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Computer vision based food grain classification: A comprehensive survey

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ABSTRACT

This manuscript presents a comprehensive survey on recent computer vision based food grain classification techniques. It includes state-of-the-art approaches intended for different grain varieties. The approaches proposed in the literature are analyzed according to the processing stages considered in the classification pipeline, making it easier to identify common techniques and comparisons. Additionally, the type of images considered by each approach (i.e., images from the: visible, infrared, multispectral, hyperspectral bands) together with the strategy used to generate ground truth data (i.e., real and synthetic images) are reviewed. Finally, conclusions highlighting future needs and challenges are presented.

1. Introduction

With the continued population growth, the food industry needs to keep increasing production and improving the quality of products. Directly or indirectly related to the increase in food production are the cereals, which are at the base of the pyramid of the food industry, both for human and animal consumption. According to the Food and Agriculture Organization's last report the world cereal production in 2020 has been 2765 million tonnes, 2% higher than 2019[1]. The report shows that the increase in production has kept the same ratio during the last decade and it is expected to keep the same ratio in the near future. Therefore, since it is difficult to increase the arable land, improvements are required in other processes in the production chain to increase productivity. One of these improvements is related to the automation of the classification of food grains, where a great effort has been devoted in recent years by proposing new approaches to perform the classification in an automatic way. It should be noticed that the food grain classification problem requires specific features according to the type of variety or problem. Some classes (seeds) have a large inter-class variability making easier the solution while others show a very tiny inter-class variability (e.g., classify between good grain and infected one). Actually, some of these challenging problems (small inter-class variability) requires the usage of multispectral or hyperspectral technology. The contributions of this survey are as follows. Firstly, it presents a general pipeline that is used to analyze the different stages generally involved in the classification process, providing discussions for each one of them. Due to the lack of common benchmarks for validation and the complexity of reproducing different approaches, quantitative comparisons become difficult. Therefore, the survey presents an analysis of the most important proposals for each stage and provides quantitative evaluations when possible. Finally, general conclusions are given pointing out the current limitations and future trends from a more general viewpoint.

2. Literature review

This section presents a deep review of works related to the different stages involved in the food grain classification problem. The reviewed works are grouped following different criteria. Firstly, the main modules generally used in grain classification are considered—i.e., image acquisition, preprocessing, segmentation, and classification (see Fig. 1). It should be mentioned that although not all these modules are present in the reviewed works, for instance in Olgun et al. (2016), Sendin et al. (2019) and Singh and Chaudhury (2016) the authors propose a classification directly from the given images, this break down is useful to cluster the approaches in the literature for further analysis and comparisons. These four modules are reviewed in Section 2.1, Section 2.2, Section 2.3 and 2.4. Then, Section 2.5 clusters the approaches in the literature according to the most common applications they are intended for. All these reviewed approaches are listed in Table 1 detailing their

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[1] http://www.fao.org/worldfoodsituation/csdb/en/.

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main features. Next, in Section 2.6, the works are grouped according to the variety of classified grains (e.g., rice, corn, coffee beans, etc.), insights on the particularity of each approach are given. Finally, a review of state-of-the-art dataset generation strategies, including both real and synthetic data, together with ground truth annotation are presented in Section 2.7.

2.1. Image acquisition

The first stage of the general pipeline is related to image acquisition. Although images from the visible spectrum (e.g., monochromatic images, color images represented in the RGB color space) are generally considered as input by the food grain classification systems, there are several works devoted to processing images from other spectral bands, for instance, infrared spectrum. Furthermore, some approaches exploit other types of images (e.g., multispectral or hyperspectral), covering not only the visible spectrum but also the ultraviolet or infrared spectral bands. These kinds of images allow us to obtain information useful for the classification process, which is not available in the classical single band domain. This section reviews state-of-the-art approaches on visible and infrared spectral bands together with multispectral and hyperspectral based approaches, highlighting their limitations, advantages, and drawbacks.

2.1.1. Visible and infrared spectral bands

Most of the approaches in the literature are based on the use of a single spectral band. In general, visible spectrum cameras are considered due to the low cost and availability of such devices. In addition to the visible spectrum, there are few approaches relying on near infrared imagery due to the possibility to better discriminate different objects in the given scene. In spite of that, the visible spectrum is more widely used, for instance, Fernandez-Gallego et al. (2018) propose a robust, low-cost, and efficient approach to evaluate wheat ear density in the visible spectrum. Also focusing on the usage of low-cost and easily available devices, Kaisaat et al. (2017) present a flat-surface scanner to measure the color of the rice and their corresponding uniformity. Similarly, Kozłowski et al. (2019) propose a flatbed scanner to acquire images and perform recognition of barley varieties. In addition to the use of scanners, in recent years, there are some proposals based on the usage of mobile devices to acquire images of the visible spectrum, which are later on used in the food grain classification process. For instance, Komyshev et al. (2017) present an approach to evaluate the phenotypic parameters of the grains using mobile devices obtaining quite precise results. More recently, Kar et al. (2019) propose a deep learning based system to estimate food grain quality by means of a mobile device with limited resources.

2.1.2. Multiespectral

In general, multispectral images correspond to shots of a given scene captured within specific wavelength ranges across the electromagnetic spectrum, including the visible spectrum together with the infrared and ultra-violet ranges. Typically, multispectral images consist of 3 to 20 spectral bands. Having several images of a given grain, at different spectral bands, allow tackling the classification problem, in a more robust and easy way. In the food grain classification problem, some approaches rely on multispectral images from the ultraviolet, visible, and near infrared spectral bands. For instance, Gomez et al. (2019) propose an approach to classify cocoa beans, from spectral signatures of the visible and near infrared spectral bands. The cocoa beans dataset has been split up into two categories: well fermented and over fermented. For the experiments, multispectral images of 64 grains were acquired. For each grain 11 spectral images, in the spectral range of 350 nm to 950 nm, have been acquired. After the image acquisition, the spectral signature of each grain has been obtained obtaining the best results.

Also working in the visible and near infrared spectral bands, Liu et al. (2014) propose a method to determine the purity of rice seeds of non-transgenic varieties from their transgenic counterparts. The approach is based on multispectral image analysis combined with the study of chemometric data. For the experiments, 200 samples of the transgenic and non-transgenic rice seeds, respectively, of the visible and near infrared spectra, in the range of 405–970 nm, were used. The use of multispectral images combined with chemometric has shown the best results of the classification. In Liu et al. (2016), the authors propose another rice seed classification method based on the usage of multispectral images. This technique uses 19 different wavelengths belonging to the visible and NIR regions—between 405 to 940 nm. From this image information, morphological features are extracted to classify the five rice varieties. Another approach in the multispectral domain has been presented in Sendin et al. (2018). In this case, the authors propose also to use 19 spectral bands, spanning from the ultraviolet, visible, and near infrared bands (from 375 nm to 970 nm). The approach is proposed to classify white corn defects. The types of defective materials were divided into 13 classes. The images were acquired with a specialized multispectral capture imaging device.

2.1.3. Hyperspectral

On the contrary to multispectral imaging, which measures spaced spectral bands, hyperspectral imaging measures continuous spectral bands. This results in a large number of images, more than 20, in general, 200 bands, covering a vast portion of the electromagnetic spectrum. In Qiu et al. (2018), the authors propose the use of hyperspectral images to identify rice seeds in four different varieties. The approach has been developed using two different spectral ranges (380–1030 nm and

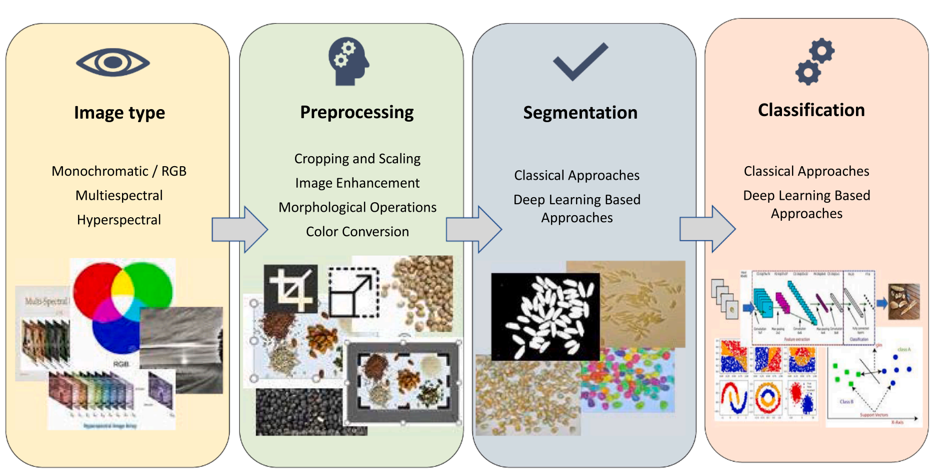

Fig. 1. Stages generally involved in a grain classification pipeline.

Table 1
Main elements of the classification pipeline for different approaches.

Author(s)	Image (T: Type; B:Background; M: Multitouch)			Segmentation	Classification	Application
	T	B	M			
Chu et al. (2020)	Hyperspectral	Black	☑	Otsu	OW-PCA-SVM	Fungi detection
Shamim et al. (2020)	RGB	Black	☐	Canny	CNN (customized architecture)	Grain purity analysis
Singh and Chaudhury (2020)	HSV	Green	☐	Hue channel thresholding	Cascade network classifier	Improve the performance of the rice classifier
Toda et al. (2020)	RGB	Black	☑	Mask R-CNN	Mask R-CNN	Plant phenotyping
Velesaca et al. (2020)	RGB	White	☑	Mask R-CNN	CNN (CK-CNN)	Grain quality
Altuntaş et al. (2019)	RGB	White	☐	Blue channel thresholding	CNN (VGG-19)	Advanced maize breeding
Aukkapinyo et al. (2019)	RGB	Black	☐	Marker-based watershed	Mask R-CNN	Localize and classify grain
García et al. (2019)	HSV/ CIELAB	White	☐	Thresholding	K-NN	Quality coffee beans
Gomez et al. (2019)	Spectral images	Black	☐	Thresholding using heuristics	SVM	Quality cocoa beans
Huang et al. (2019)	RGB	Black	☐	Grayscale thresholding & color detector	CNN (customized architecture)	Coffee bean picking system and grain quality detection
Huang et al. (2019)	RGB	Black	☑	Watershed	CNN (GoogLeNet)	Classification of seed defects
Kozłowski et al. (2019)	RGB	Black	☐	Background subtraction	CNN (customized architecture)	Quality of barley for the beer brewing process
Sendin et al. (2019)	Hyperspectral	-	☐	Background subtraction	PLS-DA	Grading maize whole kernel
Son and Thai-Nghe (2019)	RGB	Black	☑	Background subtraction	CNN (customized architecture)	Grain quality evaluation
Xia et al. (2019)	Hyperspectral	D[a]	☐	Adaptive threshold	Multi-linear discriminant analysis	Maize seed classification
Arboleda et al. (2018)	RGB	White	☐	-	Geometric features	Bean quality controller
Lin et al. (2018)	RGB	Black	☐	-	CNN (customized architecture)	Intelligent detection system of rice species
Miao et al. (2018)	Hyperspectral	-	☐	-	t-distributed stochastic neighborhood embedding	Waxy maize seed quality testing
Qiu et al. (2018)	Hyperspectral	Black	☐	Thresholding	CNN (customized architecture)	Identify rice seed varieties
Sendin et al. (2018)	Multispectral	-	☐	-	PLS-DA	Grading whole kernel
Tin et al. (2018)	RGB	Black	☑	Edge detection	Geometric features	Quality control and classification of maize grains
Wah et al. (2018)	RGB	Black	☑	Otsu	K-NN	Classification of export-rice quality
Wen et al. (2018)	RGB/ HSV/ CIELAB	-	☐	-	Correlation analysis	Determine corn seeds conditioning and parameter selection
Vlasov and Fadeev (2017)	RGB	White	☐	-	K-means clustering	Classification of grain crops seed
Sabanci et al. (2017)	RGB	Black	☐	Otsu	ANN	Classification of the wheat grains
Yin et al. (2017)	RGB	-	☐	-	Fisher discriminant analysis	Classification of moldy maize samples
Huang et al. (2016)	Hyperspectral	Black	☐	Adaptive threshold	LS-SVM	Maize seed variety classification
Liu et al. (2016)	Multispectral	Black	☐	Thresholding	SVM	Online variety discrimination of rice seeds
Ribeiro (2016)	HSV	Black	☐	-	FCC + LBP	Grain classification
Shrestha et al. (2016)	Grayscale	Black	☑	Watershed	ANN	System to separate and identify laboratory sprouted wheat kernels
Singh and Chaudhury (2016)	RGB	-	☑	-	ANN	Rice grain classification
Olgun et al. (2016)	RGB	-	☑	K-means clustering	SVM	Wheat grain classification
Tan et al. (2016)	Infrared spectrum	-	☐	-	SVM	Identification of quality of wheat grain
Birla and Chauhan (2015)	Grayscale	Black	☐	Grayscale thresholding	Geometric features	Rice quality analysis
Kaur and Singh (2015)	Grayscale	White	☐	Grayscale thresholding	Geometric features	Rice grains quality estimation
Szczypiński et al. (2015)	RGB	Black	☐	Background subtraction	ANN	Quality of barley for the malt brewing process
Wen et al. (2015)	RGB/ HSV/ CIELAB	Black	☐	-	Correlation analysis	Determines optimal physical parameters for sorting seeds
Zareiforoush et al. (2015)	RGB	Black	☐	Grayscale thresholding	Fuzzy logic	Quality measurement of milled rice
	RGB	Blue	☑	Region growing	Probabilistic neural network	Classification and quality analysis of food grains

(*continued on next page*)

874–1734 nm). Another hyperspectral based classification approach has been proposed by Pan et al. (2018), referred to as MugNet, which is a simplified deep learning model based on hyperspectral image classification. This hyperspectral imagery has 144 spectral bands between 400 to 1000 nm spectral regions. The proposed multi-grained scanning strategy could not only extract the joint spectral-spatial information but also combine different grains' spectral and spatial relationships. On the contrary to the previous approaches, in Chu et al. (2020) an infrared hyperspectral (900–1700 nm) approach has been proposed. The authors tackle the classification of healthy corn from infected from one of the three hybrid classes of fungi: dented, waxy, and semi-flint endosperms. Also working in the infrared spectral band, Berman et al. (2007) present an infrared hyperspectral approach to perform the classification of individual sound and stained wheat grains, belonging to 24 Australian different varieties. The image data were normalized based on its means, using only the spectral shape. The experiments were carried out with image samples over the 420–2500 nm, 420–1000 nm, and 420–700 nm wavelength range. Also in the infrared hyperspectral domain, Sendin et al. (2019) propose an approach to classify whole white corn kernels. The method performs 13 classes division of disposal materials using hyperspectral imaging from 1118 to 2425 nm with a 6.3 nm spectral resolution between the 209 spectral points. Hyperspectral imaging is also exploited by Chu et al. (2020), where an approach to classify infected corn seeds is proposed. It uses infrared hyperspectral images in the range of 900 to 1700 nm.

2.1.4. Discussions on image acquisition

Although most of the approaches proposed in the literature for the seed grains classification problem work on the visible spectrum (see Table 1) there is an increasing number of approaches that rely on information from other spectral bands or other types of images (e.g., multispectral, hyperspectral), mainly due to the reduction in the prices of these technologies during the last decades. According to the reviewed papers, multispectral and hyperspectral based approaches are good solutions not only to classify grains according to their features, such as healthy or fermented but also to classify the grain varieties, which sometimes are quite similar from a visual point of view. For instance, some multispectral approaches can classify transgenic and non-transgenic varieties. Another detail to highlight from this review is that most multispectral and hyperspectral approaches work on the visible and near infrared spectral bands, just a few approaches go further NIR spectral band reaching the short-wavelength infrared or even mid-wavelength infrared. Regarding the ultraviolet spectral band, just a couple of works exploit this band.

It could be mentioned as a general conclusion that multispectral and hyperspectral technologies offer many possibilities that still need to be explored. The main drawback that can be observed is the lack of well-documented and available datasets for reference. In most of the approaches presented in the literature, researchers acquire their dataset and make their contributions, which makes it difficult to compare the different techniques. Hopefully, common benchmarks will be shortly available to be used as references by the community.

Table 1 (*continued*)

Author(s)	Image (T: Type; B:Background; M: Multitouch)			Segmentation	Classification	Application
	T	B	M			
Siddagangappa and Kulkarni (2014)						
Kambo and Yerpude (2014)	RGB	Black	☑	Region growing	Geometric features	Classification of basmati rice grain variety
Liu et al. (2014)	Multiespectral	-	☐	-	SVM	Identification of transgenic rice seeds
Gujjar and Siddappa (2013)	RGB	Black, blue	☑	Thresholding	ANN	Quality of basmati rice grains
Kaur and Singh (2013)	RGB	Black	☐	Otsu	SVM	Classification and grading the different varieties of rice grains
Mebatsion et al. (2013)	RGB/ HSV/ CIELAB	Black	☐	Edge detection	Least square classifier	Classification of cereal grains
Silva and Sonnadara (2013)	Grayscale	Black	☐	Background subtraction	Multi layer perception	Classification of rice varieties
Mousavirad et al. (2012)	RGB	Black	☐	Grayscale thresholding	ANN	Expert system for rice kernel identification
Guevara-Hernandez and Gil (2011)	RGB	White	☐	Edge detection	K-NN	System for cereal grain classification
Patil et al. (2011)	CIELAB	-	☑	-	K-NN	Identification and classification of food grains
Douik and Abdellaoui (2010)	RGB	Black	☐	Background subtraction	ANN, Fuzzy logic, Statistical classifier	Cereal grain classification
Choudhary et al. (2008)	RGB/ HSV/ CIELAB	-	☐	Red channel thresholding	Linear discriminant classifier	Improvement in the classification method of cereal grains
Zapotoczny et al. (2008)	RGB	-	☐	Thresholding	Linear discriminant analysis	Exploratory investigation of classification of Polish spring barley
Berman et al. (2007)	Infrared spectrum	-	☐	-	Pixel-wise classifications	Wheat grain quality
Kılıç et al. (2007)	RGB	Black	☐	Red channel thresholding	ANN	Quality inspection of beans
Paliwal et al. (2003)	RGB	-	☐	Thresholding	ANN	Classification and identification of cereal grains

†ANN (Artificial Neural Network). †K-NN (K-Nearest Neighbor). †SVM (Support Vector Machine). †PCA (Principal Component Analysis). †OW (Object Wise). †CNN (Convolutional Neural Network). †LBP (Local Binary Pattern). †PLS-DA (Partial Least Squares-Discriminant Analysis). †FCC (Freeman Chain Code). †LS-SVM (Least Squares-Support Vector Machines).

[a] D: Diffuse reflectance whiteboard.

2.2. Preprocessing

The reviewed approaches, in general, have some kind of preprocessing to the given raw images to put them all in the same format (e.g., cropping, scaling, color space mapping, etc.), or to facilitate the segmentation and classification process by enhancing the given images (e.g., noise filtering, contrast, sharpness enhancement, etc.) (García et al., 2019). Hence, this section reviews the most relevant preprocessing approaches.

2.2.1. Cropping and scaling

In case raw data corresponds to a high resolution image, some cropping or scaling is needed. The cropping technique consists of splitting up the given image into regions of small size (patches) to obtain a more easy representation to process images (Velesaca et al., 2020). This splitting process allows to discard unwanted parts of the images and to focus just on the object of interest (e.g., Gujjar and Siddappa, 2013; Son and Thai-Nghe, 2019; Wah et al., 2018; Zareiforoush et al., 2015). Image cropping is also used by some authors, after segmenting the given image, to focus the classification process just on a region of interest that contains just a single instance (e.g., Velesaca et al., 2020; Aukkapinyo et al., 2019). Image scaling is also a very common process, it points to resize the given images to represent them all at the same size. It involves a trade-off between efficiency, smoothness, and sharpness (Gujjar and Siddappa, 2013). In Huang et al. (2019), for instance, the authors do a resize to fit and represent the data according to the model requirements, they resize the images to width and length of 180 pixels each. In Aukkapinyo et al. (2019) the authors also apply a resize to their inputs to 1024×1024, which is the default setting for Mask R-CNN. In Shamim et al. (2020), Wah et al. (2018), and Altuntaş et al. (2019) image scaling is also considered in the preprocessing stage as an important operation in their pipeline.

2.2.2. Image enhancement

Image enhancement steps are focused on the improvement of the image's quality from the human perception point of view, some examples are: removing blurring, noise, or increasing the content's contrast (Gujjar and Siddappa, 2013). In Aukkapinyo et al. (2019) an image enhancement is performed as a pre-processing step. Applying the contrast-limited adaptive histogram equalization technique. In the case of noise filtering, the most common approach is to apply a Gaussian filter. For instance, García et al. (2019) deal with this problem by using Gaussian filters with 2D Gaussian smoothing. In Shamim et al. (2020), Siddagangappa and Kulkarni (2014), and Silva and Sonnadara (2013) Gaussian filters are also applied due to the type of noise they have to tackle. On the contrary, in those cases where the noise is produced by the low lighting conditions, other filters are considered. In other words, depending on the type of noise different filters should be applied; for instance, in Gujjar and Siddappa (2013) a special median filter is used to remove noise and smooth the given image. In Kambo and Yerpude (2014) a median filter is also applied because it preserves the edges during the noise removal process; (Kaur and Singh, 2013; Kaur and Singh, 2015) follow the same approach. In most cases, a previous grayscale conversion is considered for the operations of filtering. Both Tin et al. (2018) and Shamim et al. (2020) apply a median filter while they use Sobel edge detection to preserve edges during the noise removal process.

2.2.3. Morphological operations

Morphological operations, such as classical erosion or dilation, have been also used as preprocessing to tackle some specific tasks. For instance, in Siddagangappa (2014) and Kulkarni (2011), the authors use erosion to eliminate shadows of grains followed by dilation to enhance the image after the erosion and improve the boundary sharpness. Other solutions, for instance, Wah et al. (2018), use morphological operations, during the preprocessing stage to remove white spot noise in the background. Although results are improved after using morphological operators, the main drawback lies in its high computational cost.

2.2.4. Color conversion

Color space conversion is generally used to produce robust solutions or to highlight some specific features of the given image. There are different color spaces (e.g., RGB, CIELAB, CIEXYZ, CMYK, etc.), being the RGB the one generally used in the grain classification problem. The capability of working at different color spaces is exploited by Patil et al. (2011); in this work, the RGB color model is mapped to an L*a*b and HSI color spaces to later on make possible the color feature extraction, which is going to be the input for the classifier. In Ribeiro (2016) the author proposes an approach for the classification of five types of grains, extracting morphology, color, and texture features. To increase the accuracy of the classification, the original RGB color space is converted to an HSV color, which obtains the best results. A similar approach is followed in Singh and Chaudhury (2016) where the authors present an approach to classify five types of rice, using a vector of characteristics applying the BPNN algorithm using the luminance component of the converted HSV color spaces. More recently, the same research team has proposed an extension (Singh and Chaudhury, 2020) of their previous work. In this case, the hue channel and an algorithm based on a neuro-diffuse cascade network are used to obtain similar results for all four types of rice grains. Others authors, like (Wah et al., 2018; Huang et al., 2019; Birla and Chauhan, 2015), propose to convert the given images to grayscale and use them as inputs to the system. Actually, working in grayscale, just one dimension is considered, hence in these cases the texture or intensity analysis is considered (Zareiforoush et al., 2015).

On the other hand, in Altuntaş et al. (2019), Mousavirad et al. (2012), and Guevara-Hernandez and Gil (2011) the authors propose the usage of color histograms to obtain the best threshold value. Based on the information obtained from the color histogram of the RGB image channels, some authors (e.g., Altuntaş et al., 2019; Birla and Chauhan, 2015; Choudhary et al., 2008; Kılıç et al., 2007) propose to use just one channel of the input image. Altuntaş et al. (2019) use the blue channel of the RGB image to converts it to grayscale and then apply morphological operations using a median filter to reduce noise on corn kernel images. In the case of Birla and Chauhan (2015), the authors propose to use the green channel of the given image to converts it to grayscale and then apply a manual threshold to obtain the segmented image of rice grain.

2.2.5. Discussions on preprocessing approaches

As in most computer vision applications, the quality of the final results is directly related to the quality of the input data; noisy data, low contrast, poor lighting, overlapping objects all of these factors would represent a challenging problem. Hence, there is a clear trade-off between the time and effort spent in the preprocessing stage and the quality of the final results. A common characteristic among the reviewed works is that all the image acquisition conditions are kept under control. This reduces the processing operations and helps to obtain good results. Due to the particular nature of each problem, having the correct color representation is a key factor when classifying the different types of grains, since the classic RGB representation is not always the best option, which is why it would be necessary to carry out a preliminary evaluation of the different color models within the preprocessing stage to find the best option depending on the problem to be addressed. Another challenge related to this problem is a multi-touch scenario, which makes the classification task difficult. Most of the recent works are based on deep learning; in these cases, some authors use preprocessing techniques of cropping and scaling to generate the necessary amount of diversity of scenarios to carry out the training of the model.

2.3. Segmentation

Following the pipeline defined in this work, after carrying out the preprocessing tasks the next step is to segment the grains present in the image; most of the approaches in the literature make use of state-of-the-art segmentation techniques, instead of developing an ad hoc approach for the grain segmentation problem. Segmentation techniques are operations that allow us to split up the given image into the different regions present on it. In this section approaches generally used on grain segmentation are reviewed; they are grouped into two categories: *i*) classical image processing based approaches; and *ii*) deep learning based approaches.

2.3.1. Classical approaches

One of the most widely used image grain segmentation techniques is just the **thresholding**; this technique works on grayscale images and performs the binarization using a threshold value, which depends on the type of grain analyzed together with the background color (Paliwal et al., 2003). It should be mentioned that sometimes, after the image segmentation, some postprocessing techniques are applied to enhance the results, some of these postprocessing approaches are described next. The main drawback of thresholding techniques lies in their sensitivity to the selected threshold value used to generate the binary image.

As mentioned above, in some cases, after thresholding techniques some additional processes are performed to the obtained binary image to improve the results from the further classification process; the problems generally found are related to the presence of noise and holes from the segmentation. For instance, in Kaur and Singh (2015) the authors apply smoothing and an enhancement to reduce noise and improve image contrast on the segmented rice kernels. Arboleda et al. (2018) use image processing techniques and color feature extraction of input images to segment coffee kernels. Shamim et al. (2020) use Canny's edge detection algorithm to identify the boundaries of rice grains and hysteresis thresholding to improve the binarization process. Mebatsion et al. (2013) use a set of operations—thresholding, edge detection, and chain coding—to segment the given image. Wah et al. (2018) removes the noise of binary image (areas smaller than 10 pixels) applying two morphological operations, first erosion, and then dilation. Huang et al. (2019) improves segmentation by applying a color detection method to remove the background of the coffee beans. Finally, Qiu et al. (2018) are the only one in the reviewed literature that uses the spectral dimension and then applies thresholding to obtain the binary image.

On the other hand, Silva and Sonnadara (2013), Son and Thai-Nghe (2019), and Douik and Abdellaoui (2010) use the background subtraction method for segmenting rice kernels; in Silva and Sonnadara (2013) an additional morphological opening is applied together with a contrast stretching to the given grayscale image. The usage of morphological operations has been also exploited in Guevara-Hernandez and Gil (2011) and Siddagangappa and Kulkarni (2014) to delete shadow and improve edge sharpness to get better results. Some authors (e.g., Kaur and Singh, 2013; Sabanci et al., 2017; Wah et al., 2018) use the Otsu method to convert the grayscale image to a binary image, according to the defined threshold value, to extract the grain from the background.

Watershed is another technique widely used to extract segmented grains from the background. This technique uses a grayscale image where the tonality variations could be represented as a topographic surface where the highest intensity values would be the peaks while the lowest values would be the valleys. At the beginning of the process each valley is filled in with a different color, then it continues to fill in until the adjacent regions begin to touch and the boundaries between each region are well defined. As a result of this process the regions obtained with the different colors are the resulting segmented image. Huang et al. (2019) and Shrestha et al. (2016) use the watershed method to obtain the segmented instance of each grain; in the first case, this method is used to segment corn kernels while in the second case it is used to segment wheat kernels. After generating the binary mask elements are extracted from the original given input image to proceed with the classification stage; Actually, some authors carry out several additional steps to separate each instance of grain, this will depend on whether the image has a single kernel or a cluster of grains. In the case of clusters, each instance must be identified in order to be used in the classification task. Altuntaş et al. (2019) propose an approach to extract bounding boxes using contour lines for each grain. Zareiforoush et al. (2015) and Kılıç et al. (2007) use a set of functions to separate and label each grain that existed in the image. Guevara-Hernandez and Gil (2011) calculate the center of mass of the regions obtained in the binarization process to label each instance of the wheat and barley grains. Finally, another approach is proposed in Siddagangappa and Kulkarni (2014); once the image is binarized, a labeling process is performed over connected components by using labels and the similarity of gray level values.

2.3.2. Deep Learning Based Approaches

On the contrary to the classic approaches reviewed in the previous section, the techniques based on deep learning use artificial neural networks, to extract the higher-level features present in the given image. There are two types of segmentation under the deep learning framework: semantic segmentation and instance segmentation. According to each case, there are specialized networks that can obtain the binary mask of the objects of study, which are classified (e.g., people, cars, fruits). Semantic segmentation involves linking each pixel of an image to a class label, that is, a binary image is generated for each class of object present in the image (Ronneberger et al., 2015); while instance segmentation allows differentiating between each instance of the objects (He et al., 2017).

Based on the reviewed literature, it was found that the Mask R-CNN architecture (He et al., 2017), has been the most commonly used architecture (e.g., Aukkapinyo et al., 2019; Toda et al., 2020; Velesaca et al., 2020). This network allows us to perform the segmentation of instances and obtain the binary mask of each grain present in the input image. In all these approaches the authors did not change the original architecture. It should be mentioned that the Mask R-CNN is used to segment different types of cereals; in Aukkapinyo et al. (2019) different varieties of rice grains are segmented, while (Toda et al., 2020) performs the segmentation of different types of grains, such as rice, lettuce, oats, and wheat; on the contrary to previous works, (Velesaca et al., 2020) uses the Mask R-CNN to segment corn kernels.

2.3.3. Discussions on segmentation approaches

According to the reviewed literature, one of the techniques most used by the authors was thresholding. The main reason for its popularity is because this technique presents a very low degree of difficulty in its implementation, while provides acceptable results. It should be noticed that most of the success of this technique lies in the fact that all the environmental conditions, such as lighting, background colors, among others, are controlled and very well studied to obtain the most optimal results. These approaches tend to fail in those multitouch kernel scenarios, where grains not only touch but also have partial occlusions. A common element in most of the classical image processing based approaches is the usage of some post processing stage to improve the segmentation result, before going to the classification stage. For instance, morphological operations are generally used to eliminate noise, fill in holes, and improve the grains' boundaries on the binary image resulting from the segmentation. Like in most of computer vision applications, deep learning frameworks are also getting used in the grain segmentation problem; among the different models, the Mask R-CNN architecture is the most widely used. Given the results obtained with the approaches based on the deep learning framework, the trend in recent publications indicates that this is the framework to apply in future contributions. Fig. 2 presents the chronology of segmentation approaches used in the food grain variety problem showing this trend.

2.4. Classification

Following the pipeline presented in Fig. 1, once images are segmented, every single instance is classified according to the required categories. Like in the segmentation module reviewed in the previous

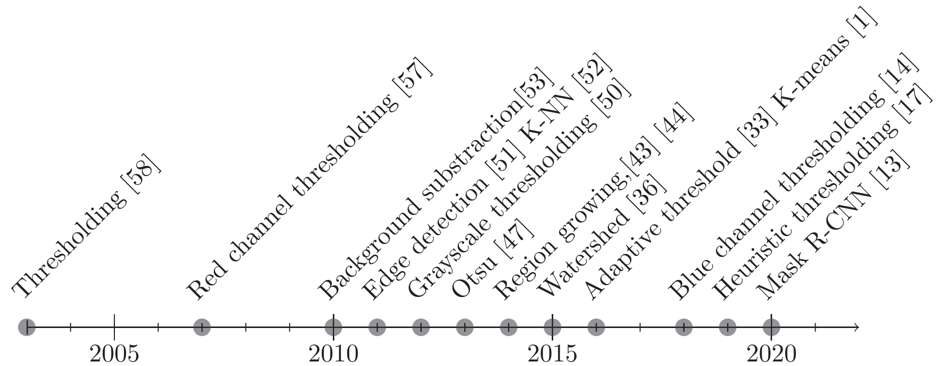

Fig. 2. Timeline of segmentation approaches used in the food grain classification; this timeline shows the first time a given approach is used.

section, approaches in the literature are grouped in two categories: classical pattern recognition techniques (e.g., SVM, K-NN, linear discriminant analysis) are reviewed first and then recent deep learning based approaches are considered.

2.4.1. Classical approaches

Most of the time, classical approaches follow a features extraction stage, where the goal is to obtain the most representatives features, which will then be used by a machine learning classification algorithm to be trained. In this context, according to the reviewed literature and before the growth and popularity of deep learning, Artificial Neural Network (ANN) was used. In Shrestha et al. (2016) an ANN model was designed using as an input the features extracted from the alpha-amylase activity, together with the corresponding labels. By using ANNs and visual features as inputs Sabanci et al. (2017) and Shrestha et al. (2016) approaches perform the classification of wheat grains. Both authors agree that features such as color, texture, and size are ideal for addressing the grain classification problem.

Also based on classical approaches, in García et al. (2019) an image processing plus machine learning approach is proposed to classify green coffee beans. The beans are classified as good or defectives (five types of defects), using the K-NN algorithm; previously, a feature extraction stage is accomplished obtaining: surface area, roundness, area relation, and eccentricity. These features are used to train the classifier. Vlasov and Fadeev (2017) also follow this approach classifying five different types of seeds with K-means clustering.

In the context of classical approaches, some authors use the SVM, also known as a hyperplane classifier, to classify food grains. The main objective of this algorithm is to determine an optimal line (plane or hyperplane, depending on the feature space dimension) that allows separating two given classes (Olgun et al., 2016). However, in the case of performing a multiclass classification, it is necessary to build a combination of several binary classifiers; this is the case of the work presented by Kaur and Singh (2013) that performs the multiclass classification of different qualities of rice grains.

Another approach followed by some authors in the reviewed literature is the usage of Partial Least Squares Discriminant Analysis (PLS-DA), which is a classification method that integrates the characteristics of conventional PLS regression with the discrimination benefits of a classification technique. The main advantage is that the relevant sources of data variability are modeled by the so-called latent variables, which are linear combinations of the original variables, and, consequently, it enables graphical visualization and understanding of different data patterns. In the reviewed literature, Sendin et al. (2018) address the problem of classifying defects in corn using the PLS-DA technique described above. This approach uses multispectral images. The same authors (Sendin et al., 2019), in an update to the previous work, use PLS-DA models to classify grains of white corn using hyperspectral images obtaining precision in the classification of about 98%.

2.4.2. Deep learning based approaches

Since the evolution of the technology, especially regarding memory capabilities and parallel processing of a big amount of data, deep learning has taken a big advantage with a variety of tasks in the computer vision field. In the particular case of image recognition, for agricultural problems, it is not the exception. CNNs ensure significant facilities by suppressing manual feature extraction, usually executed in classical approaches, and overcoming state-of-the-art results for such tasks (Altuntaş et al., 2019). Hence, in recent years new approaches have been proposed to tackle the grain classification problem; in this section, the most relevant deep learning based approaches are reviewed.

Altuntaş et al. (2019) found a solution for automating identification between haploid and diploid corn seeds. Their proposal includes the usage of very extended networks for classification such as AlexNet, VGGNet, GoogLeNet, and ResNet. A transfer learning strategy is used in that work, which consists of fine-tuning the model starting by transferring the weights from a pre-trained network to the new one. The authors of that work compare the different classification architectures and obtain the best results with VGG-19. A similar approach to the one presented above has been followed by Huang et al. (2019); in this case, the authors propose to classify defectives corn kernels from goods, with defects including mold, worm, damages, and discoloration. In this work, GoogLeNet and VGG networks were evaluated under a transfer learning scheme, and the first one obtains better results. Both approaches overcome machine learning state-of-the-art results. Finally, in Qiu et al. (2018), the authors also use VGGNet to speed up the learning process and outperforming state of the art results.

On the contrary to previous approaches, there are some recent works where authors design a custom solution (e.g., Huang et al., 2019; Velesaca et al., 2020; Lin et al., 2018). In the case of Huang et al. (2019) a two convolutional layer network, with a Rectified Linear Unit (RELU) activation function, is proposed; this network is trained with grayscale images in order to make it easier to detect the shape of green coffee beans and their dark color. In the case of Velesaca et al. (2020), the authors propose a lightweight CNN architecture, referred to as CK-CNN, to classify corn kernels into three categories: good kernels, defective kernels, and impurities. The network receives as an input a single element from the segmentation module. It consists of five layers: three convolutional layers defined with a 3×3 size kernels and two fully connected layers. Finally, in Lin et al. (2018) a novel architecture is designed with five convolutional blocks, each containing a linear operator followed by non-linearities such as RELU and max-pooling. The main purpose of this network is to improve the accuracy of the classification of three distinct groups of rice kernels. This simple architecture outperforms traditional popular hand-engineered classification algorithms such as pyramid histogram of oriented gradients, K-NN, SVM, and mixes of them.

2.4.3. Discussions on classification approaches

From all the works presented above, we could conclude that deep learning approaches are becoming the most widely used solution. Among the different architectures, although general purpose networks have been used, such as Alexnet, GoogLeNet, VGGNet, recent ad hoc models have been designed showing appealing results. One of the main advantages of such a kind of customized solution lies in the reduced number of parameters. The weakness of these type of classification approaches is that the architectures are designed according to the type of grain and the most relevant features of it, for example, the architecture that gives good results in the case of rice, perhaps is not the best model for grains such as wheat or corn. According to the recent literature, we could state that there is a lot of space for improvement in the classification module of the pipeline presented in Fig. 1. Just to have everything in a single picture, Fig. 3 depicts the chronology of classification approaches used in the food grain classification problem; it includes the approaches that have been considered to solve this problem during the last 20 years—the first time an approach is considered it is presented in the chronology.

2.5. Applications

There are several food grain applications based on computer vision, in general, they can be grouped in: *i*) quality control approaches and *ii*) grain variety classification. Some examples of each one of them are provided in the next subsections.

2.5.1. Quality control

Grain grading approaches evaluate constituent features (e.g., moisture, crude protein, fiber, etc.) as well as visual features such as shape (including perimeter, area, elongation, among others), color, and texture of a given sample set of grains. Constituent measurements are obtained using tools and machines especially devoted to such tasks, while visual features are manually extracted employing trained operators. This manual process is a time consuming operation and cannot ensure consistency due to the difference in the operator's evaluation ability. There are several works proposed in the literature to perform grain quality control. In Tan et al. (2016) the authors present an algorithm to recognize strong and weak gluten wheat. Also focusing on grain quality, Birla and Chauhan (2015) propose a method for estimating the size of Oryza sativa L rice class along with the detection of chalky and broken rice. Another rice quality control application can be found in Kaur and Singh (2013), where the authors present a multiclass SVM algorithm to determine the grade of 4 types of rice kernels. There are also approaches in the literature for wheat grain quality control, for instance in Kar et al. (2019) the authors propose a CNN approach to evaluate wheat grains according to electronic National Agriculture Market parameters of India, which enforce automatic grain quality, using inexpensive mobile phones.

Also related with the quality control problem, but for a given sample set, some approaches evaluate the sample as a whole, in other words, they measure the percentage of good kernels, defective kernels (including broken or rotten kernels), and impurities (e.g., pieces of straw, foreign elements, dust) in the given sample set. A review of these applications is found in the works proposed by Shamim et al. (2020) to grade rice quality, or (Singh and Chaudhury, 2020; Velesaca et al., 2020) to classify corn according to their quality using CNN.

2.5.2. Grain variety classification

On the contrary to previous approaches, there are some works intended to classify the kernels in the given sample set according to the different grain varieties. Choosing which variety to grow is one of the most important factors in the field of the agricultural industry. To obtain the maximum yield, cereal varieties must be effectively identified. Therefore, each variety of grains must be scored based on each of the important characteristics, such as yield, resistance to diseases, resistance to fungi, and quality of the grain to select the most suitable variety. In Kozłowski et al. (2019) the author proposes a CNN based recognition system for barley varieties identification; this approach is used to ensure the quality of the beer. In the same line of identification of varieties of barley, in Szczypiński et al. (2015) an automatic computer vision system is proposed to efficiently classify the varieties of barley grains, using their attributes of color, texture, and shape, to produce high quality malt. About corn grains classification algorithms, Huang et al. (2016) propose a hyperspectral imagery system to classified seed varieties using an LS-SVM model. In the same way, in Xia et al. (2019), the authors propose a system to effectively classify 17 varieties of maize seed based on a multi-linear discriminant analysis model. On the other hand, in Berman et al. (2007), the authors present an approach that implements a pixel-wise algorithm to classify wheat grains of 24 different Australian varieties. The authors in Liu et al. (2016) and Qiu et al. (2018) propose approaches to classify rice variety using LS-SVM and CNN respectively. Similarly, in Gujjar and Siddappa (2013) the authors propose an approach to identify six varieties of Basmati rice; the approach is based on color, morphological and textural features. This subsection is just a summary of some of the recent approaches proposed in the literature for grain variety classification.

2.5.3. Discussions on applications

As presented above, computer vision systems have been used to support grain grading, sample quality estimation, variety classification, counting elements, just to mention a few of the approaches proposed in the food grain handling units. Most of the applied approaches depend on the type of grain that is being processed; in other words, the proposed approaches are not for multi-grain variety problem, neither used for both: grain variety estimation and quality control. It can also be concluded that the use of several spectra has helped to improve the classification techniques of multiple varieties of grains, which allows addressing different problems with a single implementation. It can also be evidenced that in the quality control of grains, techniques based on deep learning have taken on greater relevance given the best obtained results. A weakness of the reviewed applications lye in the used dataset, up to our understanding there is not a benchmark dataset to be used as a reference to evaluate and compare results of applications targeting the same problem.

2.6. Grain variety

This section reviews the state-of-the-art grain classification approaches according to the type of grain. The main food grains studied in this section are: corn, rice, wheat, barley, and coffee; these categories are defined according to the number of publications on these varieties and sorted according to the statistics of the most worldwide cultivated cereals published by the Food and Agriculture Organization Statistical Database (FAOSTAT)[2]. Approaches able to tackle the classification of several varieties of grains are listed in the last subsection. Table 2 groups the reviewed literature according to the grain variety and depicts the most important features of each approach.

2.6.1. Corn

Corn is the cereal with the highest production worldwide, being fundamental in the human diet and some animal species, also has high genetic variability, which allows it to adapt to any climatic environment according to FAOSTAT. Given its high industrial use, it is important to improve the quality control of the corn grain. Hence, this section list a series of techniques focused on the automatic classification of corn kernels. Some of them have been able to classify up to 17 different classes (e.g., Xia et al., 2019; Huang et al., 2016), using hyperspectral or multispectral images. The analyzed techniques are mostly non-touching kernels (Miao et al., 2018). A few approaches have been implemented with CNNs (Altuntaş et al., 2019), which allows improving the

[2] http://www.fao.org/in-action/inpho/crop-compendium/cereals-grains/en.

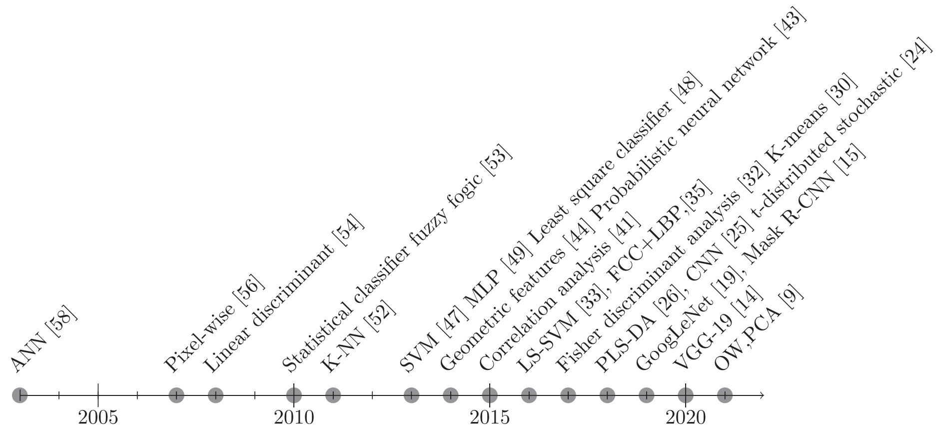

Fig. 3. Timeline of classification approaches used in the food grain classification problem; this timeline shows the first time a given approach is used.

classification accuracy. Like in the rice and wheat cases, in the corn there are approaches intended to discriminate corn grains by variety (Miao et al., 2018), while others are intended to classify according to the quality of the sample (e.g., Huang et al., 2019; Wen et al., 2018). Each implemented approach has its own data acquisition process, generating a dataset that is not available for further comparisons or improvements.

2.6.2. Rice

Rice is at the base of the food chain in many countries; according to FAOSTAT rice production represents the second-largest cereal production after corn. To improve the process of identifying the types and quality of rice an automatic and accurate classification process is required, which is a challenging problem due to the high similarity between the different varieties. This subsection lists the different approaches proposed in the literature for rice classification. In the reviewed literature, some recent approaches for classifying rice kernels according to the different varieties have been proposed (e.g., Liu et al., 2016; Wah et al., 2018), other approaches have been proposed to classify rice kernels according to their quality (e.g., Kaur and Singh, 2013; Liu et al., 2014), while other approaches have been devoted for both, classifying according to the variety and quality (Siddagangappa and Kulkarni, 2014). Among the different reviewed approaches, hyperspectral and multispectral based techniques, generally using CNNs, are the ones that allow classifying the greatest number of varieties or reaching the highest performance on quality classification (e.g., Qiu et al., 2018; Liu et al., 2014; Liu et al., 2016). In spite of that, the vast majority of techniques use images from the visible spectrum (e.g., Aukkapinyo et al., 2019; Tin et al., 2018; Lin et al., 2018; Singh and Chaudhury, 2016; Son and Thai-Nghe, 2019). Most of the approaches are intended for the non-touching kernel scenario, which represents an opportunity to explore techniques that support touching kernels.

2.6.3. Wheat

Wheat is the third most important grain in the human food chain after corn and rice. The huge volume of production needs effective methods to evaluate the quality of the grains, and to improve productivity in the industry. The main objective is to improve quality control and replace manual processes that require time, effort, and are ineffective in most cases. The following is just a summary of some of the approaches proposed in the literature for the automatic classification of wheat grains. During last decades several techniques have been designed to determine the wheat variety (e.g., Olgun et al., 2016; Douik and Abdellaoui, 2010; Guevara-Hernandez and Gil, 2011) or quality of wheat grain (e.g., Shrestha et al., 2016; Vlasov and Fadeev, 2017; Sabanci et al., 2017). On average, the approaches proposed in the literature tackle the two or three class problems. On the contrary to the rice classification problem we can find approaches for touching kernels (Shrestha et al., 2016), as well as approaches for the not touch case (e.g., Douik and Abdellaoui, 2010; Tan et al., 2016). In the vast majority of cases, the proposed solutions are based on machine learning (e.g., Shrestha et al., 2016; Sabanci et al., 2017). Like in most computer vision domains, we can find also CNN based approaches for the wheat classification (Vlasov and Fadeev, 2017), although up to our knowledge there is not that much work based on deep learning. Hence, this can be an opportunity to improve the precision of current wheat classification approaches.

2.6.4. Barley

According to FAOSTAT, barley is the fourth most cultivated cereal worldwide and is currently grown significantly as animal feed, malt products, and human food, respectively. Due to the importance of this cereal, it is necessary to have mechanisms that allow automating specific tasks within the production process to optimize the available resources as much as possible and increase productivity. During the last years, several techniques have been developed for the identification and classification of different varieties of barley (e.g., Paliwal et al., 2003; Choudhary et al., 2008; Zapotoczny et al., 2008; Douik and Abdellaoui, 2010; Guevara-Hernandez and Gil, 2011; Mebatsion et al., 2013). In addition to the identification and classification topics, other authors address the problem of quality analysis of barley grains within the beer and malt brewing process (e.g., Szczypiński et al., 2015; Kozłowski et al., 2019). On the other hand, the analysis of the barley phenotype is another of the topics addressed in the literature (Toda et al., 2020). In most of the approaches, the analyzed cluster of grains contains non-touching kernels, which is not a realistic scenario. In a large number of cases, the proposed solutions are based on machine learning although very few works are based on deep learning techniques (e.g., Toda et al., 2020; Kozłowski et al., 2019), which provides an opportunity to improve the accuracy rate of previous works.

2.6.5. Coffee

The quality of coffee grains is determined by factors such as color, odor, texture, size, among the most important. In recent years several techniques have been proposed to improve the selection processes of coffee beans. Some of these techniques are listed below, describing their scope and focus. The analyzed coffee classification techniques are based on images of the visible spectrum (e.g., Arboleda et al., 2018; Huang et al., 2019). The classification discrimination in most cases is limited to two classes (e.g., Arboleda et al., 2018; García et al., 2019). The developed methods generally use traditional machine learning based techniques (Arboleda et al., 2018). On the contrary to the previous cases, in the coffee beans classification problems, all techniques tackle the non-touching kernel classification case (Huang et al., 2019).

2.6.6. Others

In addition to the approaches listed above, which were focused on

Table 2
Literature reviewed grouped by type of grain.

Type of grain	Author(s)	# of	Classif.	Categories
Rice	Shamim et al. (2020)	8	82.00	PR, RH-10, sharbati, sona masoori, sugandha, pusa basmati (1509, 1121 and 1401)
	Singh and Chaudhury (2020)	4	96.75	class A, class B, class C, class D
	Aukkapinyo et al. (2019)	4	81.00	RD15, RD23, RD75, ML105
	Lin et al. (2018)	4	95.50	indica, japonica, glutinous, overall
	Qiu et al. (2018)	4	86.40	xiushui 134, zhejing 99, zhongjiazao 17, zhongzao 39
	Tin et al. (2018)	5	80.00	paw san hmwe, lone thwe hmwe,ayeyarmin, kauk-nyinn-thwe,kauk-nyinn-pu
	Wah et al. (2018)	4	92.00	class A, class B, class C, class D
	Liu et al. (2016)	5	94.00	FD2, QXY512, HXD3, QXY822, WKJ11
	Singh and Chaudhury (2016)	4	96.00	type1, type2, type3, type4
	Birla and Chauhan (2015)	4	93.57	normal, small, large, broken
Rice	Kaur and Singh (2015)	5	97.21	pusa 44, PR122, PR121, pusa basmati (1509 and 1121)
	Zareiforoush et al. (2015)	5	89.80	very bad, bad, medium, good, very good
	Kambo and Yerpude (2014)	4	79.00	classic basmati, rozana, mini, overall
	Liu et al. (2014)	2	100	non-transgenic, transgenic
	Sun et al. (2014)	2	98.05	indica, japonica
	Gujjar and Siddappa (2013)	6	84.83	6 varieties of basmati
	Kaur and Singh (2013)	4	86.00	premium, grade A, B and C
	Silva and Sonnadara (2013)	9	91.55	AT307, BG250, BG358, BG450, BW267, W361, BW363, BW262, BW364
	Mousavirad et al. (2012)	5	98.40	mahali, neda, gerde, fajr, hashemi
Wheat	Kar et al. (2019)	8	-	full grain, damaged, weevilled, broken, immature/shrivelled, other food grains, inorganic and organic foreign matter
	Sabanci et al. (2017)	2	99.00	bread, durum
	Shrestha et al. (2016)	3	72.80	sound, sprout-damaged, severe sprout-damaged
	Olgun et al. (2016)	40	88.33	wheat grain species
	Tan et al. (2016)	3	93.94	strong, medium and weak gluten
	Berman et al. (2007)	4	95.00	sound, blackpoint-affected, fungal stained, pink stained
Barley	Toda et al. (2020)	20	95.00	19 domesticated and 1 wild barley
	Kozłowski et al. (2019)	11	93.20	11 varieties of two-rowed barley
	Szczypiński et al. (2015)	11	91.00	11 varieties of two-rowed barley
	Mebatsion et al. (2013)	1	98.50	-
	Guevara-Hernandez and Gil (2011)	1	99.00	-
	Douik and Abdellaoui (2010)	1	98.70	Tunisian barley
	Choudhary et al. (2008)	1	98.60	Special select malt barley
	Zapotoczny et al. (2008)	2	94.94	2 varieties of polish spring barley
	Paliwal et al. (2003)	1	96.00	-
Corn	Chu et al. (2020)	3	100	jingKe, jingNuo, xianYu
	Velesaca et al. (2020)	3	95.60	good, defective, impurity
	Altuntaş et al. (2019)	2	94.22	haploid, diploids
	Huang et al. (2019)	5	95.00	worm, mold, damages, good, discoloration
	Sendin et al. (2019)	14	99.40	sound, 13 undesirable materials
	Xia et al. (2019)	17	99.13	17 varieties of corn
	Miao et al. (2018)	8	97.5	Zhou 1, TZ 23, GCT 3, XXWCT, GHT, HJ 9, XT, SL78
Corn	Sendin et al. (2018)	2	91.50	sound, defective
	Wen et al. (2018)	2	-	fresh, dry weights of seedlings
	Yin et al. (2017)	5	97.00	5 grades of moldy corn
	Huang et al. (2016)	17	92.00	17 varieties of seeds
	Wen et al. (2015)	2	-	fresh, dry weights of seedlings
Coffee Green	García et al. (2019)	6	90.00	high-quality, very long-berry; broken, sour, black and small defect
	Huang et al. (2019)	2	93.00	good, bad
	Arboleda et al. (2018)	2	100	normal, black
Beans	Kılıç et al. (2007)	5	90.60	AA, BB, BC, CB, CC
Cocoa	Gomez et al. (2019)	2	98.43	well-fermented, over-fermented
bean	Son and Thai-Nghe (2019)	2	93.85	whole, broken

the largest production grains, there are other approaches intended to classify different food grains. These approaches are mainly motivated by quality classification. They can differentiate up to two or three classes of grains' quality; some examples are the beans (Gomez et al., 2019) and cocoa beans (Kılıç et al., 2007) classification problems. In these cases, the approaches have been designed to work with untouched kernels, which reduces the complexity of the problem to be solved. In most of the cases, the proposed solutions are based on K-means clustering, SVM, and ANN techniques to obtain the best results. There is no comparison between the techniques because each one of them has implemented its own image acquisition system, generating its own datasets, which are not available for comparisons.

2.6.7. *Multi-variety*

In addition to the approaches presented above, which are focusing on grading techniques with a single variety of grains, there are some techniques able to tackle the classification of several varieties of grain with the same algorithm, such as rice, Brazilian beans called Carioca, chickpeas, lentils, corn, wheat, barley, among others. For instance, in Toda et al. (2020) the authors propose a multi-variety approach that is trained using synthetically generated images. Others multigrain classification approaches use real images of the visible spectrum, for instance in (Ribeiro, 2016; Choudhary et al., 2008) machine learning based approaches are proposed to perform multiple grading of grains. In most of the cases, the implemented multi-variety techniques use morphological characteristics in order to differentiate the specific details of the grains and perform a better classification (e.g., Douik and Abdellaoui, 2010; Guevara-Hernandez and Gil, 2011; Mebatsion et al., 2013; Paliwal et al., 2003). Although results from multi-variety approaches are interesting, they do not reach the performance of single variety approaches. Furthermore, in general, in the seed classification problem, there are not multi-variety scenarios. In other words, the grains come from the harvest of a single crop.

2.6.8. Discussions on grain variety

After reviewing the techniques that allow the classification of different types of grains it can be summarized that former works were mainly based on the analysis of color and texture features; geometry has been also considered in some cases. On the contrary to previous approaches, where handcrafted solutions were proposed, more recent techniques rely on deep learning strategies where CNNs are trained with a large labeled dataset. In most cases, the approaches use their own datasets to train and validate the techniques. Following the trend on deep learning based approaches, in the grain classification, there are some approaches based on the usage of synthetic ground truth. As mentioned above, this allows tackling the classification of different varieties at a low cost (i.e., a large amount of ground truth data is obtained easily). Although not included in the pipeline presented in Fig. 1, ground truth data generation is reviewed in the next section.

As specific conclusions for each grain variety, it can be stated the following. In the case of a rice grain, the proposed approaches have been migrating from classical machine learning techniques to CNNs models, in order to improve the efficiency of the obtained results. In the wheat grain classification domain, it could be observed that the use of multispectral or hyperspectral images is generally used to improve class differentiation. In the case of coffee grain approaches, the proposed techniques mostly use images of the visible spectrum and do not explore the use of CNNs. The touching kernel scenario has not yet been explored, which is an opportunity to tackle new problems. Additionally, exploring the use of multispectral or hyperspectral images to improve class differentiation has not been yet considered. In the case of multi-grain techniques, although attractive results have been obtained, their performance does not reach standalone single variety approaches.

2.7. Ground truth

Although not included in the pipeline presented in Fig. 1, ground truth data are an important part for both, validating results from a given approach as well as comparing performances from different proposals. In addition to these usages, ground truth data are needed to train machine learning-based approaches. In general, a large amount of tagged data are required for training algorithms, which becomes a laborious and time consuming task. A possible solution to this problem is to work with synthetic images, which include the necessary annotations, with which, there is no longer a dependency on trained human work in making annotations. This section reviews strategies followed in the literature to generate datasets, both real and synthetic, together with the corresponding annotations for a ground truth generation.

2.7.1. Real data

Most of the authors of the reviewed literature perform data acquisition from scratch, at all times controlling the conditions of the environment where the images are obtained. For example, the distance and location of the camera are always controlled, where most of the time the camera is orthogonal to the acquisition surface at a specific distance to view the largest amount of grains and also maintaining an adequate aspect ratio. Another important condition to consider was the light source, which generally is located on top of the working area where the grains were placed (e.g., Birla and Chauhan, 2015; García et al., 2019). There are different approaches to carry out annotation tasks of the ground truth, some authors use the manual labeling of the input data with the help of crowdsourcing tools such as Labelbox[3], Voxel51[4], Lionbridge[5], SuperAnnotate[6], just to mention a few (e.g., Velesaca et al., 2020; Toda et al., 2020). This way of performing data annotations is the most expensive method in terms of time and resources used and depends on the number of objects present in the scene. Hence, trying to avoid this time-consuming task, some authors (e.g., Aukkapinyo et al., 2019) use digital image processing techniques to partially automate the annotation process; among the different approaches proposed in the literature, watershed, discussed in Sec. 2.3.1, is the most used despite of the fact it has some drawbacks (e.g., over-segmentation, delimitation of incorrect contours, among others) but with controlled environmental conditions it is a good option to save time.

2.7.2. Synthetic data

In most of the approaches mentioned in previous sections, the ground truth has been obtained from images captured from the real world, as aforementioned this task requires a lot of effort and time on both activities: image acquisition and image annotation. Trying to overcome these problems some authors generate ground truth from synthetic images. This synthetic images are obtained from virtual environments where different grain distributions (e.g., Toda et al., 2020; Kar et al., 2019) may be generated. It should be noticed that the usage of 3D grain models in virtual environments not only helps to avoid the time required for the acquisition and annotation but also it helps to generate datasets with large variability, which are required for training deep learning algorithms. As more complex the 3D grain model (parametric representation that allows changes in size, texture, and color) and virtual environment (lighting conditions, camera models, etc.) as large the acquired dataset will be. Taking advantage of the generalization offered by the synthetic data acquisition framework, Toda et al. (2020) propose a deep learning based grain detection method to identify seeds of various types, for example, barley, rice, lettuce, oats, and wheat. Synthetic images acquired in a virtual environment are used to train the model; then, the validation stage is performed using real-world images. This model has been initially tested for barley grains, but given the obtained results, the evaluations were extended to other types of grains, thus minimizing the time and cost of the process of ground truth generation.

On the other hand, Kar et al. (2019) perform the classification of wheat grains by using a hybrid strategy where real images are used in a virtual environment for training the instance segmentation architecture. In this case, the authors propose the usage of a synthetic cluster generator. This generator uses three different ways of distributing the wheat grains to form the clusters. The first approach places the kernel images, obtained from real scenarios, randomly; in the second approach the kernels are also placed randomly but enforcing a maximum overlap constraint; while in the last approach, the kernels are placed using a cell-population simulator. The resulting synthetic images are used as input to a U-Net architecture that performs the task of instance segmentation.

2.7.3. Discussions on ground truth

Generating ground truth involves spending time and resources that depend on the type of approach used to generate it. In the case of real data, the labeling time is very long since each of the images obtained in the acquisition stage needs to be manually labeled, as well as having experts in the area of the type of grain to be analyzed. On the other hand, and although used in a lesser proportion, the generation of synthetic

[3] labelbox.com.
[4] voxel51.com.
[5] lionbridge.ai
[6] superannotate.com.

data seems a better option. By using synthetic images there is no need to label the data neither to have an expert devoting time to this task; obviously, results would depend on the quality of the 3D model used to represent the given grain (i.e., how similar it is to the real grain), variability of such a 3D model (i.e., model parameters used to generate different representations based on the combination of shapes, texture, and color), and the virtual environment (i.e., lighting conditions, shadows, camera, and lens modeling, etc.) used to generate the synthetic images. Although considering all the advantages synthetic data seems to be the best option, it is also true that because it is a relatively new approach applied to the area of food grain problem, just a few authors use it. Most of the works are based on the usage of traditional techniques (i.e., ground truth manually annotated on real images).

3. Conclusions

After reviewing the whole literature different conclusions and needs for further work are identified. Firstly, it is clear the need for common benchmarks for each of the grain varieties. As presented in Section 2.6, each approach is evaluated with datasets collected by the authors, most of the time without taking into account previous works. Having common benchmarks for each grain variety will allow comparisons and continuous improvement with new contributions. In addition to the need of having available benchmarks, source code available for comparisons is also needed. From all the reviewed papers just a couple of authors offer the source code of their approaches for further comparisons.

Another conclusion on the food grain classification problem is related to the type of data to process, although most of the works are based on the usage of color images, with a few contributions using infrared spectrum, it seems multispectral and hyperspectral approaches are opening new possibilities. With the improvement in technology and the reduction in the cost of these sensors, it is expected that in the near future a large set of new cameras will be available to tackle this problem in a more efficient and robust way.

Regarding the techniques used for the classification stage, as well as for the segmentation stage, it can be concluded that approaches based on deep learning are the trend. This is also supported by other applications in the computer vision literature, where deep learning has become the common framework. The results of these deep learning approaches are outperforming those based on classical techniques. Once again, having the source code available and evaluating the same dataset will be an opportunity to compare all these contributions in the same framework and identify the best option. Finally, regarding the variety of grains, it is clear that a lot of work has been done to classify rice, corn, and wheat, but the classification of other varieties of grains has also been recently explored, showing both the interest in the classification problem as well as the capabilities of the computer vision based technologies to solve it automatically.

4. List of acronyms

ANN: Artificial Neural Network; BPNN: Back Propagation Neural Network; CNN: Convolutional Neural Network; FAOSTAT: Food and Agriculture Organization Statistical Database; HSV: Hue, Saturation and Value; K-NN: K-Nearest Neighbor; LS-SVM: Least Square Support Vector Machine; NIR: Near Infra Red; PLS-DA: Partial Least Squares Discriminant Analysis; RELU: Rectified Linear Unit; RGB: Red, Green and Blue; SPA: Successive Projections Algorithm; SVM: Support Vector Machine;

CRediT authorship contribution statement

Henry O. Velesaca: Investigation, Writing – original draft, Writing – review & editing. **Patricia L. Suárez:** Investigation, Writing – original draft, Writing – review & editing. **Raúl Mira:** Investigation, Writing – original draft. **Angel D. Sappa:** Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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