Automatic Classification of Nutritional Deficiencies in Coffee Plants

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Abstract

Classification of nutritional deficiencies, in coffee plants, is a problem for coffee farmers, since they do not have the knowledge to identify nutritional deficiencies neither receive technical assistance. Moreover, the performance of automatic classification of nutritional deficiencies based on digital image processing is affected by changes in image appearance such as: illumination, noise and acquisition conditions. In addition, some nutritional deficiencies have similar visual characteristics, such as: magnesium, manganese and iron, doing difficult to distinguish among them. In this paper, Random Forest, a machine learning technique based on decision trees, is used to classify automatically nutritional deficiencies in coffee plants, using local and global features to build the classification model. The Scale-Invariant Feature Transform (SIFT) algorithm is used to extract local features. Global features are defined based on shape and color characteristics of nutritional deficiencies. Experimental evaluation was performed using 335 images of coffee leaves with one nutritional deficiency. Results showed that global features have better performance that local features with an accuracy of 67,5%.

1 Introduction

Plants require an adequate supply of nutrients to ensure its normal growth and development. When a plant grows up without enough nutrients, its development is abnormal and characteristic symptoms appear in the plant, such as changes in the leaf size, defoliation [1], chlorosis [2], necrosis [3], die-back [4] and others.

Usually, a nutritional deficiency has characteristic symptoms that are similar in all the plants. The knowledge of these symptoms is important for taking corrective actions which restore the plant normal state. Nutritional deficiencies of coffee plants are produced by lack of micro-nutrients and macronutrients: boron, calcium, iron, magnesium, manganese, phosphorus, potassium and nitrogen.

In coffee plantations, control the correct growth and development of plants is an important issue since plants with nutritional deficiencies can be attacked by plagues which reduce the coffee production. Nutritional deficiencies are visually identified on leaves by symptoms such as: chlorosis, necrosis, shape deformation and changes in the normal leaf coloration. Thus, coffee farmers control the correct growth and development of coffee plants through the observation. In some cases, when a nutritional deficiency is detected, the coffee leaf is cut and analyzed in a laboratory to take corrective actions according to the results. However, this process is expensive and time consuming.

In the literature, there are few works about image processing of coffee leaves. Image pre-processing of coffee leaves is proposed in [3] to automatically classify nutritional deficiencies as a future work. A software solution namely 'Siscafe' for automatically classify nutritional deficiencies is presented in the research project *'Desarrollo de una herramienta tecnológica para identificación preventiva de deficiencias nutricionales en plantones de café a través de procesamiento de imágenes digitales'*. The software is available at *http://siscafe.org/index.html*. In a general context, the problem of plants classification is addressed in several works [7], [16], [9]. Leaf veins provide useful information for classifying plants. In [7] a procedure to classify 3 legume species using only morphological features calculated on the segmented venation is proposed, using Support Vector Machine, Penalized Discriminant Analysis and Random Forests. New methods for vein extraction are proposed in [16], [9]. In others works [6], [15], [14], [8], [13], machine learning techniques are used to classify plants using global features. In [6] shape, color and texture features are extracted and in [15] 12 morphological features are extracted from 1800 leaves. In both works a probabilistic neural network is used to classify 32 types of plants. Other method for plant classification using an artificial neural network is proposed in [14], using several domain-related visual features, extracted with shape, dent and vein information. Other classification method for leaves is proposed in [8], where region-based features are extracted and classification is based on dissimilarity measures between the query image and the data-set. In [13] local and global features are combined to improve the plant classification, using SIFT algorithm to extract local features and Shape Context to extract global features, and the weighted K-NN algorithm for classification.

This paper presents a Random Forest model to automatically classify nutritional deficiencies in coffee plants, using global and local features extracted from leaves. Thirteen global features are extracted using shape and color information, and

[1] Premature fall of leaves.

[2] Loss of the normal green coloration of leaves.

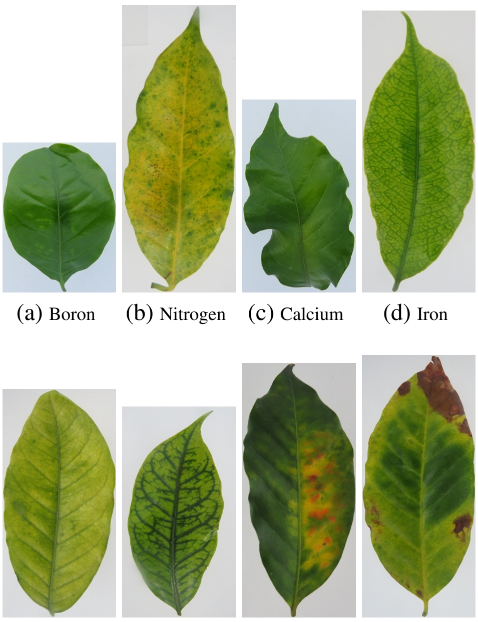
[3] Death of the most or all cells in a tissue.

[4] Plant begins to die from the tip of its leaves backward.

local features are extracted using SIFT descriptors contained in a bag of features. Results showed that global features have better performance in classification.

2 Visual symptoms of nutritional deficiencies

In healthy plants, a coffee leaf has an oval shape and an alive green coloration in the whole leaf area. The leaf apex is elongated and veins have the same alive green coloration of leaf area. In this paper, eight nutritional deficiencies are addressed and described below. Figure 1 illustrates the eight deficiencies.



(a) Boron (b) Nitrogen (c) Calcium (d) Iron

(e) Magnesium (f) Manganese (g) Phosphorus (h) Potassium

Figure 1: Nutritional deficiencies.

(a) **Boron deficiency:** Shape deformity, lack of symmetry in leaf margin and total or partial loss of the apex, in Figure 1a.

(b) **Nitrogen deficiency:** Uniform chlorosis in the whole leaf area and loss of green coloration by a yellowish color progressing from the base to the apex and from the central vein to the leaf border, in Figure 1b.

(c) **Calcium deficiency:** Shape deformation and undulations in leaf margin, in Figure 1c.

(d) **Iron deficiency:** Progressive chlorosis in leaf area, however veins remain with green coloration, in Figure 1d.

(e) **Magnesium deficiency:** The visual effects of this deficiency are similar to the visual effects of Iron deficiency, but the chlorosis is interveinal, yellow coloration appear between secondary veins, in Figure 1e.

(f) **Manganese deficiency:** Chlorosis in leaf area, principal veins remain with green coloration and a margin appear on both sides of the veins with an intense green color, in Figure 1f.

(g) **Phosphorus deficiency:** Stains with irregular shapes, yellow or reddish coloration in some leaf areas, in Figure 1g.

(h) **Potassium deficiency:** Beginning of necrosis on the leaf tip, with a yellow halo limiting it, in Figure 1h.

3 Proposed approach

The proposed approach for automatically classifying nutritional deficiencies is illustrated in Figure 2. The input is a RGB image of coffee leaf. Firstly, the image is preprocessed. Secondly, visual features are extracted by local and global descriptors. Thirdly, the extracted features are used to build a Random Forest model to classify the nutritional deficiencies of the analysed coffee leaf.

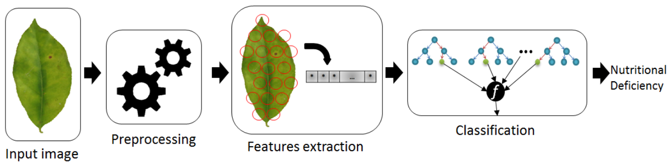


Figure 2: Flow diagram of the proposed approach.

Section 3.1 explains the preprocessing of the images, section 3.2 and 3.3 describes the local and global features respectively, and section 3.4 explains the used classifier.

3.1 Pre-processing

Leaf segmentation is performed using the Otsu algorithm [12] on the blue channel of the input image. The blue channel is selected since it has the greatest contrast in comparison with the other channels. In the obtained binary image, white pixels represent the background and black pixels represent the leaf area. Additionally, the median filter – with 3×3 window – is used to remove noise.

Finally, the image size is reduced and the background without information is removed to keep only the leaf area in order to reduce the computational cost of feature extraction.

3.2 Local feature extraction

A local feature describes properties of a pixel in relation to its neighbors. In general, an image can be described by key points. The content of interest regions around each key point can be codified by a descriptor. The most used algorithm, in the state-of-art, is the SIFT descriptor due to its performance against others descriptors [11]. In this paper, the SIFT descriptor and color information of RGB channels are chosen to construct the local feature descriptor using a Bag-of-Features method.

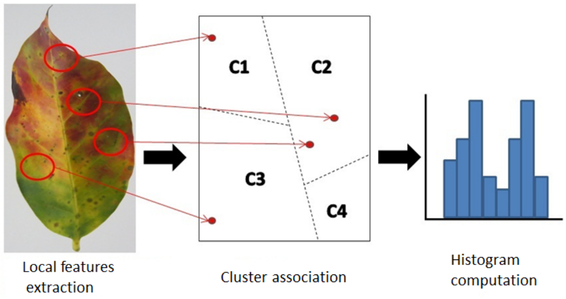


Figure 3: Illustration of the Bag-of-Features descriptor.

3.2.1 SIFT descriptor

The Scale Invariant Feature Transform (SIFT) was introduced by Lowe in [10]. SIFT is a descriptor invariant to scale, rotation, illumination and view point. The algorithm has two steps: Key points detection and key points description. Each key point is described with a vector of length 128.

3.2.2 SIFT Bag-of-Features

The objective of *Bag-of-Features* is obtain a global feature from several local descriptors [4]. *Bag-of-Features* has two steps: the visual dictionary construction and the Bag-of-Features descriptor calculation.

The visual dictionary is generated with the following steps:

1. A large image data-set of coffee leaves is selected.
2. SIFT descriptors are calculated for each image in the data-set.
3. All descriptors are quantised using the K-means algorithm and the result 'visual words' are stored.

Given an input image, the Bag-of-Features descriptor is calculated as follow:

1. SIFT descriptors are extracted from the input image.
2. Each descriptor is mapped into his respective visual word generating an histogram of length k, where k is the number of visual words in the dictionary.

This process is shown in the Figure 3.

3.2.3 Color descriptor

Color information is important to identify deficiencies such as nitrogen, potassium and phosphorus. The dominant colors in a leaf image are stored in a descriptor using the Bag-of-Features method.

The visual dictionary of the Bag-of-Features is generated with the following steps:

1. A large image data-set of coffee leaves is selected.
2. Some RGB values are extracted from each image.
3. RGB values extracted from the images are quantised using the K-means algorithm and the result 'visual words' are stored.

Given an input image, color descriptor is calculated by Bag-of-Features method as follow:

1. RGB values are extracted from the input image.
2. Each RGB value is mapped to his respective visual word, generating an histogram of length k.

3.2.4 Final local descriptor

The final local descriptor of a leaf image correspond to the concatenation of SIFT and color descriptors. In Figure 4 is illustrated this process. In this work, the number of visual words of SIFT and color dictionaries were 1000 and 15 respectively.

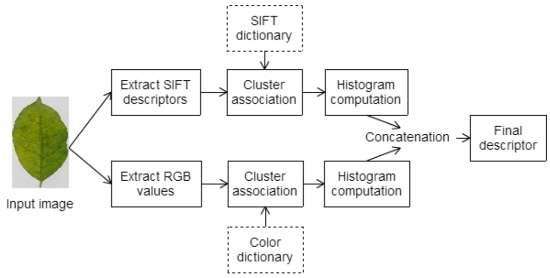


Figure 4: Illustration of the final descriptor of local features.

3.3 Global feature extraction

Global features are calculated based on shape and color information derived from the visual symptoms. In total, 13 global features, 5 shape features and 8 color features are extracted and described as follows.

3.3.1 Basic features

1. **Leaf area:** denoted by A, is calculated by counting the number of pixels segmented as leaf in a binary image.
2. **Leaf perimeter:** denoted by P, is calculated counting the number of pixels in the leaf margin.
3. **Leaf diameter:** denoted by D, is the maximum distance between two points, (x_i, y_i) and (x_j, y_j), in the leaf margin:

$$D = max\{\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}\}. \quad (1)$$

3.3.2 Shape features

Shape information is necessary to identify nutritional deficiency of boron, calcium, iron, magnesium and manganese.

1. **Apex height:** The top position (x_a, y_a) on the apex is found. Then, the distance h_1 from the position $(x_a - m, y_a)$ to the position (x_1, y_1) is calculated. In the same way, the distance h_2 from the position $(x_a + m, y_a)$ to the position (x_2, y_2) is calculated. The apex height calculation is shown in Figure 5.

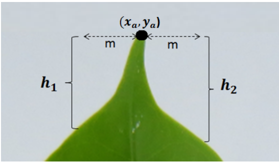


Figure 5: Illustration of the calculation of the apex height.

Finally, apex height is defined as:

$$apex\ height = \frac{h_1 + h_2}{2}. \quad (2)$$

2. **Roundness:** Roundness is defined as the ratio between the leaf area and the area of the perfect circle that content the leaf:

$$Roundness = \frac{100A}{\pi r^2}, \quad (3)$$

where r is the circle radius defined as:

$$r = \frac{D}{2}. \quad (4)$$

3. **Undulations:** Undulations is defined as the number of changes on the right and on the left of the leaf margin. Undulations are found by analysing the changes in the $X-$axis. Figure 6 shows the undulations found in a leaf with calcium deficiency.

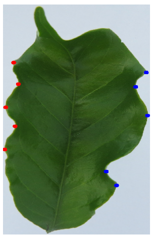


Figure 6: Illustration of undulations in a leaf with calcium deficiency.

4. **Compactness:** Compactness is defined as the ratio between the perimeter and the area of leaf [8].

$$Compactness = \frac{P^2}{A}. \quad (5)$$

5. **Vein features:** The Sobel algorithm is used to calculate the gradient magnitude of the input image, I. Then, the Otsu method[12] is applied on the gradient magnitudes to separate veins. Finally, the follow formula is applied:

$$Veins = \frac{V}{A} \times 100, \quad (6)$$

where V is the number of pixels identified as edges or veins, and A is the leaf area.

3.3.3 Color features

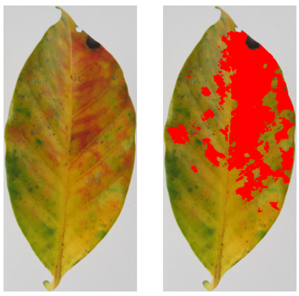
Color information is useful to detect nutritional deficiency of nitrogen, potassium and phosphorus.

1. **Percentage of red color:** The following function is defined to detect red color on the leaf:

$$R(x,y) = \begin{cases} 1 & : (0 \leq Hue(x,y) \leq 18 \\ & \quad and\ Val(x,y) > 110 \\ & \quad and\ Sat(x,y) > 150) \\ & \quad or\ 348 \leq Hue(x,y) \leq 360 \\ 0 & : otherwise \end{cases} \quad (7)$$

where $Hue(x,y)$, $Sat(x,y)$, and $Val(x,y)$ are the Hue, Saturation and Value of a pixel (x,y) respectively, in the HSV color space. The percentage of red color, illustrated in Figure 7, is defined as:

$$Red\ percentage = \frac{\sum_i \sum_j R(x_i, y_j)}{A} \quad (8)$$



(a) Leaf image (b) Red detected

Figure 7: Illustration of red percentage of a leaf with phosphorus deficiency.

2. **Necrosis in a leaf tip:** Necrosis is detected using the following function:

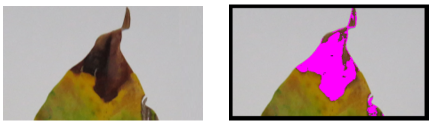
$$N(x,y) = \begin{cases} 1 & : (0 \leq Hue(x,y) \leq 15) \\ & \quad and\ Val(x,y) < 90 \\ & \quad and\ Sat(x,y) < 100 \\ 0 & : otherwise \end{cases} \quad (9)$$

where $Hue(x,y)$, $Sat(x,y)$, and $Val(x,y)$ are the Hue, Saturation and Value of a pixel (x,y) respectively, in the HSV color space.

Potassium deficiency produces necrosis in the leaf tip. Thus, the following formula calculates the percentage of necrosis in the leaf tip:

$$Necrosis\ percentage = \frac{\sum_i \sum_j N(x_i, y_j)}{A_t}, \qquad (10)$$

where A_t is the number of pixels in leaf tip area, approximated to the first quarter part of the leaf. Figure 8 illustrates the measure calculation.



(a) Leaf image (b) Necrosis detected

Figure 8: Necrosis percentage on the tip of a leaf with potassium deficiency.

3. **Mean:** For each channel RGB of the input image I, the mean is calculated using the following formula:

$$\mu = \frac{\sum_i \sum_j I(x_i, y_j)}{A}. \qquad (11)$$

4. **Standard deviation:** For each channel RGB of the input image I, the standard deviation is calculated using the following formula:

$$\sigma = \frac{\sum_i \sum_j (I(x_i, y_j) - \mu)^2}{A}. \qquad (12)$$

3.4 Classification

Random Forest is used for building a classifier. The term 'Random Forest' was introduced by Leo Breiman in [1]. Random Forest is an ensemble of decision trees, where each tree is trained by randomly sampling from a labeled training data. Given an input feature vector, each decision tree of the forest classify it, and the ensemble output is the most popular class. The advantages of Random Forest is speed and minimal storage in comparison with others classifiers [2].

4 Experiments and Discussion

A data-set with 335 images of coffee leaves, 255 images for training set and 80 images for testing set (10 images for class) were used for experimental evaluation. Images used in the evaluation were provided by Cenfrocafe in Peru. Images were taken with a white background, in vertical position with the apex upward. The number of images for each class in the training set are shown in Table 1.

Four models were built with Random Forest: 1) Using local features. 2) Using global features. 3) Combining local and global features. 4) Combining SIFT local features and global features.

Table 1: Number of leaf images for class

Deficiency	# of images	Deficiency	# of images
Boron	43	Magnesium	20
Nitrogen	39	Manganese	23
Calcium	42	Phosphorus	43
Iron	26	Potassium	19

Different numbers of trees, denoted by T, are used to train each model. The classification accuracies obtained for each model are shown in Table 2.

Table 2: Accuracies of classification.

Model	Accuracy (%)				
	T = 20	T = 40	T = 60	T = 80	T = 100
1	$40,0$	$33,8$	$38,8$	$41,3$	$41,3$
2	$67,5$	$62,5$	$66,3$	$67,5$	$67,5$
3	$56,3$	$55,0$	$53,8$	$58,8$	$58,8$
4	$48,8$	$51,3$	$55,0$	$53,8$	$55,0$

Table 2 shows that the larger accuracy of classification is obtained using global features and training Random Forest with $T = \{20, 80, 100\}$ trees. The SIFT descriptors do not have good accuracy values for this problem. For evaluating the proposed model built with global features, the leaves of the testing set were classified with *Siscafe*. Results for each nutritional deficiency are shown in the Table 3.

Deficiency	Correct classes	
	Proposed model	Siscafe
Boron	10	2
Nitrogen	8	7
Calcium	9	7
Magnesium	3	1
Manganese	4	0
Iron	5	1
Phosphorus	10	5
Potassium	5	6

Table 3: Correct classes classified by the model 2 and by Siscafe.

In general, nutritional deficiencies of boron, nitrogen, calcium, and phosphorus were classified correctly with the proposed model. Nutritional deficiencies of magnesium, manganese and iron have similar visual symptoms. Thus, it is necessary to incorporate better features for representing veins in order to improve the performance of the classification of those nutritional deficiencies. Additionally, it is necessary to improve the features to detect necrosis on the leaf tip to identify nutritional deficiency of potassium.

In general, the proposed model has better performance in the classification in comparison with *Siscafe*. However, the performance of the classifier may have been affected by the number of deficiencies because coffee leaves frequently have two or more nutritional deficiencies at the same time. Another reason of the low performance may be the progress of nutritional deficiency in a plant. Visual changes are more evident when a plant has an advanced nutritional deficiency. However, the used data-set contains images with different stages in the development of nutrient deficiencies that may affect the classification model.

5 Acknowledgment

This work is part of the research project *'Desarrollo de una herramienta tecnológica para identificación preventiva de deficiencias nutricionales en plantones de café a través de procesamiento de imágenes digitales'* developed by Universidad Señor de Sipan and Cenfrocafe in Peru, with collaboration of Universidad del Valle and Universidad San Buenaventura in Colombia. The project was founded by the Fondo Nacional de Desarrollo Científico, Tecnología e Innovación Tecnológica - Peru.

6 Conclusions

In this paper, a solution for identifying nutritional deficiencies through digital image processing is proposed. However, variability in the acquisition conditions such as: changes in illumination and location conditions where images are taken, affect the classification results, due to the ill-posedness of the problem – in the sense of Hadamard [5].

Local and global features were explored to identify eight nutritional deficiencies. Local features are extracted using Bag-of-Features method, and combining SIFT and color descriptors. Thirteen global features are extracted, five shape features: apex height, undulations, roundness, compactness, and veins; and eight color features: mean and standard deviation for each RGB channel, red percentage and necrosis in the leaf tip. The global features produce a better classification since they have into account information on the application domain.

Nutritional deficiencies of boron, nitrogen, calcium and phosphorus are correctly classified by the proposed model. In a future work, a better feature to represent vein characteristics should be proposed for classifying nutritional deficiencies of iron, magnesium and manganese. Also, a better feature for detecting necrosis in the leaf tip should be explored for classifying nutritional deficiency of potassium.

References

[1] Leo Breiman. Random forests. *Machine learning*, 45(1):5–32, 2001.

[2] Antonio Criminisi and Jamie Shotton. *Decision forests for computer vision and medical image analysis*. Springer Science & Business Media, 2013.

[3] Luis Alberto Vives Garnique, Hever Ivan Mejía Cabrera, Kevin Leandro Vilcherrez Chavarry, and Marcelo Jesús Vassallo Barco. Visión artificial: Aplicación de filtros y segmentación en imágenes de hojas de café. *Ingeniería: Ciencia, Tecnología e Innovación*, 1(2), 2014.

[4] Kristen Grauman and Bastian Leibe. *Visual object recognition*. Number 11. Morgan & Claypool Publishers, 2010.

[5] Jacques Hadamard. Sur les problèmes aux dérivées partielles et leur signification physique. *Princeton university bulletin*, 13(49-52):28, 1902.

[6] Abdul Kadir, Lukito Edi Nugroho, Adhi Susanto, and Paulus Insap Santosa. Leaf classification using shape, color, and texture features. *arXiv preprint arXiv:1401.4447*, 2013.

[7] Mónica G Larese, Rafael Namías, Roque M Craviotto, Miriam R Arango, Carina Gallo, and Pablo M Granitto. Automatic classification of legumes using leaf vein image features. *Pattern Recognition*, 47(1):158–168, 2014.

[8] Chia-Ling Lee and Shu-Yuan Chen. Classification of leaf images. *International Journal of Imaging Systems and Technology*, 16(1):15–23, 2006.

[9] Yan Li, Zheru Chi, and David D Feng. Leaf vein extraction using independent component analysis. In *Systems, Man and Cybernetics, 2006. SMC'06. IEEE International Conference on*, volume 5, pages 3890–3894. IEEE, 2006.

[10] David G Lowe. Object recognition from local scale-invariant features. In *Computer vision, 1999. The proceedings of the seventh IEEE international conference on*, volume 2, pages 1150–1157. Ieee, 1999.

[11] Krystian Mikolajczyk and Cordelia Schmid. A performance evaluation of local descriptors. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 27(10):1615–1630, 2005.

[12] Nobuyuki Otsu. A threshold selection method from gray-level histograms. *Automatica*, 11(285-296):23–27, 1975.

[13] Zhiyong Wang, Bin Lu, Zheru Chi, and Dagan Feng. Leaf image classification with shape context and sift descriptors. In *Digital Image Computing Techniques and Applications (DICTA), 2011 International Conference on*, pages 650–654. IEEE, 2011.

[14] Qingfeng Wu, Changle Zhou, and Chaonan Wang. Feature extraction and automatic recognition of plant leaf using artificial neural network. *Advances in Artificial Intelligence*, 3, 2006.

[15] Stephen Gang Wu, Forrest Sheng Bao, Eric You Xu, Yu-Xuan Wang, Yi-Fan Chang, and Qiao-Liang Xiang. A leaf recognition algorithm for plant classification using probabilistic neural network. In *Signal Processing and Information Technology, 2007 IEEE International Symposium on*, pages 11–16. IEEE, 2007.

[16] Xiaodong Zheng and Xiaojie Wang. Leaf vein extraction using a combined operation of mathematical morphology. In *Information Engineering and Computer Science (ICIECS), 2010 2nd International Conference on*, pages 1–4. IEEE, 2010.