Identification of Diseases and Pests in Tomato Plants Through Artificial Vision

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Abstract. The extraction of characteristics, currently, plays an important role, likewise, it is considered a complex task, allowing to obtain essential descriptors of the processed images, differentiating particular characteristics between different classes, even when they share similarity with each other, guaranteeing the delivery of information not redundant to classification algorithms. In this research, a system for the recogntion of diseases and pests in tomato plant leaves has been implemented. For this reason, a methodology represented in three modules has been developed: segmentation, feature extraction and classification; as a first instance, the images are entered into the system, which were obtained from the Plantvillage free environment dataset; subsequently, two segmentation techniques, Otsu and PCA, have been used, testing the effectiveness of each one; likewise, feature extraction has been applied to the dataset, obtaining texture descriptors with the Haralick and LBP algorithm, and chromatic descriptors through the Hu moments, Fourier descriptors, discrete cosine transform DCT and Gabor characteristics; finally, classification algorithms such as: SVM, Backpropagation, Naive Bayes, KNN and Random Forests, were tested with the characteristics obtained from the previous stages, in addition, showing the performance of each one of them.

Keywords: Tomato diseases · Artificial vision · Feature extraction

1 Introduction

Currently, México has an important role in exporting a great diversification of open-air crops; with a production percentage of 97.7%, and protected agriculture (greenhouses) of 2.3%; in addition, of the total tomato production, 60.8% [1] are obtained from protected environments; Chiapas is the main producer of coffee in protected environments, Guanajuato of broccoli, Mexico City of christmas eve and Sinaloa of tomato; therefore, in the country the number of greenhouses has increased; achieving an increase in production per plant and fruit quality; these results have been get with the implementation of new automated methods for the care of greenhouses, such as: controlling temperature, humidity and lighting; impacting on the care of planting,

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nutrition, growth and harvest of it. However; producers have reported economic declines, due to diseases y pests that have attacked tomato plants. Some of the most common diseases in tomato plants, the following are considered: root rot, bacterial cancer of the tomato, freckle and bacterial spot, leaf mold, gray mold, early blight, late blight and dusty ashes [2], presented by variations in humidity, drought, temperature, residues of previous crops, wind, insects, overcast and negligence of greenhouse operators; diagnosing the disease, through the root, stem, leaf or fruit. After the identification of any anomaly in the plant, the producer goes to experts to accurately diagnose the disease, which is considered a late detection and with a certain degree of progress; likewise, the recommended dose of some pesticide or fungicide is applied to control and/or eliminate the disease, generating additional expenses. One of the main causes of loss of tomato production is the inaccurate identification of pests and diseases; for this reason, artificial vision algorithms have identified early and accurately: leaf mold, late blight, early blight, bacterial spot, septoria leaf spot, target spot, tomato mosaic virus, tomato yellow leaf curl virus, spider mites two-spotted and a completely healthy class, in tomato plant leaves, avoiding the excessive application of chemical products to combat diseases and pests, reducing the impact on plants and humans, in addition, contributing to the decrease in production loss and reducing financial losses.

2 State of the Art

Today, computer science, has been dedicated to solving problems in the environment in which we live, likewise, digital image processing and machine learning, among others, are considered areas that have stood out and have become fundamental techniques for this purpose. In this section, a study of investigations focused on the agricultural area is proposed, likewise, the works focus on the proposal of methods to solve different topics, such as: classification and recognition of leaves and identification of diseases and pests in leaves of different plants; solved with computer vision techniques. Plants, in their gender diversity, are currently of great importance, since they have a primary role for all living beings, and their development in all their environment; therefore, researchers who are in charge of the study and classification of plants, make the detection, through ocular methods, considering an inaccurate procedure; however, in literature, there are works focused on leaves recognition, achieving its mission with its own proposals with deep learning techniques, specifically, convolutional neural networks CNN, comparing performance with existing ones [3, 4]; on the other hand, the identification and classification of plants, through leaves that share similarities with each other, is a complex task, in previous works, this problem has been solved with the implementation of extraction techniques and selection of characteristics, considering color, shape and texture, classifying with machine learning algorithms, obtaining favorable results [5–8].

In addition, numerous works have been carried out; where, different methods are proposed to detect and classify diseases in leaves of different plants, through computer vision techniques [9]; likewise, in previous works, researchers have contributed in the field of segmentation, in color images and grayscale, considered an area with great opportunities, since it is still rigorously studied, both in controlled and non-controlled environments controlled; therefore, in-depth reviews of work related to color image segmentation have been developed [10], being a topic with a lot of impact, since it influences the performance of the classification algorithms; in addition, other works have segmented with the implementation of modified fully-convolutional networks FCNs through the leaves [11].

As previously mentioned, crops are affected by the unwanted arrival of pests [12] and diseases [13], both in protected environments and in the open air, likewise, this directly impacts production, reducing the financial balances of producers; therefore, computer science has made a great contribution trying to solve this problem, however, the resolution has not reached the top. In previous investigations, they have developed disease detection in different plants, using GWT feature extraction techniques and classifying with support vector machines SVM [14], on the other hand, improvements to CNN models have been proposed, based on CNN VGG, recognizing diseases, through the leaves [15] and the trunk of the plant [16].

Also, with the wave of deep learning implementation, it has taken a lot of strength and they have sought to solve multidisciplinary problems; however, and without lagging behind, CNN networks have been evaluated for the detection of diseases and pests in tomato plants [17]; as well as, both deep learning and machine learning techniques have been merged for the same purpose [18].

On the other hand, in the literature, the systems of detection and identification of diseases in tomato plants, through the leaves, deep learning, have turned to see with great momentum, since CNN networks have been implemented and evaluated, monitoring the performance of each proposed architecture [13, 19, 20]; without leaving behind, the development of robotic systems in conjunction with methods of computer vision [21]. The development of this research, has stood out for the low computational cost compared to [13, 20], since for training and testing, they use additional hardware or completely dedicated computing; likewise, for this proposed system, a portable computer equipment with mid-level characteristics has been used, considering taking the application to a real and/or mobile environment.

3 Methodology

In this section, a modular system was proposed that allows the precise identification of diseases and pests in tomato plant leaves, based on the implementation of characteristic extraction techniques and artificial intelligence algorithms, contributing to the reduction of financial losses and the excessive application of chemical products in crops, reducing their consumption in humans and plants. The adopted method is represented by three modules, segmentation, feature extraction and classification. For this work, a portable computer equipment has been used, with the following characteristics: MacBook Pro, Intel Core i5 2.6 GHz, 8 GB of memory (Fig. 1).

3.1 Segmentation

The experimentation applied in this section was executing the segmentation algorithm adaptive border Otsu [22, 23] and a phase of principal component analysis PCA [21]. By successfully segmenting an image, the system uses only the region of interest,

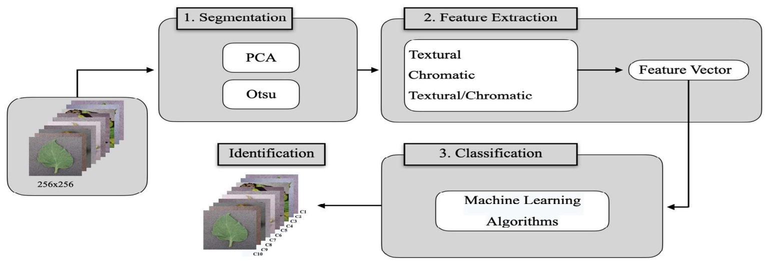

Fig. 1. Methodology used.

determining its edges and calculating properties by extracting features of textural, chromatic and textural/chromatic. Likewise, the segmentation results with both techniques are very similar, in some cases identical, so it was not necessary to use any technique such as: Probabilistic Rand Index (PRI), Variation of Information (VoI) and Boundary Displacement Error (BDE). In the Fig. 2, is shows the execution of segmentation methods on images of tomato plant leaves, in row one, there are images in RGB format; in row two, images segmented with the PCA algorithm and finally in row three, segmented images with Otsu.

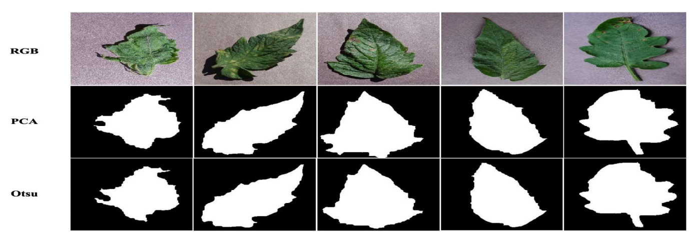

Fig. 2. Segmentation with PCA and Otsu.

3.2 Feature Extraction

The extraction of characteristics is a delicate process and is considered a cornerstone for machine learning algorithms, the correct implementation of extraction methods, define the descriptors gathered for the process of recognition of diseases and pests in tomato plant leaves. Furthermore, the characteristics obtained are invariant to scaling, rotation and translation, allowing the classifier to recognize objects despite having different size, position and orientation. Developing a comparative analysis with two methods of extraction of characteristics; textural features, chromatic features and the combination of both, textural/chromatic, measuring the performance of the system with machine learning classifiers on the Plantvillage dataset.

Textural Features. These structures give rise to a property that can be roughness, harshness, granulation, fineness, smoothness, among others. The texture is invariant to displacements, because it repeats a pattern along a surface, therefore, it is explained why the visual perception of a texture is independent of the position. The texture characteristics are extracted from the surface of the leaf, manifesting with variations in the region of interest, for this purpose the Haralick [24] algorithm has been implemented, using co-occurrence matrices of gray levels. The vector of textural features X_t obtained can be represented as: $Xt = [x_1, x_2, \ldots, x_{85}]$ and $Xt = [x_{Rlbp}, x_{RH}, x_{Glbp}, x_{GH}, x_{Blbp}, x_{BH}]$; where $x_{Rlbp}, x_{Glbp}, x_{Blbp}$ represent the characteristics Local Binary Patterns (LBP) [25, 26] obtained in the color channel R, G and B respectively, x_{RH}, x_{GH} and x_{BH} represent the textural characteristics of Haralick obtained in the channels R, G and B respectively.

Chromatic Features. Color characteristics provide a lot of information, and can be extracted starting from a specific color space, basically, are obtained starting from three primary channels, such as RGB, hue saturation value HSV and grayscale, among others, locating descriptors through different algorithms, considering: Hu moments, Fourier descriptors, discrete cosine transform DCT y characteristics of Gabor. The Hu moments [27], integrate information of the color variable of the region of interest; likewise, other characteristics were obtained with the Fourier descriptors, calculated using: $d_u = |F(u)|$; where $F(u)$ is calculated for $u = 1, \ldots, N$, where N is the number of descriptors to calculate. The discrete cosine transform DCT, use base transformations and cosine functions of different wavelengths. A particularity about DCT in relation to the discrete Fourier transform DFT, is the limitation to the use of real coefficients. On the other hand, they were used the characteristics of Gabor [14, 28], it is considered another robust technique, used for the extraction of features in images; being a hybrid technique, composed of the nucleus of the Fourier transformation on a Gaussian function.

3.3 Classification

In this section, machine learning algorithms have been used to classify leaves images; identifying ten different classes, including eight diseases, a plague and a completely healthy class; likewise, the performance of each of them is measured. The classifier, support vector machines (SVM), ANN Backpropagation, Naive Bayes, K-Nearest Neighbours (KNN) and Random Forests, were tested with different feature extraction techniques.

Support Vector Machines (SVM). SVM is one of the most widely used classification methods in recent years. The main characteristic that identifies it, is the use of kernels when working in non-linear sets, the absence of local minima, the solution depends on a small subset of data and the discriminatory power of the model constructed by optimizing the separability margin between the ten classes. When this is not possible, a function called Kernels is used, which transforms the input space to a highly dimensional space, where the sets can be linearly separated after the transformation. However, the choice of a function is restricted to those that satisfy the Mercer conditions [29].

ANN Backpropagation. Humans, to solve problems of daily life, take prior knowledge, acquired from the experience of some specific area, likewise, artificial neural networks, collect information on solved problems to build models or systems that can make decisions automatically. The multiple connections between neurons, form an adaptive system, the weights of which are updated using a particular learning algorithm. One of the most used ANN algorithms and the one that was implemented in this work was backpropagation (BP); which in general, performs the learning and classification process in four points; initialization of weights, forward spread, backward spread and the updating of weights. For further analysis of the BP algorithm, refer to [30].

Naive Bayes. A Bayesian classifier uses a probabilistic approach to assign the class to an example. Be C the class of an object, that belongs to a set of m class (C_1, C_2, …, C_m) and X_k is object with k characteristics $X_k = [x_1, x_2, \ldots, x_k]$, for this case, the set of characteristics defines a specific disease. For further analysis of the algorithm, refer to [31].

K-Nearest Neighbours (KNN). KNN, classifies a new point in the dataset, based on Euclidean distance, finding the k closest distances to the object to classify, later, the class of the closest point in the dataset is assigned by majority vote [32].

Random Forests. Random Forests is an algorithm composed of decision tree classifiers, each tree depends on the values of a random vector con with sampling independently and with the same distribution for all trees in the forests. Generalization error for forests converges to a limit, as the number of trees in the forest increases. When a model is generalized and fails, depends on the strength of individual trees in the forest and the correlation between them. By randomly selecting features to divide each node, error rates occur that compare favorably with the Adaboost algorithm but are more robust with respect to noise. For further analysis of the algorithm, refer to [33].

4 Experimental Results

In this section, the description of the metrics, the used dataset is presented, and the analysis of the results obtained, product of the experimentation developed for this proposed method. The selection of parameters is a very essential step, since a good selection of parameters has a considerable effect on the performance of the classifier. In all the classifiers used, the optimal parameters were obtained through cross validation. In the experiments carried out, cross validation with $k = 10$ was used to validate results, that is, 10 tests were performed with 90% and 10% of the data for training and testing respectively.

4.1 Metrics

In the experimental results presented in this research the evaluation metrics used for classification were the following.

Accuracy: represents the portion of instances that are correctly classified, out of the total number of cases, $Acc = \frac{TP + TN}{TP + TN + FP + FN}$; Precision: for each classifier used, performance was evaluated with this metric, getting the correct values of the classifier between the total of the dataset, $\Pr ecision = \frac{TP}{TP + FP}$; Recall: other metric used, is Recall, where, represents the number of positive predictions divided by the number of positive class values in the test data. Recall can be thought of as a measure of a classifiers completeness, $\mathrm{Re}call = \frac{TP}{TP+FN}$; F-Measure: can be interpreted as a weighted average of the precision and recall, where an its best value is 1 and worst score is 0, $F - Measure = \frac{2*precision*recall}{precision+recall}$; true positive rate (TP Rate), $TP \ \ Rate = \frac{TP}{TP+FN}$; false positive rate (FP Rate), $FP \ \ Rate = \frac{FP}{FP+TN}$; MCC: is Matthews Correlation Coefficient, is used in machine learning as a measure of the quality of binary classifications, $MCC = \frac{(TP*TN)-(FP*TN)}{\sqrt{(\mathrm{TP+FP})(\mathrm{TP+FN})(\mathrm{TN+FP})(\mathrm{TN+FN})}}$; ROC Area: is Receiver Operating Characteristic, the ROC curve is defined by sensitivity, which is the true positive rate and 1-specificity, which is the false positive rate; and PRC Area: is Precision Recall Curve, is a plot of precision of positive predictive value against the Recall.

4.2 Dataset

In the process of the development of a disease or pest, the symptoms and the sign are factors that appear on the surface of the leaf, likewise, between these two stages there are some very similar visual characteristics; therefore, it is a complex task for machine learning algorithms to discriminate between classes. In the experimentation developed in this work, a free environment dataset has been used, Plantvillage [13, 18–20]; composed of ten different classes, eight diseases, such as: C1 = tomato mosaic virus with 373 images, C2 = leaf mold with 952, C3 = early blight with 1000, C4 = target spot with 1404, C7 = septoria leaf spot with 1771, C8 = late blight with 1908, C9 = bacterial spot with 2127 and C10 = tomato yellow leaf curl virus with 5357; and a plague, C6 = spider mites two-spotted with 1676 images, in addition to the C5 = completely healthy class with 1591 images; adding a total of 18159 processed images, the images are in a RGB color space with dimensions of 256x256 pixels, see Fig. 3. In the Fig. 3, some classes visually share color and texture characteristics; for example: classes C1, C2, C3, C6 and C10 have color characteristics in common; classes C3, C7 and C8 share color and texture characteristics; finally classes C7 and C9 have small brown spots; however, despite the similarities, the algorithms used in this work have managed to discriminate each class. The Plantvillage dataset has demonstrated its effectiveness; even when it's out of balance; this has been achieved under the implementation of performance metrics, defined in Sect. 4.1.

4.3 Experimental Results

In this section, the results of the different experiments carried out are shown, displaying the models build times, see Table 1; detailed accuracy by class, see Table 2 and Table 5; percent correctly classified instances, see Table 3 and Table 4, and comparison of results with two segmentation methods, see graph of the Fig. 4.

Build Times of the Models. The Table 1, shows the performance of the construction times of the models, considering the Naive Bayes, Backpropagation, KNN, Random Forests and SVM algorithms. The classifiers performed this calculation with different

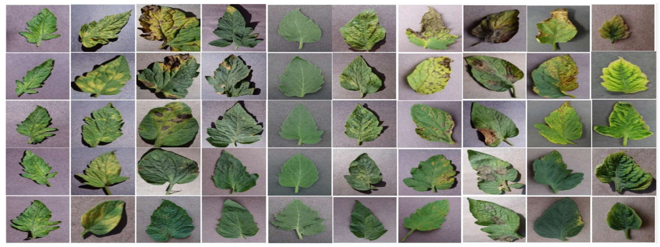

Fig. 3. Dataset Plantvillage.

Table 1. Build times of the models.

	Otsu			PCA		
Classifier	T	C	T/C	T	C	T/C
Naive Bayes	0.32	0.92	1.13	0.3	0.97	1.14
Backpropagation	507.2	7403.48	12817.64	499.51	7718.28	12417.69
KNN	0.01	0.01	0.01	0.15	0.02	0.01
Random Forests	21.59	34.63	32.07	22.46	34.3	32.41
SVM	1754.61	914.96	570.3	1982.99	528.07	459.66

Table 2. Results by class, with segmentation Otsu, textural/chromatic features and classification SVM.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
C1	0.923	0.002	0.901	0.923	0.912	0.910	0.997	0.897
C2	0.914	0.006	0.884	0.914	0.899	0.893	0.986	0.855
C3	0.854	0.010	0.831	0.854	0.842	0.833	0.969	0.758
C4	0.899	0.010	0.881	0.899	0.890	0.881	0.983	0.837
C5	0.981	0.002	0.981	0.981	0.981	0.979	0.998	0.981
C6	0.929	0.007	0.929	0.929	0.929	0.922	0.991	0.898
C7	0.890	0.009	0.903	0.890	0.896	0.887	0.983	0.861
C8	0.879	0.012	0.893	0.879	0.886	0.872	0.975	0.837
C9	0.950	0.006	0.954	0.950	0.952	0.945	0.990	0.928
C10	0.977	0.008	0.982	0.977	0.979	0.970	0.994	0.977

techniques of processing digital of images, applied to the dataset, such as: segmentation Otsu and PCA; extraction of characteristics, considering, T = Textural, C = Chromatic and the combination of both T/C = Textural/Chromatic. The results show that the shortest processing time was obtained by the KNN algorithm, while Backpropagation was the most costing. For these results, the unit of measurement is expressed in seconds.

Table 3. Results with segmentation Otsu, textural features, chromatic features and both textural/chromatic.

Classifier	Textural	Chromatic	Textural/Chromatic
Naive Bayes	37.86%	38.26%	40.37%
Backpropagation	81.44%	87.69%	82.21%
KNN	72.39%	74.59%	79.66%
Random Forests	76.17%	79.67%	81.95%
SVM	88.87%	91.73%	**93.46%**

Table 4. Results with segmentation PCA, textural features, chromatic features and both textural/chromatic.

Classifier	Textural	Chromatic	Textural/Chromatic
Naive Bayes	39.12%	44.76%	46.13%
Backpropagation	81.81%	88.27%	81.46%
KNN	73.57%	76.10%	80.23%
Random Forests	77.27%	80.77%	82.77%
SVM	89.81%	92.71%	**93.86%**

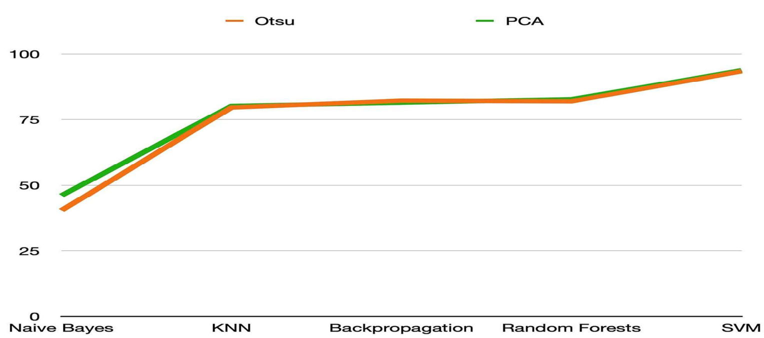

Fig. 4. Graph of results with two segmentation methods.

Results with the Otsu Segmentation Method. In this part of the article, are shows the results obtained from executing the experimentation with the method Otsu. The Table 2, contains the detail of percentages of accuracy by class, these results, are product of the tests of the highest percentage obtained, including techniques of feature extraction of textural/chromatic, classifying with the SVM algorithm. The metrics displayed, are described in Sect. 4.1.

In the following results, Otsu was applied, in addition, SVM, Backpropagation, Naive Bayes, KNN and Random Forests; were tested with textural features, chromatic and the combination of both textural/chromatic. The best performing algorithm was SVM, obtaining a percent correctly classified instances for textural features, 88.87%, for chromatic features, 91.73% and for textural/chromatic features, 93.46%, see Table 3.

Table 5. Results by class, with segmentation PCA, textural/chromatic features and classification SVM.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
C1	0.910	0.002	0.877	0.910	0.893	0.891	0.997	0.874
C2	0.936	0.005	0.914	0.936	0.925	0.921	0.991	0.903
C3	0.853	0.012	0.805	0.853	0.828	0.818	0.967	0.738
C4	0.903	0.009	0.890	0.903	0.897	0.888	0.985	0.853
C5	0.982	0.002	0.984	0.982	0.983	0.982	0.999	0.984
C6	0.918	0.008	0.916	0.918	0.917	0.909	0.990	0.887
C7	0.916	0.006	0.933	0.916	0.924	0.917	0.986	0.895
C8	0.881	0.010	0.909	0.881	0.894	0.882	0.977	0.850
C9	0.950	0.006	0.955	0.950	0.952	0.945	0.991	0.930
C10	0.981	0.007	0.984	0.981	0.982	0.974	0.995	0.980

Results with the PCA Segmentation Method. In this part of the article, are shows the results obtained from executing the experimentation with the method PCA. The Table 5, contains the detail of percentages of accuracy by class, these results, are product of the tests of the highest percentage obtained, including techniques of feature extraction of textural/chromatic, classifying with the SVM algorithm. The metrics displayed, are described in Sect. 4.1.

In the following results, PCA was applied, in addition, SVM, Backpropagation, Naive Bayes, KNN and Random Forests; were tested with textural features, chromatic and the combination of both textural/chromatic. The best performing algorithm was SVM, obtaining a percent correctly classified instances for textural features, 89.81%, for chromatic features, 92.71% and for textural/chromatic features, 93.86%, see Table 4.

In the Fig. 4, the best results of this research are observed, considering the algorithms, the percent correctly classified instances and the features textural/chromatic. The orange line belongs to the tests with segmentation Otsu, and the green line to the tests with segmentation PCA. The highest percent was obtained with segmentation PCA, except, in the backpropagation algorithm.

5 Conclusion

Derived of analysis, the applied digital image processing techniques, the integration of classification algorithms and the experimentation carried out; it was shown, that by combining the segmentation PCA method, the conjunction of textural/chromatic feature extraction, and the SVM classification process, the system has achieved a performance of 93.86% respectively. The main contribution of the method developed in this research, is the identification of diseases and pests in tomato plant leaves early and accurately, reducing the financial losses and the excessive application of chemical products, minimizing the affectation to plants and human beings; likewise, the proposed system can be implemented in a real and/or mobile environment, since the computational cost is low compared with other works, and can be executed in a portable computer equipment, without requiring additional hardware.

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