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Wheat varieties identification based on a deep learning approach

Karim Laabassi [a,*], Mohammed Amin Belarbi [b], Saÿd Mahmoudi [b], Sidi Ahmed Mahmoudi [b], Kaci Ferhat [a]

[a] Department of Agricultural Machinery and Agro-equipments, National Higher School of Agronomy, Hassen Badi El-Harrach, Algeria
[b] Department of Computer Science, Faculty of Engineering, University of Mons, 7000 Mons, Belgium

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ABSTRACT

Wheat variety recognition and authentication are essential tasks of the quality assessment in the grain chain industry, especially for seed testing and certification processes. Recognition and authentication by direct visual analysis of grains are still achieved manually. The automatic approach, based on computer vision and machine learning classification, provided rapid and high throughput methods. Even thus, the classification task stays a complex and challenging case at the varietal level.

The present work proposes a deep learning-based approach that provides an accurate classification for wheat varietal level classification (VLC). Particularly, the Convolutional Neural network (CNN) was used to classify the wheat grain image into four varieties (*Simeto, Vitron, ARZ*, and *HD*). Furthermore, five standard CNN architectures were trained based on Transfer Learning to boost the classification performance. To assess the proposed models' quality, we used a dataset of 31,606 single-grain images collected from different Algeria regions, and their images were captured using different scanners.

The results showed that the test accuracy ranged from 85% to 95.68% for varietal level classification. The best test accuracy was obtained with the DensNet201 architecture (95.68%), Inception V3 (95.62%), and MobileNet (95.49%). Hence, the proposed approach results are accurate and reliable, encouraging the deployment of such an approach in practice.

1. Introduction

The evolution of wheat crop production into a complex *Grain Chain* (Wrigley, 2017a) has required a quality assessment process and technology that include an inspection system and product certification programs. The ultimate objective is to make and keep available more quantity of a high-quality wheat product on the market. The seed testing is an essential process (Copeland and McDonald, 2001; Powell, 2009) that provides the necessary quality information about purity, viability, germination, and noxious weed seed content, for labeling seed to be sold (Elias et al., 2012).

The seeds purity test is imperatively performed to determine the level of physical and varietal purity of a seed lot. The original wheat cultivar's genetic integrity can be modified by a mechanical mixture and incorrect labeling (Copeland and McDonald, 2001). The purity test is a *Grain Identity Recognition* (GIR), this test is achieved following a taxonomic classification approach, using a non-destructive and direct visual grain features analysis (ISTA, 2018; Meyer and Wiersema, 2016; OCDE, 2019). Indeed, the seed tester performs two classification levels, a *Species-Level Classification (SLC)* for the physical purity test and a *Varietal Level Classification (VLC)* for varietal purity.

The VLC could be difficult or even impossible because of the high-level similarity between *Triticum spp* features (Chiara Delogu, 2013). The grain's characteristics can also be affected by the growing conditions (Howitt and Diane, 2017). The actual purity test operation is still a low throughput method, and the accuracy depends on expert performance and his cumulated experience.

In this context, a GIR by an automatic identification process, using the Computer Vision (CV) associated with deep learning (DL), particularly CNNs (Davies, 2012; Makridakis et al., 2018), could be a reliable solution for a VLC. It could improve the labor conditions and gives other advantages for seed testing, and preserve the advantages of direct visual grain features analysis, and consequently, it allows performing a VLC accurately.

Image classification is the main CV and Machine Learning (ML) technique used for automatic identifying and recognizing tasks (Du and Sun, 2006; PatrÚcio and Rieder, 2018). This technique

* Corresponding author.
E-mail address: karim.laabassi@edu.ensa.dz (K. Laabassi).

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had been already applied successfully in many production chains (Dutta Gupta and Ibaraki, 2014; Vithu and Moses, 2016), as well as for cereals (Davies, 2009; Pridmore, 2015; Tripodi et al., 2018) and specifically for automatic grain classification as reported in (PatrÚcio and Rieder, 2018; Vithu and Moses, 2016).

Image classification includes two mainly used approaches, *the Shallow classical approach* and the *DL approach* (Brahimi et al., 2017; Davies, 2012). The first approch consists of a hand-crafted features extraction (CV) as an input data for a trainable classifier (ML).The second one is an all-in-one pipe, in which the images are inputted directly to the DL classifier, making the classification task more advantageous.

Several *Shallow classical approaches* using Artificial Neural Networks (ANNs) classifier among other classifiers were conducted for wheat VLC, for example, (Choudhary et al., 2009; Khoshroo and Arefi, 2014) have achieved an accuracy of 92.1% and 85.72% respectively. Visen et al. (2002), report that if the objects to be classified have very subtle differences in morphological, color, and textural features, the use of one neural network may not result in a high classification accuracy.

Using a multi-classifier was an attempt to improve accuracy and make a more specialized classifier to identify a particular object type. Indeed, Ebrahimi et al. (2014) have combined two classifiers, Imperialist Competitive Algorithm (ICA) and Artificial Neural Networks (ANNs). The classification rate of this approach for SLC (wheat grains vs. non-wheat seeds) was 96.25%.

A robust classifier with high accuracy must be trained on a big data set (Brahimi et al., 2017), which needs an adapted architecture and framework, which implies using a more powerful machine and new computing approaches. The Deep Learning approach had become possible with the use of the Deep Learning (DL) and the Graphical-processing unit GPU that allows parallel when processing a large image dataset.

Deep Learning is a set of universal machine learning methods (LeCun et al., 2015), which have been recently successfully and widely applied in many areas to perform all machine learning tasks (Alom et al., 2019). The Convolutional Neural Networks (CNNs) is one of the best DL architecture used to recognize, detect, and retrieve image content.

Several authors have used deep learning models for plant classification (Kamilaris and Prenafeta-Bold[a], 2018). State of the art shows two trends. The first one is related to high-throughput phenotyping and plant identification, such as the study performed in this sense by Ubbens and Stavness (2017). The second concerns plant health monitoring and disease detection (Brahimi et al., 2017; Ferentinos, 2018).

Thenmozhi and Srinivasulu Reddy (2019) proposed a CNN model for classifying insect species in wheat crops using three sets of public insect data. The proposed model was with fine-tuning architectures AlexNet, ResNet, GoogLeNet, and VGGNet for insect classification. Classification accuracy obtained for three insect dataset was 96.75%, 97.47%, and 95.97%.

Referring to the Transfer Learning (Tan et al., 2018) point of view, the models trained on a large dataset in a transfer learning process can successfully classify images in a new domain (LeCun et al., 2015). In a recent plant identification study, Too et al. (2019) have proposed a comparative study between fine-tuned deep learning models in which the DenseNet model had achieved a classification test accuracy of 99.75%.

Concerning the wheat grains case, Shen et al. (2018) had tested the possibility of detecting insects in stored-grain using deep learning. The authors used a Fast R-CNN to extract areas that might contain the insects in images and classify them in these areas. The results showed that the developed method could detect and identify insects under stored grain condition, and the mean Average Precision (mAP) reached 88%.

A recent VLC using CNNs on barley varieties was proposed by Kozowski et al. (2019). Nine experiments were conducted to determine the best CNN architecture. The best accuracy was over 93%, which was achieved by one of the five proposed architectures. This result was similar to the fine-tuned ResNet18, but with fewer parameters. The authors Kozowski et al. (2019) used a balanced dataset of 60 753 single grain images representing six barely varieties. The authors performed a pre-processing step following the approach presented in Szczypiski and Zapotoczny (2012). Only one flat-bed scanner was used for the acquisition step. The grain captured side was taken in random dorsoventral orientations but the longitudinal axis was normalized to be in a vertical direction .The lemma base was in the same position (at the top).

Regarding the dorsoventral orientation, the nature of the imaging process is unpredictable; each side of the grain has an impact on classification as investigated by Dolata and Reiner (2018). Szczypiski et al. (2015) confirmed the same statement early, their study showed that the analysis of the tow side of barely wrinkled regions has a significant impact on the results of grain classification. Furthermore, in the study of (Kozowski et al., 2019), the background was removed, and images have been resized to 80 pixels æ 170 pixels. Removing the background could make CNN focus on the grain. However, segmentation can be challenging, leading to the loss of grain pixels and could affect feature extraction. In our study, we have chosen to keep the original background.

The CNN classifier executes the same tasks besides the fact that wheat and barley belong to different cereal genre. Accuracy and performance are related to CNN's architecture and hyperparameters, also to the quality of the image dataset, including size and diversity.

The dorsoventral side of the wheat grain, compared to barely, is characterized by the presence of specific features called crease (ventral furrow) and includes more other features, e.g., the brush hair, flange, and radicle tip (Wrigley, 2017b).

We consider that a one-side analysis is more challenging than two sides; a random longitudinal axis orientation (the brush hair as the grain head) makes the acquisition step technically more flexible and practicable; the most robust CNN has to achieve a good result.

A low-cost device-based technique could be more useful and available in certain situations, such as laboratories in developing countries. Indeed, the flatbed scanner was primarily used by several authors because it offers ease of use without a complex calibration and image stability (no focus is needed). However, any computer vision system for grain analysis should be independent of the acquisition device. Building the dataset with several acquisition devices can increase the variability, making a vision system device-independent. This independence should be beneficial in practice when the system is used with a different acquisition system.

To the best of our knowledge, wheat GIR by VLC based on CNN image classification has not been investigated yet. Moreover, VLC and SLC with several flatbed scanner types under uncontrolled conditions have not previously been considered. Therefore, in this paper, we propose a deep VLC pipe by fine-tuning a pre-trained CNN standard architectures. Furthermore, we have adopted a data collection strategy based on diversification using several axesfirst, a spatial diversification, as we have collected grains from several regions. Second, a two-way sampling, from the field as whole ears and a bulk sample from regional storage facilities. Finally, device diversification using several flatbed device types to ensure diversity.

2. Material and method

The experiment workflow was conducted flowing two steps: a) **Data collection,** which includes grains samples preparation and image dataset collection; b) **Deep learning classification implementation.**

2.1. Data collection

We adopted a strategy for data diversification by incising the sources of variation in order to collect a representative database that reflects the ground truth situation and allow a robust learning, we considered the following sources of variation:

1. The spatial variability source, by collecting the grain samples from different growing zones located in different Algerian regions.
2. The agronomical variability source provided by being collecting grains from different farmers practicing different farming systems.
3. The acquisition system, by using four different commercial flatbed desktop scanners.

2.1.1. Grains collection

The collected vegetal material is composed of four common cultivated varieties in Algeria (Simeto var, Vitron var, ARZ var, and HD var) belonging to two wheat species hard wheat (Triticum durum Desf) and soft wheat (Triticum aestivum). Table 1 summarizes the quantity and the origin of each grain variety. The prepared collection contains 31 606 certified intact seed grains. These wheat grains were sampled in the same harvest year 2017 from 12 provinces distributed in Algeria's principal bioclimatic areas. Furthermore, we obtained the grains from 48 farmers and 48 specific locations (spatial variation).

The Grains samples were collected according to two approaches (Fig. 1). First, the field collection approach (representing 50% of dataset), where we have randomly picked up directly from the field wheat ears, then we manually threshed them. The approach aims to preserve all grain's features that can be eventually affected by mechanical threshing and handling operation at post-harvest stages. However, in the second approach, we obtained the bulk grain samples (remained 50% of dataset) from the regional official storage facilities. Most of the grain shape and size variations are expected to be present in each sample, because no calibrating sifting step was applied. The samples were packaged in suitable bags, labeled, and stored under ambient conditions.

2.1.2. Image dataset collection. The experimentation was performed on a set of images acquired from four flatbed scanners. The datasets are 2D dorsoventral grain RGB images with a random and regular anteroposterior direction (Fig. 2). Using different device models for image acquisition aims to reduce the eventual uniformity that could be provided from using the same device.

The image acquisition step began with the acquisition of 65 principal images. All grains were scanned with a black background. Each main image included 500 to 1013 grains and had the following characteristics: depth of 24bit, taken in JPEG and TIFF format, with a resolution of 300 and 600 dots per inch (Dpi).

The image segmentation step was performed to obtain single grain images from the principal image, as shown in Fig. 2. The segmentation consisted of cropping the principal images into single grain ones without removing the background. We obtained 31 606 single grain RGB images with a random and regular anteroposterior direction. The images were saved in TIFF format.

Due to the natural variability of grain size and shape, we have obtained a heterogonous image shape; we used them without normalization. Table 2 represents the dataset input related information. The build model folder contains 22 478 images (representing 72.35% of the total dataset). This dataset was divided into 80% for the training step and 20% for the validation step. The built models were tested on an independent sample set of 9 128 images.

2.2. Deep learning classification. We have used five standard CNN architectures: (InceptionV3, MobileNet, Xception, ResNet50, and DensNet201) trained using a transfer learning by fine-tuning. These architectures were pre-trained on the ImageNet dataset. The transfer learning strategy is chosen because it can improve accuracy while accelerating the training (Alom et al., 2019). Transfer learning can provide important benefits for automated plant identification and can improve low-performance plant classification models (Kaya et al., 2019).

2.2.1. Model structure. To build the model, we have replaced the top layers of standard architectures. The remaining part of the architecture is called base model. We replaced the original top layers with the following top layers:

The global Average Pooling layer calculates the global average of each base model's last layer's feature maps, which decreases the risk of overfitting.
A fully connected layer of 1024 neurons is used as the first layer in the top layers.
The last fully connected prediction layer with SoftMax activation function. The number of neurons in this layer is four according to the number of classes (*Simeto, Vitron, ARZ, HD*).

We have a ReLU activation function in all top layers except the output layer. The output layer should use the SoftMax to output probabilities of classes.

2.2.2. Deep learning framework and machine specifications. All our training and testing script are written in *Python 3* programming language. We have used python deep learning framework *Keras 2.2*[1], thanks to its simplicity. As *Keras* backend, we have used *Tensorflow 1.9*[2]. Our experiments were performed on a machine having the following specifications:

Ram: 64 GB
GPU: 4 æ Nvidia Geforce 1080ti 11 Gb
CPU: Intel(R) Xeon(R) CPU E5-2620 v4 @ 2.10 GHz

2.2.3. Training hyperparamaters. The batch size was set at 32, and the number of epochs was 100. The model optimization during the training is achieved using gradient descent algorithm Adam with learning rate 0.001. Moreover, we have used the early stopping regularization method that helps to avoid overfitting. In early stopping, the training is stopped when the loss function does not improve on the validation set; rather than finishing all the 100 epochs.

3. Results and discussion

3.1. Building stage results

Table 3 presents the training and validation accuracy of the different CNNs architectures. All models have achieved a validation accuracy of up to 97%. The best validation accuracy (Table 3) were

[1] https://www.keras.io/
[2] www.tensorflow.org

Table 1
Grains number and origin.

Species	Variety	Grains/variety	Total grains/species		Provinces		Farmers
Hard Wheat (*Triticum durum Desf*)	**Simeto**	9 842	16 565	31 606	6	11	16
	Vitron	6 723			5		12
Soft Wheat (*Triticum* aestivum)	**ARZ**	4 235	15 041		4	9	8
	HD	10 806			5		12

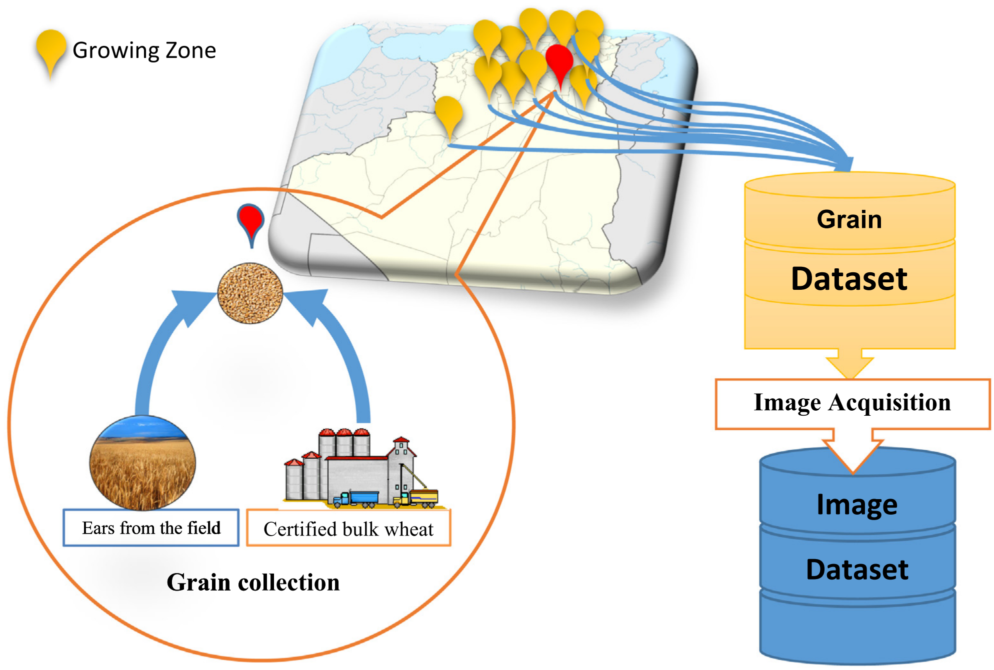

Fig. 1. Grains collection workflow.

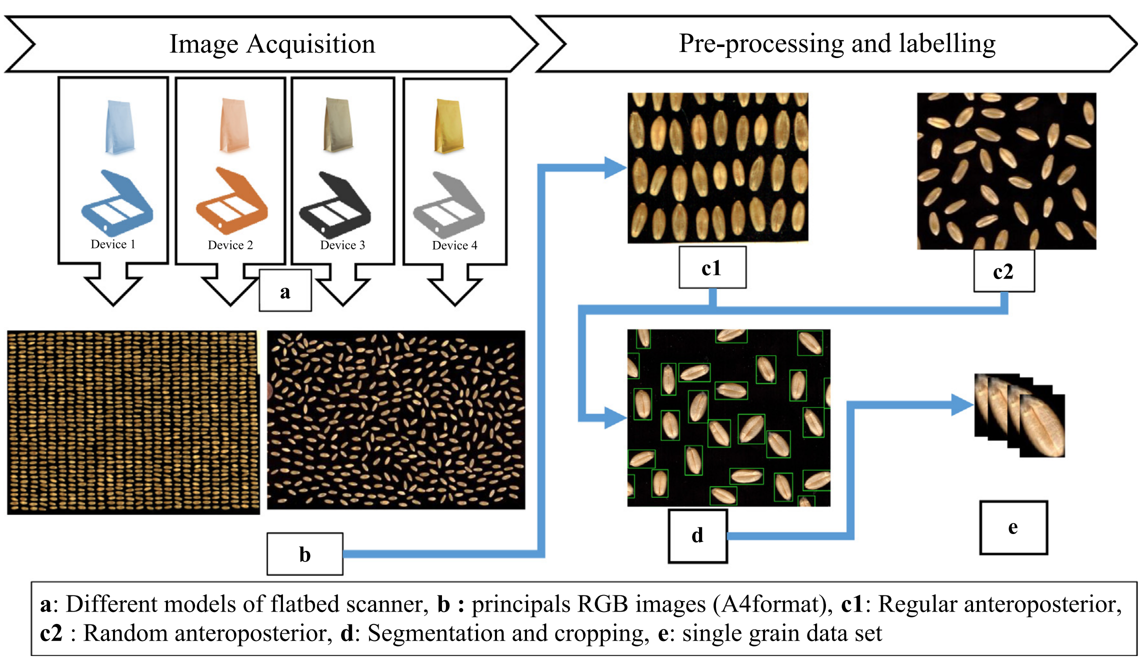

Fig. 2. Image acquisition and pre-processing.

Table 2
Data information for VLC deep model experimentation.

Variety	**Simeto**			**Vitron**			**ARZ**			**HD**		
Number of	**Growing zone**	**Farmers**	**Images**	**Growing zone**	**Farmers**	**Images**	**Growing zone**	**Farmers**	**Images**	**Growing zone**	**Farmers**	**Images**
Build data	6	12	6124	5	10	5146	4	6	3484	4	8	7724
Test data	3	4	3718	2	2	1577	2	2	751	3	4	3082

Table 3
VLC Models results in the building stage.

Architecture	Building Model						
	Early stopping epoch	Model size (MB)	Training results		Validation results		Ranking
			Training accuracy (%)	Training loss	Validation accuracy (%)	Validation loss	
InceptionV3	73	92	99.92	0.003	97.55	0.13	4
MobileNet	72	17	99.84	0.005	**98.10**	**0.12**	**3**
Xception	87	88	99.86	0.004	**98.22**	**0.10**	**2**
ResNet50	86	99	99.53	0.020	97.30	0.13	5
DenseNet201	76	79	97.92	0.010	**98.30**	**0.07**	**1**

obtained with a slight difference by DenseNet201 98.30%, the Xception 98.22%, and MobileNet 98.10%, while ResNet50 had achieved the lowest validation accuracy of 97.55%. We notice that the MobileNet model takes less space in building the VLC model, compared to ResNet50.

Fig. 3 shows the curve variation per epoch of loss and accuracy value in both train and validation steps for the first three CNNs.

3.2. Testing stage results

During the test phase, all CNNs have achieved accuracy values ranging between 94% and 95%. These results had decreased compared to those of the training and the validation step. The best test scores were achieved overlay by the same architectures as in the validation step, but the best accuracy was achieved by DensNet201 95.68%, followed by InceptionV3 with 95.62% and finally MobileNet 95.49%.

Table 4 indicates each architecture's accuracy for each variety and the most suitable CNN for each variety and wheat species. The best CNN classifier for Vitron var is DensNet201 with an accuracy value of 80%; in contrast, the same architecture achieves a high accuracy when classifying HD var with a value of 99.50%. InceptionV3 classifies better Semito var than the other wheat varieties with 98.93%. ARZ var had been the most correctly classified by all architectures, and the Xception had achieved the highest accuracy value of 99.87%. When it comes to Wheat species level, they are better classified by InceptionV3 with test accuracy of 99.64% and 99.59% for hard wheat and 99.71% for soft wheat.

The Confusion Matrix (Tables 58) gives a clear view of the VLC performances and indicates the misclassified object. The *Vitron Var* is the most misclassified variety.

3.3. Pheno-deep discussion and analysis

This study's central question spun around whether it is possible to identify wheat varieties through the grain dorsoventral side, regardless of the grain's origin. To investigate this problem, we proposed a methodology for Varietal Level Classification based on image classification using a DL approach.

We verified the performance and the ability of five pre-trained CNNs architectures to accomplish the VLC tasks through our study-case and methodology. The results demonstrate the ability of CNNs to correctly classify wheat varieties at a rate greater than 95% (test accuracy on an independent sample). The best first three models for VLC were respectively the DensNet201 (95.68%) followed by InceptionV3 with 95.62% and finally MobileNet 95.49%. Also, when it comes to Wheat SLC, the InceptionV3 achieves the best test accuracy of 99.64%.

The accuracy rate obtained in this study is higher than that obtained by Kozowski et al. (2019), who applied deep learning for barley varieties classification using AlexNet and ResNet18 and obtained an accuracy exceeding 93% both for his fully built CNN (64 filters of size 3x3) and fine-tuned ResNet18 model.

Also and referring to the fine-tuning technique, when we compare our results to the recent comparative experimentation of fine-tuning DL models for plants healthy identifications achieved by Too et al. (2019), we notice that we got a similar level of accuracy and the best achievement was for DenseNet model with 99.75%. As a reminder, the CNNs were pre-trained using the ImageNet database; this latter contains more intricate image details than those of wheat grain. Our images dataset specification (diversity) was sufficient to enable CNNs to recognize each variety.

The results also show a dissimilarity of each CNN to deal with each class with the same accuracy (Table 4); we qualified this find as a specific CNN specialization to classify a specific variety correctly due to CNNs architecture and depth. This late relates to layers number and plays a crucial role in creating and modeling features at the training stage until finding out the best model corresponding to the highest accuracy without overfitting when the accuracy does not increase.

Our work is an organism-centered scale study case (Fahimirad and Ghorbanpour, 2019), since we have used the grain, one of the phenotypes that most characterize the Triticum species. The grain contains specific features that permitted distinguishing each variety from another. The images we have taken for each grain contain visual information about the observable traits witch were converted into groups of pixels. So we can consider that the information contained in the wheat grain dorsoventral side was sufficient for CNNs to build a grain model for each wheat variety by performing a self-extract all potential features key. Indeed, this is a deep learning capacity to abstract the information relating to the wheat plant phenotype. We could have better results if 3D object images were used.

The Confusion Matrices (Tables 58) gives a clear view of the VLC performances and indicates the misclassified object. The misclassification is proportional to the resemblance between individuals of

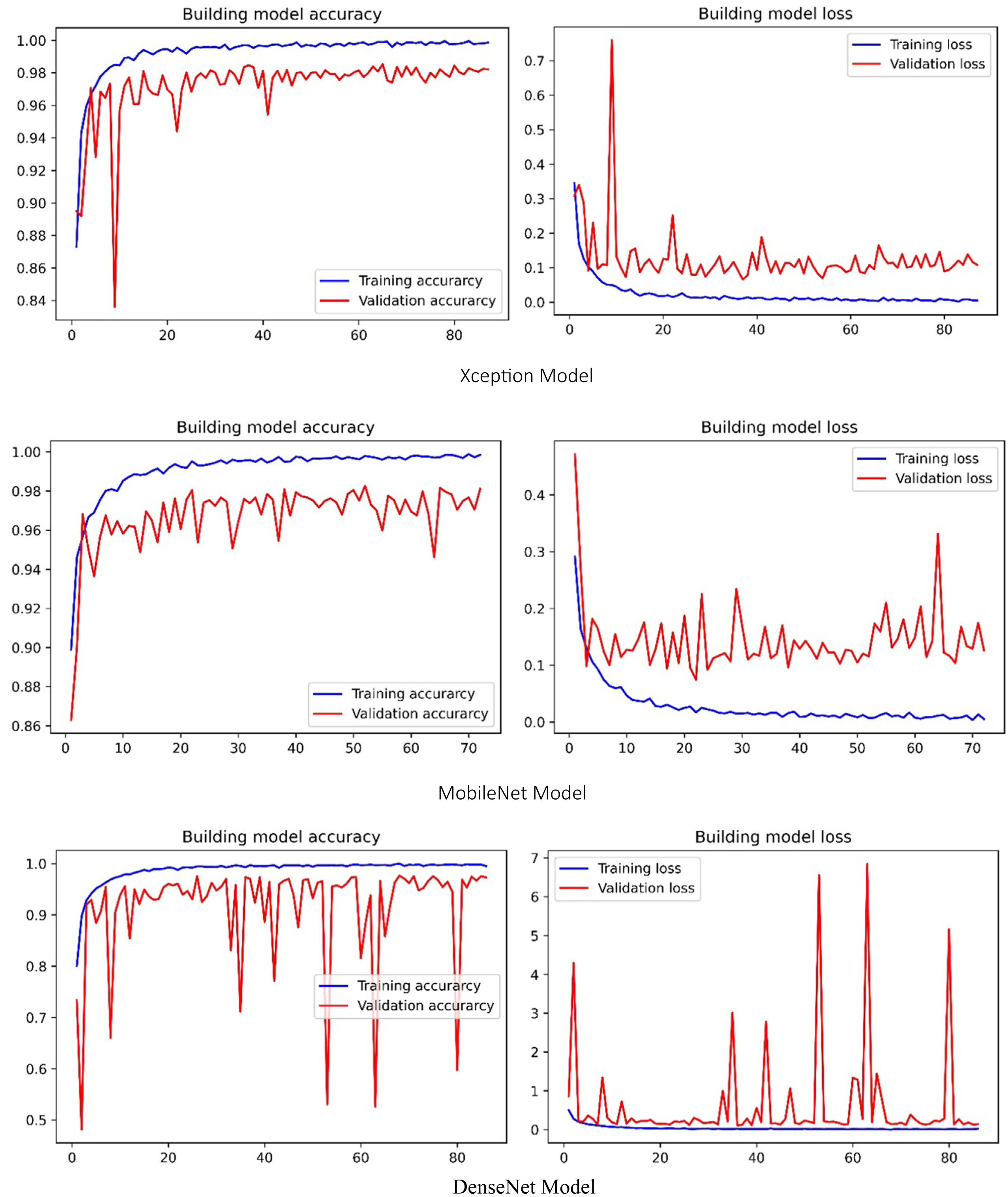

Fig. 3. First best three CNN architectures curves.

two different classes; we explain this by how much closer are some varieties to each other; the Vitron var is the most misclassified variety. The soft Wheat varieties have been the most correctly classified. It could be correlated to the growing zone and data set size, but we do not have the evidence, and this should be the subject of another study. According to seeds testing rules, our results are not applicable when the varietal purity must be at 100% pure, as for the breeding seed level or the pre-base seed grad of the seed's multiplication program.

We carried out this study on samples from the same harvest year; the impact of a temporal variation was not evaluated because this can influence the grains' quality, but the temporal variation should increase data diversity. Another issue is related to storage duration and conditions, this point was not considered sufficiently

Table 4
Accuracy (%) results on test dataset.

Classes\CNNs	**InceptionV3**	**MobileNet**	**Xception**	**ResNet50**	**DenseNet201**	**1st**	**2nd**
Vitron	**78.69**	**79.07**	72.04	76.67	**80.15**	**DenseNet201**	**MobileNet**
Simeto	**98.93**	**98.66**	**98.60**	98.20	98.44	**InceptionV3**	**MobileNet**
HD	99.42	99.06	98.93	**99.51**	**99.51**	**DenseNet201**	**ResNet50**
ARZ	99.20	**99.60**	**99.87**	97.60	98.94	**Xception**	**MobileNet**
VLC Test	**95.62**	**95.49**	94.23	94.87	**95.68**	**DenseNet201**	**InceptionV3**
Hard Wheat	**99.59**	99.34	99.04	99.42	**99.53**	**InceptionV3**	**DenseNet201**
Soft Wheat	**99.71**	**99.69**	99.64	99.40	99.64	**InceptionV3**	**MobileNet**
Wheat Species	**99.64**	99.49	99.23	99.41	**99.56**	**InceptionV3**	**DenseNet201**

Table 5
Confusion Matrix for Xception Model.

Real class \ Prediction class	Vitron	Simeto	HD	ARZ
Vitron	1136	398	17	26
Simeto	44	3666	2	6
HD	3	10	3049	20
ARZ	0	1	0	750
Xception				
Correct Class	8601	Wrong Class		527
Accuracy (%)	**94.227**	Error (%)		5.773

Table 6
Confusion Matrix for InceptionV3 Model.

Real class \ Prediction class	Vitron	Simeto	HD	ARZ
Vitron	1241	322	11	3
Simeto	32	3678	2	6
HD	5	4	3064	9
ARZ	2	0	4	745
Inception V3				
Correct Class	8728	Wrong Class		400
Accuracy	**95.618**	Error		4.382

Table 7
Confusion Matrix for MobileNet Model.

Real class \ Prediction class	Vitron	Simeto	HD	ARZ
Vitron	1247	301	15	14
Simeto	44	3668	0	6
HD	3	7	3053	19
ARZ	0	2	1	748
MobileNet				
Correct Class	8716	Wrong Class		412
Accuracy	**95.486**	Error		4.514

Table 8
Confusion Matrix for DenseNet.

Real class \ Prediction class	Vitron	Simeto	HD	ARZ
Vitron	1264	294	8	11
Simeto	52	3660	3	3
HD	6	3	3067	6
ARZ	0	5	3	743
DenseNet				
Correct Class	8734	Wrong Class		394
Accuracy	**95.684**	Error		4.316

in this study. We suggest in these situations to consider each grain as a new learning case for the entire system. Future studies should take into account these gaps.

4. Conclusion

The labor efficiency and conditions are improving by introducing CV, ML, and artificial intelligence (AI) into agronomics processes and activities. All the operations based mainly on human perception and decision could be smart and automated with new reshaped ergonomic methods, which are more effective, precise, and traceable.

The results we obtained in this study suggest the remarkable ability of machine learning and fine tuning techniques to classify wheat grain based on simple RGB images. All fine-tuned CNNs achieved good accuracy values during the test phase ranging between 94% and 95%. This ability allowed us to attempt a varietal identification of the most cultivated wheat varieties in Algeria, based on a database of wheat grain images collected from different cultivation zones.

The bests first three models, according to their test accuracy, are respectively the DenseNet (95.68%) followed by InceptionV3 with (95.62%) and finally MobileNet (95.49%). Based on the current results, a first immediate application would be in the seeds testing process, through the design of a device based on the most performing deep learning architecture that identifies the grain variety in real-time. We considered the InceptionV3 as most adequate for wheat species-level classification. However, for VLC, we consider that the MobileNet architecture is the most adequate to be implemented for an intelligent device. This model presents a small size and less computing time; that is why it is suitable for intelligent embedded devices, improving cereal grains quality assessment and management.

In our future work, we will attempt to build a DL approach to predict the wheat grain's geographic origin so that we can have end-to-end product traceability. We also plan to improve our results by using regularization techniques that allow us to improve accuracy without overfitting. The learning rate will also be defined automatically to provide accuracy and loss curves without peaks.

Machine learning should contribute to both the phenotyping and genetics field. We will attempt to apply our methodology to other target plant species and make a linkage between visualization results and phenomic analysis.

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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