsequently, the PC were used to train an MLP, which consisted of 1 hidden layer, with six neurons, with rectified linear activation function, Ridge penalty or regularization (L2 = 10), a constant learning rate ($\eta = 0.001$), a numerical tolerance of 1E-04, a maximum number of iterations of 500 and L-BFGS [7, 8] was used as the optimizer of the MLP weights. Finally, as a training, validation, and testing method, stratified 10-fold cross-validation was used (Fig. 2). The confusion matrix of the MLP classifier was obtained in order to obtain the Classification accuracy (CA), F1-score (F1), Precision and Recall metrics [7, 8]. The results obtained from the MLP were compared with the K-nearest-neighbors (KNN) algorithm with five nearest neighbors, Euclidean metric and uniform weight through a Bayesian t-test [13]. The Orange Data Mining software was used for the analysis presented in this work (https://orange.biolab.si/) [10, 14].

RESULTS AND DISCUSSION

Figure 3 shows the results obtained from the classification of the type of fruit using MLP and KNN as supervised learning methods. In Figure 3a) see the classification metrics for MLP and KNN, appreciate higher classification precision for all metrics in MLP method (CA = 0.833, F1 = 0.829, Precision = 0.875 and Recall = 0.833) compared to KNN method (CA = 0.792, F1 = 0.782, Precision = 0.853 and Recall = 0.792), which can be clearly seen in Figure 3b) where the MLP confusion matrix is shown, that is, the 12 images of the apples have been correctly classified, while 4 images of bananas

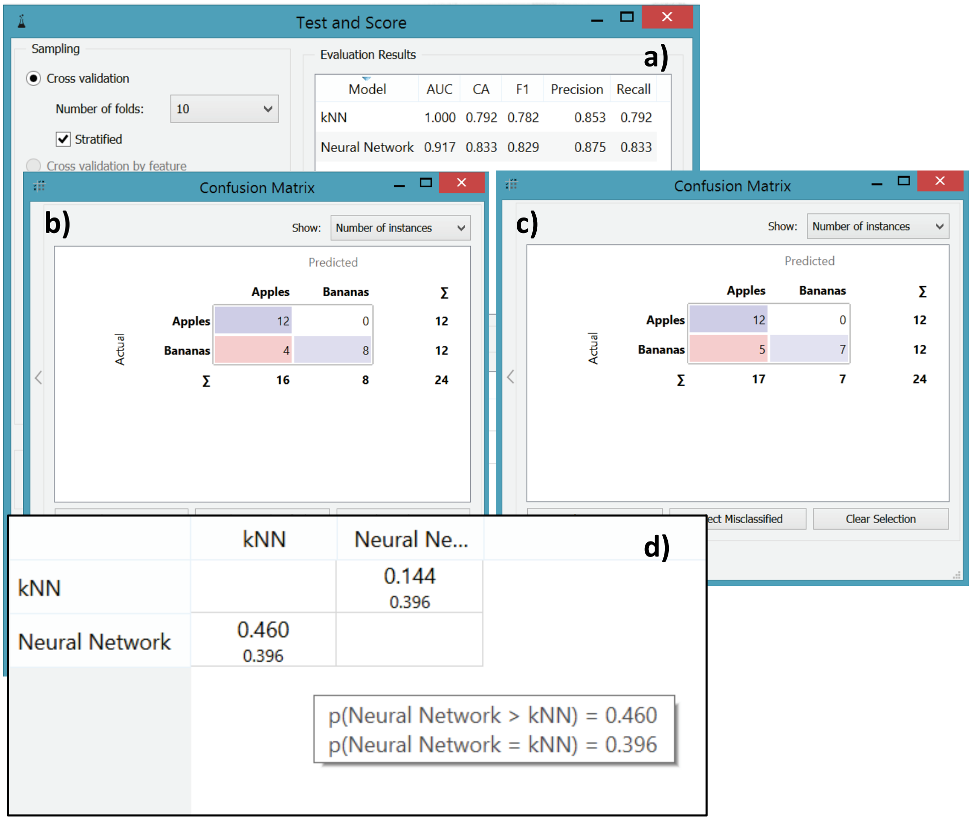

Figure 3. Results obtained from Orange, a) window that shows the widget "Test and Score," in it you can distinguish the evaluation technique (stratified 10-fold cross-validation) and the classification metrics, b) confusion matrix of the MLP method, in which it is identified that four images of bananas have been incorrectly classified as images of apples, c) KNN method confusion matrix, where it can be seen that five images of bananas have been incorrectly classified as images of apples, and lastly d) Bayesian t-test that shows that the MLP method is indeed a better classifier than the KNN method for the problem raised in this work

have been incorrectly classified as images of apples. On the other hand, Figure 3c) shows the confusion matrix of the KNN method, which shows that 12 images of apples have been classified correctly, while five images of bananas have been incorrectly classified as apples; therefore, the classification metrics of the KNN method are lower than those of the MLP method. However, to test if those differences are significant, a Bayesian test procedure [12] is performed, the results of which are considered in Figure 3d). This figure shows the probability that the method in the rows is a better classifier than the method in the columns; the small numbers inside the boxes show the probability that the difference is negligible. As can be seen p(Neural network> KNN) = 0.460, compared to p(KNN> Neural network) = 0.144 and p(Neural network = KNN) = 0.396, so the MLP method is a better classifier (for the problem posed in this work) than the KNN method. However, the MLP method classification metrics are still less than 0.9, so it is necessary to generalize the model, increasing the size of the database and test it with different evaluation techniques.

On the other hand, Figure 4a) shows the implementation of unsupervised learning to determine the existence of any pattern on the days of ripening from the images of the bananas. In Figure 4b), the “Distances” widget is shown, which calculates the distance between rows in the database (in this case formed by the 5 PC extracted after embedding the images with CNN SqueezeNet), to apply a Hierarchical Clustering to determine if possible clusters or groups [15]. As shown in Figure 4c), the resulting dendrogram is seen, observing four groups, which correspond to the days of maturation. With the above, it is possible to distinguish the days of ripening using only photographs of the fruits.

CONCLUSIONS

From the models compared in this work, we can conclude that the MLP is a better classifier than the KNN method, so it is possible to generalize the MLP method by increasing the variety of fruits and vegetables and incrementing the number of photographs. We can conclude that unsupervised learning, precisely the Hierarchical Clustering method, can determine the stages of fruit ripening using only photographs.

With the results obtained in this work, it is clear that it is possible to implement Machine Learning tools to classify between different types of fruits and their ripening stages, which may allow creating a mobile application that processes the photographs of the fruits in real-time, thereby decreasing the cost of food shipping losses.

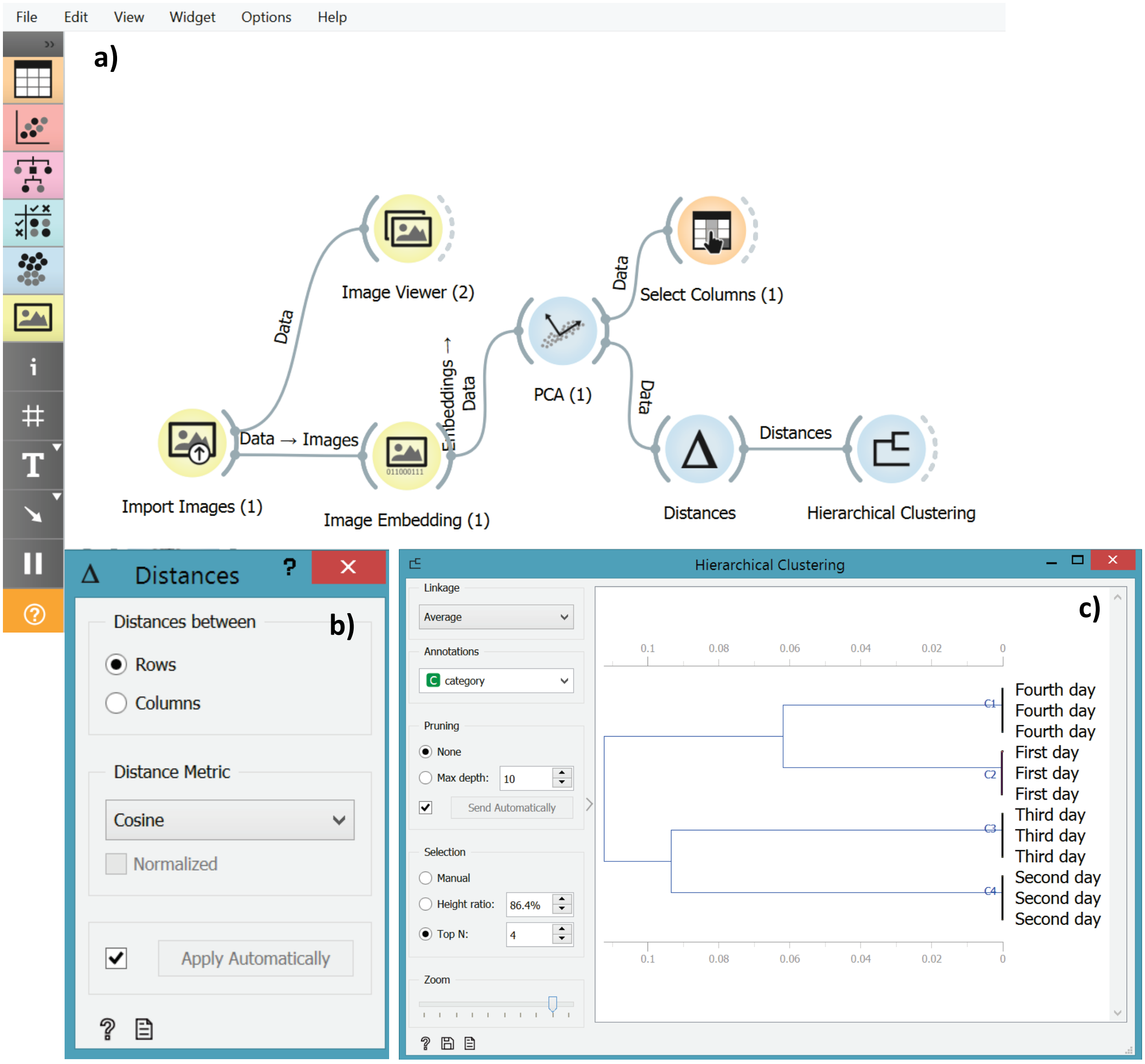

Figure 4. Results obtained from applying unsupervised learning to determine the ripening stage in days of bananas, a) workflow of the unsupervised learning method. The images are embedded with CNN SqueezeNet, which outputs a vector of dimension 1000 for each image. Vectorized the images, we proceed to extract the five PC, which explains 90% of the total variance. Obtained the PC, we continue to get the matrix of distances between rows of the PC to apply the Hierarchical Clustering subsequently and obtain the dendrogram, b) window that shows the "Distances" widget and finally, c) widget window "Hierarchical Clustering" which shows the dendrogram as a result

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