XL CILAMCE
IBERO-LATIN AMERICAN CONGRESS ON COMPUTATIONAL METHODS IN ENGINEERING
NOVEMBER 11-14, 2019
Praiamar Natal Hotel & Convention
Natal, RN-BRAZIL

A CONVOLUTIONAL NEURAL NETWORK-BASED APPROACH FOR VISUAL QUALITY INSPECTION OF READY-TO-EAT CRISP LETTUCE LEAVES

Wilson David Marques
Sidnei Alves de Araújo
contato@wilsonmarques.com.br
saraujo@uni9.pro.br
Programa de Pós-graduação em Informática e Gestão do Conhecimento (PPGI), Universidade Nove de Julho - UNINOVE,
Rua Vergueiro, 235/249 - Liberdade, São Paulo/SP, Brasil

Abstract. Among the leafy vegetables, lettuce is considered a product of great importance, especially in the context of healthy eating. The species *Lactuca sativa var. crispa*, or crisp lettuce, is one of the most produced and consumed vegetables in Brazil. Packaged lettuces have represented a new marketing model and have been gaining space in the final consumer's table. As they are minimally processed to be ready for consumption, there may still exist points of dirt or rot in the leaves due to failures in the visual inspection process that is conducted manually, and consequently the possibility of contamination of the product. This work presents an approach for automatic visual inspection of the quality of ready-to-eat crisp leaf lettuce. To this end, we employed computer vision methods and a convolutional neural network (CNN) that was trained with two databases, one composed by 12400 sub-images (windows) of 30×30 pixels and another composed by 2560 sub-images of 50×50 pixels. These sub-images were extracted from healthy parts of lettuce leaves and parts containing the major defects (burnt edges, putridity, and dirt and pest infestation). In the experiments conducted, the databases were enlarged during the training phase of the CNN employing the data augmentation technique, which increases the training set in about 1000 times. To evaluate the proposed approach two other databases containing 4211 and 1551 of sub-images were employed. For the 30×30 and 50×50 sub-images, the average hit rates were 96.1% and 91.6%. These results demonstrate the feasibility of the proposed approach and indicate that smaller windows provide better CNN performance.

Keywords: lettuce, defects, visual inspection, computer vision, convolutional neural network

1 Introduction

The Fourth Industrial Revolution, or Industry 4.0, is promoting a digital revolution that is characterized by the use of technologies such as Artificial Intelligence, Computer Vision, Internet of Things, and Cloud Computing, which are already around us in applications like drones and autonomous cars, virtual assistants, and software able to translate or make investments. The use of such advanced manufacturing technologies and concepts has also been extended to the agricultural sector with the aim of increasing productivity, reducing environmental impacts, increasing profits and improving product quality.

Massruhá and Leite [1] explain that agribusiness 4.0 marks a new milestone in agricultural development and that it will undoubtedly bring about major changes for the coming years involving the massive use of different technologies to develop smarter processes, optimize decision making in the field and improve production processes, enabling the production of higher quality and environmentally friendly products.

However, in the agricultural sector, new technologies have been widely used in soil preparation, planting, and harvesting, but still very little in automating the visual inspection processes of product quality, despite the increasing number of scientific works on this subject in the field in the last decade.

Siddagangappa and Kulkarni [2], for example, proposed a computer vision system (CVS) for visual inspection of agricultural grain quality. Also on this theme, there are the works of Dubosclard et al. [3], focused on rice grains, and the works of Araújo, Pessota and Kim [4], Belan, Araújo and Alves [5], and Belan et al. [6], who explored the development of CVS for visual inspection of Brazilian beans.

Arribas' work [7] aimed at proposing a computational approach based on artificial neural networks to automate the classification of sunflower leaves from digital images for use in selective herbicide applications.

Patil et al. [8] explored the development of a computer system that identifies plants from physical parameters extracted from digital images.

Sibiya and Sumbwanyambe [9] used a convolutional neural network (CNN) to recognize and classify corn leaf diseases. The developed CNN model was able to recognize three different types of diseases from digital leaf images.

Mattos [10] proposed an image analysis method to identify the presence of Septoriosis disease (*Septoria lycopersici*), with its severity, in plant leaves.

Silva [11] and Souza [12] explored the development of computer vision approaches for identifying defects and bacterial spots in tomatoes.

Although there are numerous studies in the literature focusing on automatic visual inspection of the quality of agricultural products, none of them explore the development of computational approaches to inspect lettuce leaf defects, which, according to Oliveira et al. [13], is considered the main leafy vegetable marketed and consumed by the entire Brazilian population, due to the ease of acquisition and production throughout the year in Brazilian territory.

It is in this context that this work is inserted, presenting an approach for automatic visual inspection of the quality of crisp lettuce leaves ready for consumption. Such an approach can assist in automating the visual inspection process of hardwoods bringing productivity gains, greater security in the inspection process and consequently greater added value to the product. Nevertheless, the artifacts generated here can contribute to agribusiness 4.0.

2 Theoretical Background

2.1 Visual quality inspection of ready-to-eat crisp lettuce leaves

Lettuce is considered among the leafy vegetables a product of great importance in food and human health and has prominence for being a source of vitamins and minerals. According to Ohse [14], when it is consumed fresh, lettuce has the following average composition per 100 g: water: 94%; caloric value: 18 Kcal; protein: 1.3 g; ether extract: 0.3 g; total carbohydrates: 3.5 g; fiber: 0.7 g; calcium: 68 mg;

phosphorus: 27 mg; iron: 1.4 mg; potassium: 264 mg; thiamine: 0.05 mg; riboflavin: 0.08 mg; niacin: 0.4 mg; Vitamin C: 18.0 mg, information for lettuce produced in the soil.

In a survey conducted by the Brazilian Seed and Seedling Trade Association (Associação Brasileira do Comércio de Sementes e Mudas) [15] lettuce, *Lactuca sativa*, was listed as the most consumed leafy vegetable in Brazil and the third largest vegetable in production volume, behind only watermelon and tomato, with a production of more than 1.5 million tons per year.

Sousa et al. [16] mention that in Brazil lettuce planting occupies an area of approximately 35,000 hectares, both for intensive production and for family producers, generating around five jobs per hectare.

According to the Farmer's House (Casa do Produtor Rural) - ESALQ / USP [17] the consumption of vegetables is extremely important for the human being's diet. And in search of healthy eating, the consumption of vegetables is increasing every year. However, the demand for greater ease is making the consumption of quick-to-prepare or ready-to-eat products more attractive to the end consumer.

In this context, sanitized or minimally processed vegetables have been growing in demand for consumers, becoming a worldwide phenomenon. This fact is associated with factors resulting from social changes, which imposed new habits, and agility to reduce meal preparation time, standardization of products, easy access to fresh and healthy vegetables, reduced storage space, more practical packaging and waste reduction. In addition to the many advantages of using sanitized or ready-to-eat vegetables, this form of commercialization adds greater value to the final product, ensuring better sales prices to producers and boosting agribusiness. However, vegetable consumers have become more demanding, requiring greater and better quality production and maintaining production to enable year-round supply.

Vidgal and Duarte [18] conducted a survey in the municipality of Anchieta, located in the state of Santa Catarina, Brazil, in which they analyze 20 ready-to-eat lettuce samples from 20 different households. The authors found that even after the sanitation process 50% of the samples presented some type of contamination, 11% presented the presence of insects and only 39% were in good conditions for consumption. This indicates that there is still plenty of room for the application of new technologies in the visual quality inspection processes of ready-to-eat vegetables.

Visual quality inspection is of utmost importance for most agricultural products. In many cases, their visual properties such as color, shape, and size are the main characteristics evaluated by consumers and are important factors in determining their market price [4,5]. Obviously, from sowing to the final consumer table, agricultural product quality inspection steps are required to ensure that the products are free of abnormal odors, moisture, foreign material, residues, and pest infestations to ensure that they reach consumers quickly and in full condition [16].

According to Chitarra and Chitarra [19], the properties that make fruits and vegetable quality food are appearance, taste, odor, texture, and nutritional value. According to Shewfelt et al. [20], in the case of leafy leaves, a greater emphasis should be given to appearance and shape. The minimally processed product must be fresh in appearance, consistent, acceptable in color and reasonably free from defects.

The process of visually inspecting the quality of ready-to-eat crisp lettuce leaves, as well as many other agricultural products, is done manually, which can be time-consuming, humanly prone, and high operating costs. This process, whose description is presented below, was observed over a month (03/01/2019 to 02/02/2019) by one of the authors of this work in an agribusiness belonging to an agricultural cooperative located in the city of Ibiúna / São Paulo, Brazil, under the supervision of the food engineers from the agricultural cooperative.

In the first step, illustrated in Figure 1, lettuce leaves are removed from the head and inserted into a water tank to be separated, the apparent defective leaves being discarded.

Figure 1. First step: leaf removal and visual selection. Source: the author

In the next step, illustrated in Figure 2, the leaves in good visual condition (selected in the previous step) are transferred to a chlorine-containing water stream to eliminate any dirt or even insects clinging to them.

Figure 2. Second step: first stream with chlorine for leaf hygiene. Source: the author.

In the third step, the leaves are transferred to a second stream that passes through a tunnel that prevents the passage of larger objects along with the leaves, such as a tool used in the inspection process. Afterward, the leaves pass through one last conveyor that transports them to plastic boxes, to be taken to the drying stage performed by industrial centrifuges, as illustrated in Figure 3.

After drying, lettuce leaves are taken to one of the most important steps of the inspection process which is the final selection and sorting, illustrated in Figure 4. In this step, the leaves are arranged on a lighted white table for trained staff to remove those that do not comply, that is, containing one or more defects such as mechanical damage, stains, scars, disease, frost burnt leaves, punctured leaves, rotten leaves, burnt edges, and dirt or pests. It is at this step that one or another nonconforming leaf ends up among the selected ones.

In the sixth and last step, the sheets are weighed and packaged, as shown in Figure 5.

Figure 3. Third and fourth steps: second stream for sanitation, tunnel, leaves conveyor belt and drying process. Source: the author.

Figure 4: Fifth step: Selecting Compliant leaves. Source: the author

Figure 5. Sixth step: weighing and wrapping the leaves. Source: the author.

As can be seen from the description of the product quality inspection process, the approach proposed in this paper may be useful to support the activities of the fifth step by automatically identifying defective leaves, dirt or pests. Specifically, we are considering in this work the defects of burnt edges, putridity, and leaves containing dirt or pests, which are described below.

2.1.1 Burnt edges

The leaves containing this defect have a color ranging from yellow to brown at the edges, as shown in Figure 6. In this case, the lettuce leaf loses its natural green color and becomes burnt at the edges due to sun, frost or physiological factors.

Figure 6. Crisp lettuce leaves with burns or discoloration at the edges. Source: the author.

2.1.2 Putridity

Regarding putridity, it is possible to visually identify that the tissue of the crisp lettuce leaf ends up decomposing causing holes in the leaf. At the rotting points, the leaf has a disintegrating and fermenting appearance which results in changing the standard color to a dark brown or black tone. When putridity occurs at the edges, the leaf loses its standard geometric structure, which is serrated, as shown in Figure 7.

Figure 7. Crisp lettuce leaves presenting putridity. Source: the author.

2.1.3 Pest Infestation or Dirt

In crisp lettuce leaves, we can find various types of insects including arachnids, mollusks, snails, slugs, caterpillars, and other leaf organisms, which can be visually identified by changing the standard color in the place where they are housed. In most cases, they have circular, dark-hued patterns that set them apart on crisp lettuce leaves, characterizing some abnormality, as illustrated in Figure 8.

(a) (b) (c)

Figure 8. Crisp lettuce leaves presenting dirt (a and b), and pest infestation (c). Source: the author.

2.2 Computer Vision

For Ballard and Brown [21], computer vision (CV) is an area of study that addresses the extraction of data and information from an image to construct clear and explicit descriptions of objects contained therein. CV can also be defined as a set of methods and techniques to enable a computer system to interpret images. Gonzalez and Woods [22] mention that a computer vision system (CVS) must provide a machine with some capabilities of the human visual system, such as the ability to describe and interpret the content of a digital image.

However, pattern recognition in images is a major challenge and requires a lot of prior knowledge and judgment to make conclusions about the extracted data. For example, a food quality agent needs to have prior knowledge of the product compliance and non-compliance details along with deciding what action to take, such as disposal or reuse.

Basically, a CVS involves the steps of image acquisition, preprocessing, segmentation, representation and description, and recognition [20]. Image acquisition involves the way the image is acquired, considering the various existing acquisition devices. Preprocessing aims to improve image quality to increase the chances of success in the next processing steps. Segmentation is employed to separate objects from the background. In the representation and description, the characteristics of the objects are extracted, which are used in the recognition and interpretation step, which consists of the process that assigns a label to the object based on the descriptor information set. Interpreting the content of a digital image also involves assigning a meaning to a set of recognized objects.

2.3 Convolutional neural networks

Convolutional neural networks (CNN) are a class of feed-forward artificial neural networks (ANN) and have been successfully applied in digital image processing and analysis. A CNN can be described as a variation of an ANN Multilayer Perceptron (MLP) designed to require as little preprocessing as possible. This is because the CNN uses the "learning" acquired by the filters used in image processing, which in a traditional CVS would have to be implemented separately. This feature is one of the main advantages of CNN application in pattern recognition in digital images [22, 23].

Basically, a CNN consists of three sets of layers: convolutional layers, pooling layers, and fully connected layers, as illustrated in Figure 9. Each layer has a specific function in the input signal propagation [18].

Convolutional layers are responsible for extracting attributes from images. They employ filters that trigger small locations throughout the image. A convolution can be interpreted as a mathematical operation between two functions, from which a third function is produced, which can be viewed as a modified function. In digital image processing, where the image can be defined as a two-dimensional function, the convolution is useful for edge detection, image smoothing, and extraction of various other attributes. For Araújo et al. [23], the convolution operation can be viewed as a summation of the multiplication of each digital image element (pixel) along with their local neighbors by the elements of a matrix representing the convolution filter.

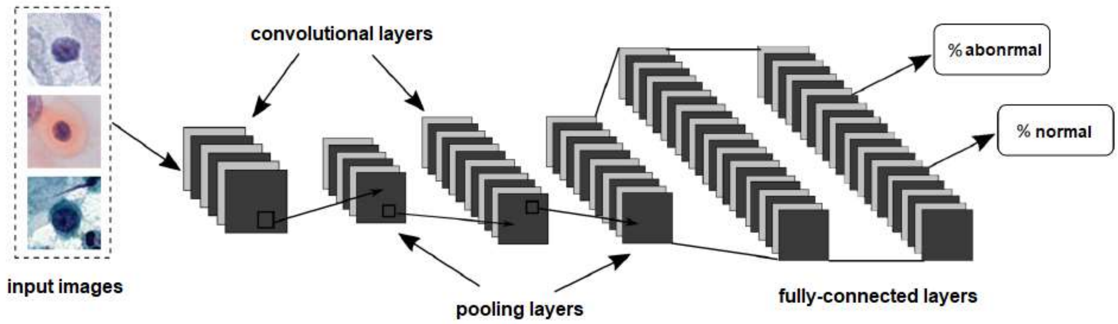


Figure 9. Illustration of a CNN architecture: adapted from Araújo et al. [23]

Pooling layers, which are located between the convolution layers, perform spatial sampling operations using filters that are applied to the image. They produce lower-resolution versions of the convolution layers and help make representations invariant to small translations [18].

Finally, the fully connected layer acts as a classifier. It receives input from the previous layer and produces an n-dimensional vector, where n is the number of output classes. Thus, each vector element is used to signal the probability of the input pattern of belonging to that class.

3 Materials and methods

As already mentioned, to carry out the research presented in this work, detailed observations of the visual quality inspection process of crisp lettuce leaves ready for consumption in an agro-industry were made from 03/01/2019 to 02/02/2019. After these observations, images of leaves containing the main defects (putridity, burnt edges, and leaves containing dirt or pests) were acquired.

For image acquisition, we used a white infinite background (A), a smartphone tripod (B), and an iPhone 5 smartphone with an 8 megapixels camera (C), as shown in Figure 10.

Fifty images with a resolution of 1024 × 768 pixels were acquired, 30 of them were used to compose two training bases, one composed by 12400 30 × 30 pixels sub-images (windows) and the other formed by 2560 50 × 50 pixels sub-images. The other 20 acquired images were used in the experiments to validate the proposed approach. The sub-images were extracted from the acquired images to contemplate healthy and defective regions of the lettuce leaves.

The next step was to train a convolutional neural network (CNN). For this, we used the library Keras, an open-source deep learning framework for the Python language, which was also used to implement the computer vision routines. It is noteworthy that the Keras library allows the training image set of the CNN to be expanded by up to 1,000 times using a data augmentation technique.

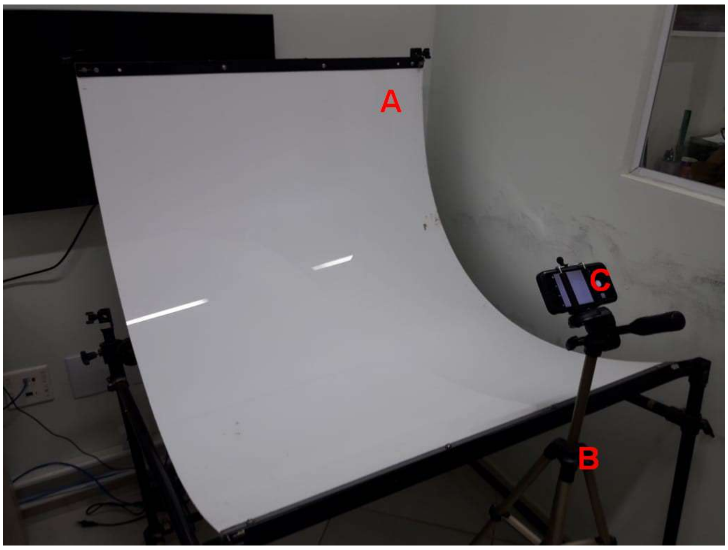


Figure 10. Equipment used for image acquisition. Source: the author.

To measure the CNN performance, the hit rate was used, which consists of dividing the hits (true positives) by the total amount of samples of each class, as indicated in Equation 1.

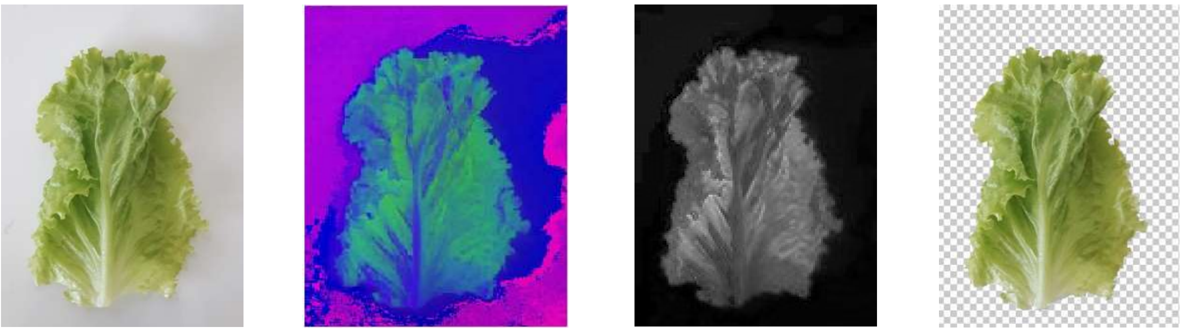
$$Hit\ rate = \frac{True\ positives}{Total\ amount\ of\ samples\ of\ each\ class}. \tag{1}$$

The number of true positives (TP) and the total amount of samples of each class are demonstrated through confusion matrices, in which the TP are positioned in the main diagonals.

4 Proposed approach

The proposed approach receives as input an RGB (I_{RGB}) color image of a lettuce leaf, as illustrated in Figure 11a. In the first processing step, I_{RGB} is converted to the HSV (hue, saturation and value) color space generating a new image denoted by I_{HSV}, illustrated in Figure 11b.

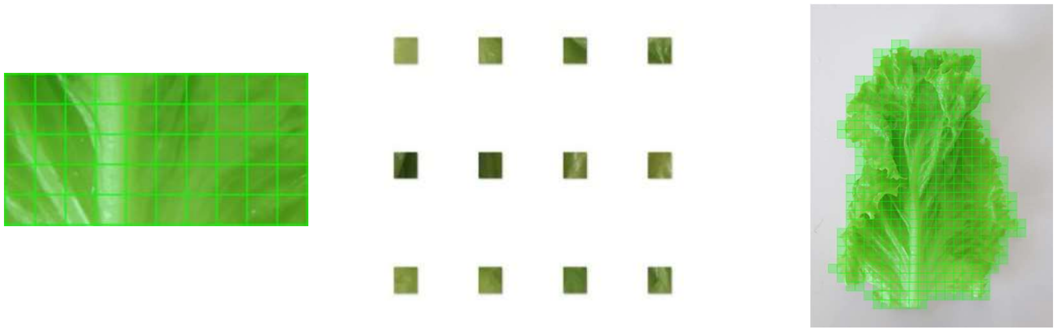
In the second step, background image removal is performed. For this, the HSV bands are separated and only the S band (image I_S illustrated in Figure 11c) is used. Then, a thresholding operation is applied to the I_S image to segment only regions where pixels have saturation greater than 0.15 (value determined experimentally). Considering the segmentation applied in I_S, the image I_{seg} shown in Figure 11d is obtained from the input image I_{RGB}.



(a) (b) (c) (d)

Figure 11. Intermediate steps of the processing of the proposed approach. Source: the author

After background segmentation, the image is divided into windows (30 × 30 or 50 × 50), as illustrated in figures 12a and 12b. Each window not belonging to the background of the I_{seg} image is then subjected to the CNN trained to predict which of the four classes (normal, burnt edges, putridity, dirt and pest infestation) the window belongs to. Then, finally, an I_{out} output image is generated (Figure 12c) by applying a colored mask to each sorted window in the I_{RGB} image, being green for the normal class, red for the burnt edges class, blue for putridity class and yellow for dirt and pest infestation class.



(a) (b) (c)

Figure 12. Final processing steps of the proposed approach. (a) Input image region, (b) windows of 30 × 30 pixels, (c) Output image showing that all windows have been classified as normal by the CNN and therefore are marked by the mask in green. Source: the author.

Figure 13 below briefly illustrates how the proposed approach works.

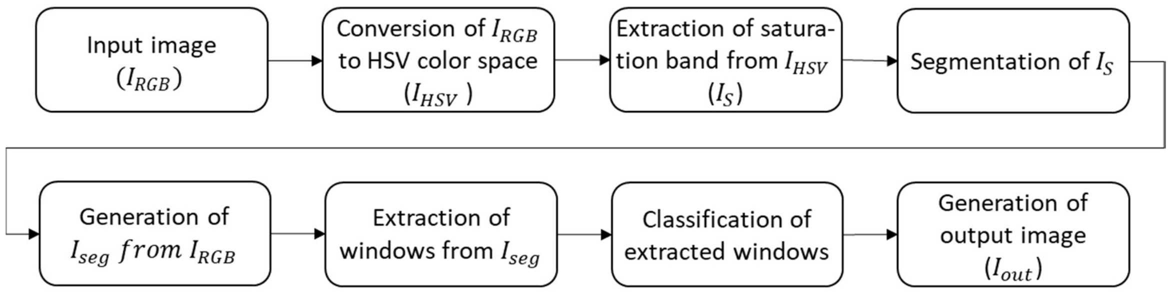


Figure 13. Processing steps of the proposed approach. Source: the author.

4.1 CNN Training and Prediction

The proposed CNN was implemented with two convolution layers, two pooling layers, and two fully connected layers, as shown in Figure 14. A total of 8000 steps per epoch was defined for the training, and 2000 epochs were defined. During validations, the K-fold cross-validation method was employed. For training with 30 × 30 pixels windows, the base was composed of 12400 samples taken from 30 images, as already mentioned, representing the four predefined classes. In training with 50 × 50 pixels windows, 2560 samples were taken from the same 30 images.

To perform the data augmentation, a Keras library method called ImageDataGenerator was used, which generates batches of new samples using transformations such as zooming, rotation, flipping and noising, on training time. To get an idea, using this method the training base has been increased up to a thousand times.

After the training performed considering the two bases (30 × 30 and 50 × 50 pixels sub-images), the trained models were saved in files to be used in the predictions.

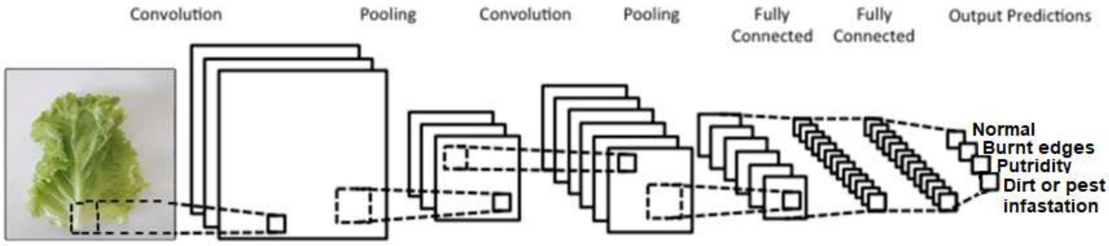


Figure 14. CNN architecture proposed. Source: Adapted from Dvorak and Menze [24]

To perform predictions, the trained CNN receives windows extracted from a color image in the RGB color space (I_{RGB}) as input and sorts them according to predefined classes (normal, burnt edges, putridity, and dirt and pest infestation). Then, the reconstruction of the classified image with the application of the color mask is done, as already explained.

5 Experimental Results

To validate the proposed approach, 20 images with dimensions of 1024 × 768 pixels were used, from which 4211 windows of 30 × 30 and 1551 windows of 50 × 50 pixels were extracted. It is noteworthy that such images were not used in CNN training. The confusion matrices presented in Tables 1 and 2 contemplate the prediction results made by the developed CNN considering sub-images of 30 × 30 and 50 × 50 pixels, respectively.

As can be seen in Table 1, in the experiments considering sub-images of 30 × 30 pixels, the hit rates of 98.2% for normal regions, 92.8% for burnt edges, 52.7% for putridity, and 75.9% for pests or dirt were obtained.

The putridity class had the worst hit rate because it is easily confused with the burnt edges and pests or dirt classes, as shown in the confusion matrix of Table 1. A good hit rate was obtained for the normal class, although in some cases this class has been confused with the pest or dirt class, probably due to the occurrence of small regions in the leaf with a change in color or natural stain that make the CNN classify such regions as pests or dirt. However, it is noteworthy that these cases were rare.

The hit rate for 30 × 30 sub-images considering all classes was 96.1%. It can be obtained by dividing the sum of the true positive cases (main diagonal of the confusion matrix) by the total number of sub-images classified, as indicated in Equation 1, i.e. (3813+90+77+66)/4211. Multiplying this result by 100 we obtain the hit hate in percentage.

Table 1. Confusion matrix synthesizing the results obtained for 30×30 pixels sub-images.

		REAL CLASS				**HIT RATE (%)**
		NORMAL	**BURNT EDGES**	**PUTRIDITY**	**DIRT AND PEST INFESTATION**	
PREDICTED CLASS	**NORMAL**	3813	3	8	57	**98.2%**
	BURNT EDGES	0	90	6	1	**92.8%**
	PUTRIDITY	1	30	77	38	**52.7%**
	DIRT AND PEST INFESTATION	0	16	5	66	**75.9%**

For the 50 × 50 pixels sub-images, the hit rates were 96.8% for the normal class, 82% for burnt edges, 55.1% for putridity, and 67.0% for pests or dirt, as shown in the confusion matrix of Table 2.

As in the 30 × 30 pixels sub-image experiments, the putridity class had the worst hit rate and was often confused with the normal and burnt edges class. CNN misclassification of burnt edges can be explained by the fact that the physiological evolution of burnt edges is putridity, which makes the leaf regions containing these two defects very similar. Errors related to the normal class require further investigation.

Again, the normal class got the best hit rate, and the percentage of times this class was mistaken for any other class was very low. The overall hit rate (considering all classes) for 50 × 50 pixels sub-images was 91.6%.

Table 2. Confusion matrix synthesizing the results obtained for 50 × 50 pixels sub-images.

		REAL CLASS				HIT RATE (%)
		NORMAL	**BURNT EDGES**	**PUTRIDITY**	**DIRT AND PEST INFESTATION**	
PREDICTED CLASS	**NORMAL**	1255	11	6	25	**96.8%**
	BURNT EDGES	6	41	1	2	**82.0%**
	PUTRIDITY	18	16	54	10	**55.1%**
	DIRT AND PEST INFESTATION	18	17	0	71	**67.0%**

Finally, based on Tables 1 and 2 it can be seen that the overall result is better for smaller sub-images. This can be explained by the fact that the same sub-image may contain parts of healthy and defective regions, which is clearly easier to occur in larger sub-images. Figure 15 illustrates the results of two CNN predictions for 30 × 30 and 50 × 50 pixels sub-images.

(a) Sub-images of 30×30 pixel

(b) Sub-images of 50×50 pixel

Figure 15. Predictions made by the CNN. Source: the author

As can be seen in Figure 15, both leaves have the highest percentage of burnt edges (red mask) defects. Figure 15 also shows some cases where the defect was incorrectly classified as putridity (blue mask in the image of Figure 15a) or dirt and pest infestation (yellow mask in the images of figures 15a and 15b).

6 Conclusions and future work

From the experiments performed, it can be observed that the use of a CNN to classify defects in crisp lettuce leaves is a good alternative since it was possible to obtain good rates of global hit rates (96.1% and 91.6%). In addition, it was possible to identify that it is better to use 30 × 30 pixels sub-images rather than 50 × 50 pixels sub-images since the hit rates obtained for smaller windows were generally higher. However, it was found that for the putridity class, using 50 × 50 pixels windows gives a higher hit rate, which leads to further investigation. This research may contribute to the development of agribusiness 4.0, as it may subsidize new research involving the automatic visual inspection of vegetables to improve the quality of the marketed product, with the consequent reduction of losses, maximization of labor, generation of higher value added to the final product, and greater food safety for the end consumer. The next steps of this research include: (i) refinement of the training parameters to obtain better hit rates, mainly for the putridity class; (ii) more experiments with windows smaller than 30 × 30 pixels; (iii) employ other forms of classification, such as a support vector machine (SVM) trained with local feature vectors extracted from the image and (iv) include other defects in the experiments with the proposed approach.

Acknowledgements

The authors would like to thank Universidade Nove de Julho – UNINOVE for the financial support.

References

[1] S. M. F. S. Massruhá and M. A. A. Leite. Jc na escola ciência, tecnologia e sociedade: mobilizar o conhecimento para alimentar o brasil. Jornal da cidade, 2° edição, 2017.
[2] M. R. Siddagangappa and A. H. Kulkarni. Classification and quality analysis of food grains. iosr journal of computer engineering (iosr-jce), v. 16, n. 4, p. 01–10, 2014.
[3] P. Dubosclard; S. Larnier; H. Konik; A. Herbulot and M. Devy. Automatic method for visual grading of seed food products. Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics), v. 8814, n. figure 1, p. 485–495, 2014.
[4] S. A. Araújo; J. H. Pessota and H. Y. Kim. Beans quality inspection using correlation-based granulometry. Engineering applications of artificial intelligence, 2015.
[5] P. A. Belan; S. A. Araújo and W. A. L. Alves. Image analysis and recognition. Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics), v. 9730, p. 801–809, 2016.
[6] P. A. Belan; R. A. G. Macedo; M. M. A. Pereira; W. A. L. Alves and S. A. Araújo. A fast and robust approach for touching grains segmentation. Lecture notes in computer science, v. 10882, p. 482-489, 2018.
[7] J. I. Arribas; G. V. Sánchez-Ferrero; G. Ruiz-Ruiz and J. Gómez-Gil. Leaf classification in sunflower crops by computer vision and neural networks. Elsevier - Computers and electronics in agriculture, 2011.
[8] N. K. Patil; R. M. Yadahalli and J. Pujari. Comparison between HSV and YCBCR color model color-texture based classification of the food grains. International journal of computer applications, v. 34, n. 4, p. 51–57, 2011.
[9] M. Sibiya and M. Sumbwanyambe. A computational procedure for the recognition and classification of maize leaf diseases out of healthy leaves using convolutional neural networks. University of South Africa, 2019.
[10] A. P. Mattos. Determinação da severidade de doenças de plantas por meio de imagens digitais, 2017.
[11] R. V. Silva. Identificação de defeitos superficiais em tomates (*solanum lycopersicum*) utilizando técnicas de processamento de imagens, 2015.

[12] M. H. S. Souza. Identificação de doenças em folhas de tomateiro usando visão computacional, 2015.
[13] A. C. B. Oliveira; M. A. N. Sediyama; M. W. Pedrosa; N. C. P. Garcia, and S. L. R. Garcia. Divergência genética e descarte de variáveis em alface cultivada sob sistema hidropônico. Acta Scientiarum. Agronomy n. 2, p. 211–217, 2004.
[14] S. Ohse; D. Dourado-Neto; P. A. Manfron and O. S. Santos. Quality of lettuce cultivars grown in hydroponic solution. Scientia Agricola, p. 181–185, 2001.
[15] ABCSEM. Associação brasileira do comércio de sementes e mudas. Seminário nacional apresentado em 10 de agosto de 2016, Hotel Premium Campinas.SP, 2016.
[16] P. T. Sousa; P. E. Souza-Neto; R. L. S. Silveira; F. E. S. Filho and B. P. Maracajá. Produção de alface (*lactuca sativa l.*), em função de diferentes concentrações e tipos de biofertilizantes. Revista verde de agroecologia e desenvolvimento sustentável, v. 9, n. 4, p. 168–172, 2014.
[17] A casa do produtor rural - ESALQ-USP. Etapas do processamento mínimo de hortaliças 03/01/2019. Disponível em: http://www.esalq.usp.br/cprural/noticias/mostra/6400/etapas-do-processamento-minimo-de-hortalicas.html. Acesso realizado em 28 de julho de 2019.
[18] P. Duarte. Presença de estruturas parasitárias e sujidades em amostras de alface prontas para o consumo no município de Anchieta. Trabalho de Conclusão de Curso, 2015.
[19] M. I. F. Chitarra and A. B. Chitarra. Pós-colheita de frutas e hortaliças. Livro fisiologia e manuseio, 2005.
[20] R. L. Shewfelt; E. K. Heaton and K. M. Batal. Nondestructive color measurement of fresh broccoli. Journal of food science, Chicago, v.49, n.8, p.1612, 1987.
[21] D. H. Ballard and C. M. Brown. Computer vision. Prentice hall. Isbn 0131653164, 1982.
[22] R. C. Gonzalez and R. E. Woods. Digital image processing. Massachusetts: Addison-Wesley, 2002.
[23] F. H. D. Araújo; A. C. Carneiro; R. R. V. Silva; F. N. S. Medeiros, and D. M. Ushizima. Redes neurais convolucionais com Tensorflow: teoria e prática. Escola regional de informática do Piauí. Sociedade brasileira de computação, 2017.
[24] P. Devorak and B. Menze. Structured Prediction with Convolutional Neural Networks for Multimodal Brain Tumor Segmentation, 2015.