

ORIGINAL PAPER

Oat grains classification using deep learning

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Received: 2022-06-06. Revised: 2023-04-09. Accepted: 2023-04-25.

Abstract

Background: Based on their nutritional benefits, oat is classified as a cereal of great importance for both human and animal feeding. Throughout the production process, species and variety identification are vital for agricultural systems. The present work establishes SeedFlow, a method for image acquisition, processing, and classification of oat grains using deep learning techniques. We apply these techniques to the identification of the grains from the different oat species *Avena sativa* and *Avena strigosa* and to classify grains as varieties of *Avena sativa*, such as UPFA Ouro, UPFA Fuerza, and UPFA Gaudéria. **Results:** To achieve this proposition, we executed our solution considering six different deep learning architectures to evaluate which model presents the best performance. This approach attained an accuracy of 99.7% for oat species identification and 89.7% for oat varieties classification using DenseNet architecture. **Conclusions:** As a result, this tool can provide high value for practical quality control applications, and it is feasible to use in pre-screening tests, laboratory analysis pipelines, or computer support tools geared toward breeding programs or intellectual property assessment.

Keywords: Classification; computer vision; deep learning; oat.

Resumo

Background: A aveia é um cereal de grande importância para a alimentação humana e animal devido aos benefícios nutricionais que oferece. Ao longo do processo de produção, a identificação de espécies e cultivares é vital para os sistemas agrícolas. O presente trabalho estabelece SeedFlow, uma metodologia para aquisição, processamento e classificação de imagens de grãos de aveia utilizando técnicas de aprendizado profundo. Estas técnicas são empregadas para a identificação de espécies de aveia *Avena sativa* e *Avena strigosa*, e para classificar grãos quanto a cultivar de *Avena sativa*, como UPFA Ouro, UPFA Fuerza, e UPFA Gaudéria. **Resultados:** Para tanto, a solução proposta foi executada considerando seis diferentes arquiteturas de aprendizado profundo para avaliar qual modelo apresenta o melhor desempenho. Esta abordagem atingiu uma precisão de 99,7% para identificação de espécies de aveia e 89,7% para classificação de cultivares de aveia usando a arquitetura DenseNet. **Conclusões:** Como resultado, esta ferramenta pode ser vista como de alto valor para aplicações práticas de controle de qualidade, viável para ser usada em testes de pré-triagem, em fluxo de análise laboratorial, ou como ferramenta de suporte computacional voltada para programas de melhoramento ou avaliação de propriedade intelectual.

Palavras-Chave: Aprendizado profundo; aveia; classificação; visão computacional.

1 Introduction

Oat holds a vital importance for world grain production. According to [Food and of the United Nations \(2022\)](#), 22.9 million tonnes were produced globally in 2016. The results of this production were mainly aimed for human and

animal feeding, due to the high nutritional value and the high amount of dietary fiber. While the grain morphology is similar to other cereals, the oat grain is longer and thinner when compared to wheat and barley and may or may not have hairiness ([Ramaswamy and Riahi, 2003](#)).

Examples of usage are varied and include: functional and fiber-rich diets, food stabilizer, heat resistance in chocolates, and moisture retainer in bakery flour.

Classification systems are tools that aid the grain marketing processes. In the oat production chain, these systems have an essential role in addressing the needs of buyers and, at the same time, encouraging producers to seek the desired quality by providing means to produce equitable returns concerning what is being marketed. Handling, transportation, processing, treatment, and storage operations are significantly influenced by the characteristics of the grain classification system that is adopted. Grains produced and harvested in the field are physically heterogeneous due to the diversity of the other elements present, such as plants, insects, inert matter, and soil. Environmental conditions also influence so that the grains do not have uniform characteristics in their physical appearance. Therefore, the classification process will consist of segregating mixed material into a set of classes that will reflect the characteristics of essential qualities for consumers (Hulasare et al., 2003).

Indeed, the use of image processing and computer vision applications to better address the challenge to classify assets automatically has grown in the last decade due to reduced equipment costs and increased computational power. Also, the interest in non-destructive methods in food assessment and classification (Mahajan et al., 2015) has increased substantially. The use of these techniques presents advantages when compared with traditional methods of classification that are based on manual work, allowing a raise in the quality of the final product in an automated, non-destructive and economically efficient way (Patricio and Rieder, 2018).

In contrast to automatic methods, manual grain assessment are challenging even for individuals who are able to perform these tasks. One of the difficulties of such methods is the lack of specific training of the evaluators. There are scarce places that train people with the necessary quality. Another issue is the time required to carry out such evaluations, which makes it impossible to make decisions quickly and evaluate subjects on a large scale (Zareiforush et al., 2015). Although automatic grains assessment can provide benefits in this context, the task of identification and classification is hugely challenging and computationally intensive (Visen et al., 2002) due to the natural variability of the products. One way to overcome those limitations would be to use techniques combined with pattern recognition algorithms and automatic classification tools to address this challenge (Vithu and Moses, 2016).

Another area that can be benefited by the use of an automatic classification system is cultivar development and commercialization. A new cultivar requires a great deal of effort in the genetic improvement process. Developing new varieties and focusing on cost-effective returns are key objectives of breeding companies and breeders (Yang et al., 2020). Therefore, it is essential that the protection of the cultivar generated in order to ensure that the breeder can expect commercial return relative to this intense work when it is accomplished.

A variety is distinguishable from other known varieties

through a set of descriptors, being homogeneous and stable for these descriptors through successive generations (Kays, 2011). It is up to the qualified entities to establish these descriptors and for breeders to assess the stability of cultivars over generations when they wish to ensure the intellectual property. Once the variety is ready for the market, another critical stage is necessary for it to be effectively used. The selection of the cultivar to be used in the field by the producer primarily involves economic circumstances, maturity, and resistance to diseases. However, the primary challenge in this context would be in guaranteeing the purity of a cultivar, considering that phenol-typical characteristics of the grains are very similar (Ansari et al., 2021). Once the cultivar which will be used in the field is chosen, a second challenge that would be face would be how the inspection will be done for royalties.

Consequently, it is understood that there is a demand for fast methods to identify cultivars at different points along the oat production chain, from the stage of creation and registration of new varieties, through planting and finishing with grain processing by the industry. Grain purity is also an important aspect evaluated by the industry upon receipt of a new delivery of grains. In regard to this, a manual approach would require time and availability of specific laboratories.

Some approaches have been presented to address the problem of identifying species from grains. Sabanci et al. (2017) presented a system capable of classifying wheat grains of the species *Triticum aestivum* (common) and *Triticum durum* (hard) according to their visual characteristics through the use of artificial neural networks. Olgun et al. (2016) evaluated the performance of the use of the DSIFT (Dense Scale Invariant Feature Transform) technique, in conjunction with an SVM (Support Vector Machine) classifier to classify wheat grains in 40 different species. Kuo et al. (2016) developed a high-resolution grain imaging system to classify 30 rice varieties. Studies have shown that the use of deep learning and computer vision, when applied to those areas, can provide high accuracy, surpassing the commonly used image processing techniques, such as those presented earlier (Kamilaris and Prenafeta-Boldú, 2018). Sun et al. (2016) compared the classifiers SVM, BPNN (Back-Propagation Neural Network), CNN (Convolution Neural Network) and DBN (Deep Belief Network) towards detecting fungal colonies in rice caused by microorganisms, such as *Aspergillus* and *Penicillium*. In his work, CNN (Convolutional Neural Network) was presented to have the highest accuracy when compared to the other methods. Barré et al. (2017) used deep learning to identify plant species. One of his conclusions was that learning the features through a CNN can provide better feature representation for leaf images when compared to hand-crafted features. That characteristic of deep learning models is one of the most attractive benefits of this technology since it greatly simplifies the image processing and classification. Cheng et al. (2017) achieved similar results when SVM classifiers were compared with CNN to identify pests in a complex background.

Considering the above, it would be interesting to evaluate the effectiveness of the classification through

the use of state of the art deep learning techniques for oat grain classification, along with how to apply it in a proven robust pipeline. Ali et al. (2020) introduce an optimized hybrid features classification framework, for the classification of corn seed varieties. For each corn seed image, a total of fifty-five hybrid-features was acquired on every non-overlapping region of interest. A MLP approach performed outstanding classification accuracy (98.93%). Thakur et al. (2022) propose laser backscattering and deep transfer learning based photonics sensor for automatic identification and classification of high-quality soybean seeds. Transfer learning-based processing framework is proposed for only analysing speckle data. High accuracy (97.88%) was obtained for classifying high- and low-quality seeds.

In this context, we proposed SeedFlow, a methodology through a computer vision system to automatically identify oat species and classify oat varieties using digital images of grain samples in order to decrease the time of analysis, reduce the necessity of the specialist presence, and increase the reliability and efficiency of the overall process. Six common deep learning architectures were evaluated (LeNet5, AlexNet, VGG16, InceptionV3, ResNet, DenseNet121), and several techniques of computer vision and image processing (e.g. background subtraction, image denoising and segmentation) were combined to provide a full pipeline in the classification of oat grains. We selected these deep CNN architectures because they represent classic algorithms from deep learning literature Alzubaidi et al. (2021), trained on large datasets such as ImageNet for image recognition purposes Deng et al. (2009).

Although several different deep network models can be used to this task, we aim to show that simple CNN models, like AlexNet, can have similar results when compared to more complex models, like DenseNet. We also analyzed our methodology by using human accuracy to verify the feasibility of using it in real applications, such as laboratory tasks for grain analysis. With all this in mind, the solution can be considered a valuable tool to the oat production process.

2 Materials and Methods

In comparison with the related work, we observed that no approach had as an object of study the classification of oat grains, an relevant food in human and animal nutrition. Although other studies have considered technologies for grains, we noted a gap in the study of classification methods for this crop. With this in mind, we present SeedFlow, a method for image acquisition, processing, and classification of oat grains using deep learning techniques. The main contribution of our proposal is to present a useful computational tool for the seed analysis laboratories' daily routine, enable to count and classify cultivar oats by specie.

The proposed computer vision system is composed of image acquisition, image processing, and result presentation (Fig. 1). The image processing step is subdivided in preprocessing, segmentation and classification parts.

To acquire images, a photographic scanner provided with CCD (Charged Coupled Device) sensor like Epson Perfection V370 was used. Scanners provided with CIS

(Contact Image Sensor) were not adequate because of their inability to scan three-dimensional objects, such as grains. Due to its cylindrical shape, not all the grain's surface will be in direct contact with scanner glass. Two cases are considered in this work: grain quality and intellectual property assessment. In the first case, the identification of different oat species was evaluated since this was a parameter commonly evaluated in grain samples analysis in order to assess the purity of the batch. In the second case, the classification of different oat varieties was evaluated since this information is beneficial for the breeding programs and intellectual property assessments.

An image database containing RGB images of 224x224 pixels was built through scanning the grains and performing background removal and segmentation operations. It was used for the training and testing of the evaluated CNN models. Grains were scattered in the scanner in an unrestricted way. The database is composed of two datasets, one for oat species classification and other for oat varieties identification. Table 1 presents the categories subdivision and the picture amount related to each one. Fig. 2 depicted some sample images of oat grains. Each dataset used a 75/25 split ratio of training/testing images sets, with images being randomly selected from each group. Training images were used to obtain the optimal parameters for the model, and testing images were used to evaluate the final performance of the model.

Table 1: Oat categories and pictures amount.

Name	Amount	Name	Amount
a) Oat Species		b) Oat Varieties	
<i>Avena strigosa</i>	5000	UPFA Ouro	2500
<i>Avena sativa</i>	5000	UPFA Fuerza	2500
Total	10000	UPFA Gaudéria	2500
		Total	7500

The default white background of the scanner was replaced with a blue background to improve the effectiveness of the background removal step. The pre-processing step was primarily intended to remove the background from the image. Initially, the RGB images acquired in the previous step were converted to the HSV color model. Using this color model, the hue channel was selected to separate the grains and the background, as the blue tone vector has the most substantial angular distance with the predominant shades of the grains. Through this method, the use of binarization methods is facilitated, and the method of automatic binarization employed is Otsu (Otsu, 1979). Next, flood fill methods are used to eliminate the holes in the mask. Removal of the background is achieved through the use of a binary subtraction operation between the input image and the generated mask. In the segmentation stage, the binarized image is also used for edge detection.

In some cases, small objects may have borders that are detected due to noises or small artifacts captured in the image. In this regard, objects with 10% small area size of the most significant area size found in the image were automatically ignored. Finally, the image is segmented using the information of the identified contours (Suzuki and be, 1985). For each contour extracted, the region

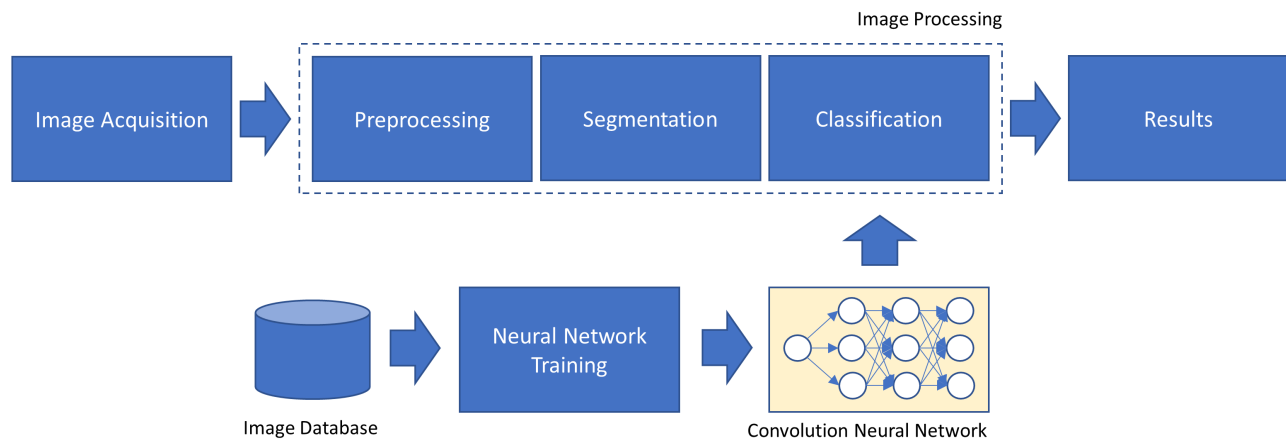


Figure 1: Computer vision system schematic.

of interest maintaining the original dimensions of the grain, and each segment is generated using a square aspect ratio. This approach allows each segment to be resized to the most appropriate size of each classification algorithm without the proportions of the original image being modified. It is to be noted that grain overlap cases are not considered.

In the classification step, a pre-trained classifier is used to assign classes to the segments determined in the previous steps. The overall process is depicted in Fig. 3.

Six CNN models were evaluated: LeNet5, AlexNet, VGG16, InceptionV3, Resnet, and DenseNet121.

LeNet5 is a CNN comprised of seven layers: convolutional layer with six features maps, subsampling layer with six features maps, convolutional layer with 16 feature maps, subsampling layer with 16 feature maps, convolutional layer with 120 feature maps, fully connected layer with 84 units and, finally, an output layer (Lecun et al., 1998).

AlexNet is composed of five convolutional layers and three fully connected layers. The second and third convolutional layers received the input of the predecessor layer after max pooling and normalization operations. In addition, AlexNet architecture uses ReLu neurons to reduce the time necessary to train it. Two dropout layers with a probability of 0.5 were also positioned between the first and second fully connected layers (Krizhevsky et al., 2017).

VGG is an architecture composed by convolutional layers with 3x3 filters with stride and pad of 1 and 2x2 max-pooling layers with stride 2 organized in the sequence: input, two convolutional layers 64 feature maps, max pooling, two convolutional layers 128 feature maps, max pooling, three convolutional layers 256 feature maps, max pooling, three convolutional layers 512 feature maps, max pooling, three convolutional layers 512 feature maps, max pooling, and three fully connected layers. It uses ReLu as a neuron model and reinforces the notion that the network depth is related to the hierarchical representation of visual data (Simonyan and Zisserman, 2014).

Inception presents a design to allow create deeper networks while also keeping the number of parameters

from growing too large. The approach apply the use of multiple filter sizes on the same level instead of chaining convolutional layers with different filter sizes. As such, the network would get “wider” rather than “deeper”. This concept would thus be defined as the inception module. The architecture has 22 layers deep when only the layers with params are counted and 27 if we also consider the max-pooling layers (Szegedy et al., 2015).

ResNet proposes the concept of a residual block to address the degradation of training accuracy in deeper architectures. Using shortcuts connections, it is possible to transfer activation data much deeper into the network, thereby reducing the effect of vanishing gradient problem. When the gradient is back-propagated to the earlier layers, the gradient can become very small, and the performance can degrade severely (He et al., 2015).

DenseNet is an architecture based on ResNet idea that deeper networks can be more efficiently trained if they contain shorter connections between the layers. Mainly, each layer in a DenseNet (Densely connected convolutional network) are is connected to every other layer in a feed-forward fashion. As the creators pointed out, there are many advantages when this is compared to plain architectures, and these would include the mitigation of vanishing gradient problem, strength feature propagation, and parameters number reduction (Huang et al., 2016).

One of the main objectives of this work would thus be to show that CNN models can be used in oat grain classification and to evaluate which model has the best accuracy for the dataset utilized. According to Barbedo (2018), several aspects may affect the performance of CNN models. In the present work some of those aspects were addressed to reduce their impact on the final results. The dataset was built from scanned images of the grains. When CNN is used, the availability of an image database correctly labeled is one of the significant aspects. In this context, the ground truth is guaranteed by the origin of the samples. Each category was acquired separately from the others. This process is slow and expensive, and not through the use of specialized hardware, but demanded man work hours. Grains are harsh when attempting to determine their origin if they are mixed.

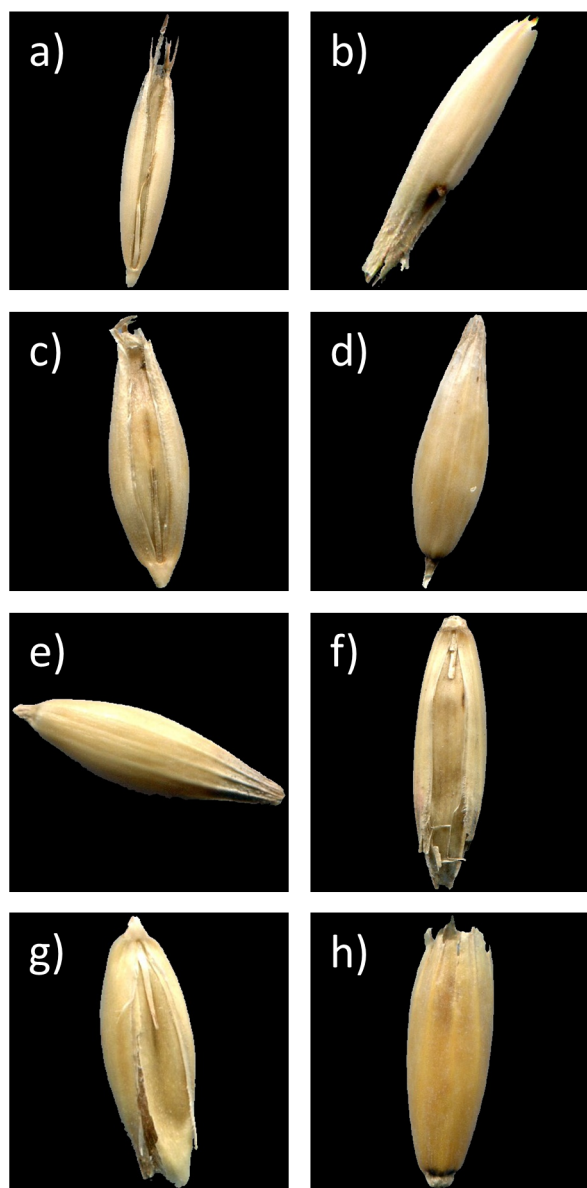


Figure 2: Oat grain samples after background removal and segmentation. a) and b) *Avena strigosa* - UPFA Moreninha, c) and d) *Avena sativa* - UPFA Fuerza, e) and f) *Avena sativa* - UPFA Gaudéria, g) and h) *Avena sativa* - UPFA Ouro.

Another important aspect is the image capture conditions. A scanner was chosen in order to provide the same conditions of illumination and image background to every acquired image. Backgrounds may contain elements that interfere in the training process, and thereby reducing their efficacy. To avoid non-realistic results, the grains used to train the CNN models were obtained from different batches and grown under different crop conditions.

All the pipeline of preprocessing, segmentation, and training was automated using Python scripts. [Table 2](#)

present resources used to develop the entire pipeline. Each evaluated CNN model was trained using Batch Stochastic Gradient Descent optimizer with Nesterov Momentum with value 0.9. When training neural networks, this is often used to reduce the learning rate when the model steps, in order to improve accuracy. In order to achieve this, it a variable learning rate starting in 0.1 was adopted. At every five epochs without improvement, the learning rate was divided by two until the minimum of 0.0001. All models were trained until 100 epochs.

Table 2: Experiment setup.

Hardware	Software
CPU: Intel Core i7 6700	Windows 10
Memory: 16 GB DDR4	CUDA 9.0 +
	CuDNN 6.1
GPU: NVIDIA GTX1070 (8GB GDDR5)	Python 3.6
	Keras
	Tensorflow

3 Results and discussion

In order to compare human accuracy with the CNN model accuracy, a small experiment was performed through the use of six technical volunteers that usually performed this operation in a seed laboratory daily routine. The experiment consists of evaluating the accuracy of oat species identification using SeedFlow. Two species are used: *Avena sativa* (cultivar UPFA Ouro) and *Avena strigosa* (cultivar UPFA Moreninha). The kit consists of 20 planks of 100 grains each, totaling 2000 grains. Each plank has a random amount of species and therefore did not necessarily contain a 50/50 ratio.

The UPF Seed Laboratory, certified by the Brazilian Ministry of Agriculture, Livestock, and Food Supply, provided the seed samples containing the cultivar identification. A senior seed analyst prepared these planks for the experiment using the laboratory categorization.

Once the experiment started, the participants were instructed to evaluate all the planks until the end of the experiment so that we can also evaluate whether fatigue affects accuracy throughout its performance. The planks were marked with the coordinates of the cells so that the user can use it to indicate which species each cell corresponds to.

3.1 Oat species identification and varieties classification

As expected, the CNN models obtained high values for accuracy, highlighting DenseNet as the best performance: 99.7% for oat species classification and 89.7% for oat variety classification. DenseNet also was more efficient in memory usage and number of epochs that converged. [Table 3](#) and [Table 4](#), presented the values for accuracy and the training time for 100 epochs and evaluation time for 1600 grains to the different CNN models.

Conversely, AlexNet obtained excellent results, although it was shallower and older compared to

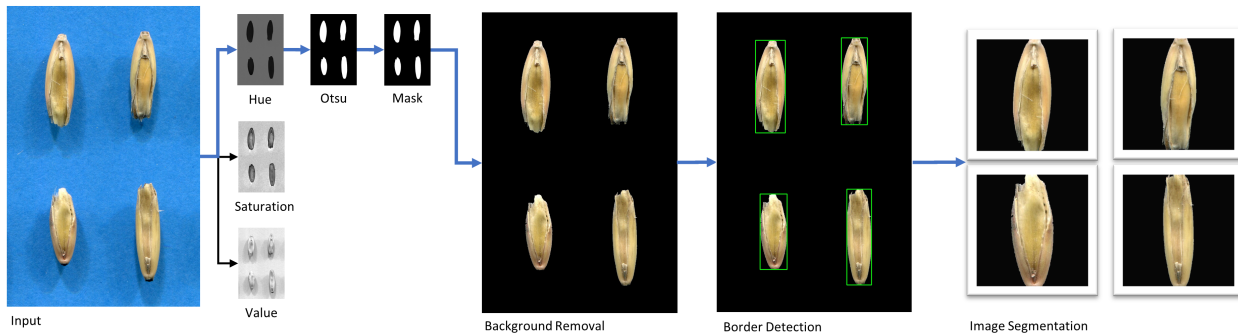


Figure 3: Preprocessing and segmentation schematic.

Table 3: Comparison of results for identification of oat species. Training: 100 epochs. Evaluation: 1600 grains.

Model	Validation Accuracy	Validation Loss	Training Time	Epoch	Evaluation Time No GPU	Evaluation Time GPU
LeNet5	0.978	0.143	3368.915	72	41s	6s
AlexNet	0.992	0.019	9198.336	79	269s	9s
VGG16	0.992	0.045	13598.435	73	386s	14s
InceptionV3	0.989	0.050	8832.317	61	148s	9s
ResNet	0.996	0.030	12207.191	74	355s	10s
DenseNet121	0.997	0.012	12892.266	22	440s	10s

Table 4: Comparison of results for classification of oat varieties. Training: 100 epochs. Evaluation: 1600 grains.

Model	Validation Accuracy	Validation Loss	Training Time	Epoch	Evaluation Time No GPU	Evaluation Time GPU
LeNet5	0.657	2.244	2553.968	97	39s	5s
AlexNet	0.859	0.439	6954.503	75	264s	16s
VGG16	0.715	2.733	13489.934	43	369s	9s
InceptionV3	0.852	0.749	6649.607	45	160s	8s
ResNet	0.838	0.744	8921.818	58	353s	9s
DenseNet121	0.897	0.414	9811.436	53	465s	11s

DenseNet and ResNet, both of which applied residual network concepts to improve accuracy. These results can be attributed to the fact that grain images have a simple shape and a very similar structure. They have the same oval form and small color spectrum. Therefore, a simpler network such as AlexNet would already be able to identify and classify the images. Fig. 4 and Fig. 5 present the accuracy and loss for the evaluated models. Also, Fig. 6 and Fig. 7 present the confusion matrix for AlexNet and DenseNet models.

The effect of using GPU was also measured. As the Table 3 and Table 4 shows, this kind of specialized hardware reduces, on average, times the time necessary to evaluate 1600 grains by 25 times.

To evaluate the AlexNet and DenseNet models performance on a limited dataset, k-Fold cross-validation was performed using ten folds. Table 5 shows the mean, maximum, minimum and standard deviation values for the two models analyzed.

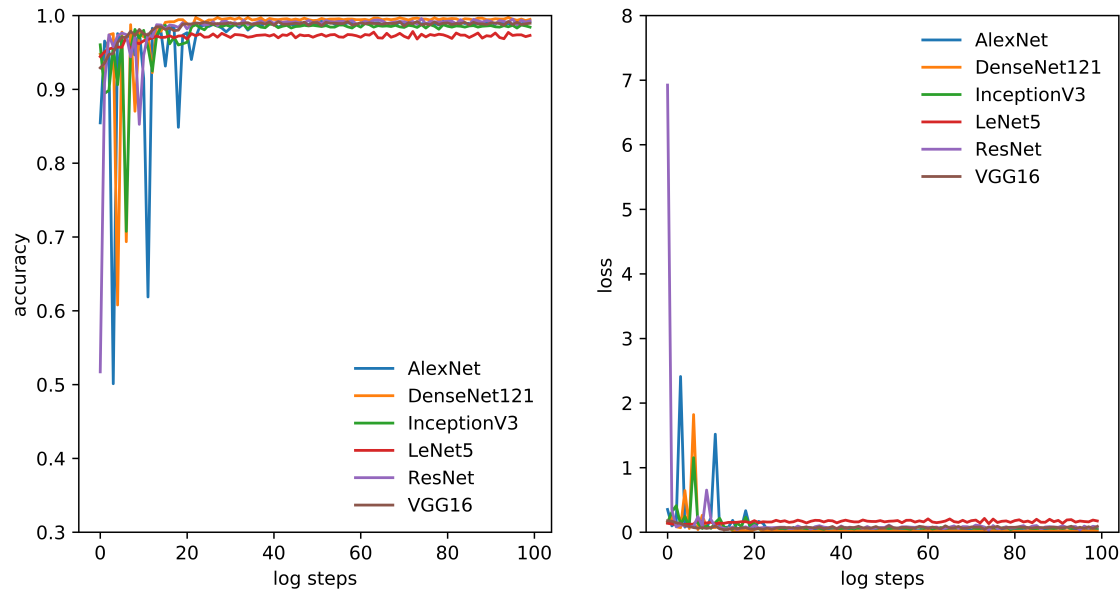
3.2 Human accuracy in oat species classification

The average human accuracy found in the experiment was 93.77% (5.72% of standard deviation). The preliminary tests have shown that it is a hard task for a person to determine which variety corresponds to each grain. The approach customarily applied is through identifying its similarity, and a grain is rarely analyzed in an isolated way. Each person spends about 1 to 2 hours evaluating the 20 planks. In comparison, the computer that utilizes the GPU spends about 10 seconds on the same task with an accuracy of 99.7%, disregarding the time expended to capture the images. No reasons were identified to confirm that fatigue can interfere in the final accuracy. However, a majority of the participant comments included the comment that the task was exhaustive.

Another point worth highlighting is that even with the participants who were trained in the same way and routinely performed the task of identifying oat species, the experiment showed high variability in the accuracy of the participants (Fig. 8). The objective of this experiment was not to have a definitive conclusion about accuracy. Rather, it was to provide a start point to human-computer comparison and evaluate whether, as seen in this scenario,

Table 5: k-Fold cross validation for AlexNet and DenseNet models.

k-Fold Cross Validation	AlexNet				DenseNet			
	Min	Max	Avg	Std. Dev.	Min	Max	Avg	Std. Dev.
UPFA Moreninha × <i>Avena sativa</i>	0.978	0.993	0.986	0.004	0.985	0.995	0.990	0.003
UPFA Ouro × UPFA Fuerza × UPFA Gaudéria	0.798	0.859	0.833	0.016	0.803	0.887	0.830	0.026

**Figure 4:** Classification results between UPFA Moreninha × *Avena sativa*.

the replacing of human labor with by computer analysis is feasible.

3.3 Methodology Analysis

In the present method, only a scanner device was evaluated to acquire grain images. Different grain image acquisitions could be evaluated to decide the most efficient device and process, considering a protocol to reduce lighting influences. One approach would be the use of cameras to provide still photos or video stream to real-time analysis of the grains. In addition to the cameras, smartphones could be explored to capture images.

CNN models are suitable to be embedded in a smartphone application and make our solution more flexible and portable. Once the network is trained, it is no longer necessary to use advanced hardware. Thus single board computers could be exploited embedding a more compact and adaptive solution for most diverse situations.

Another improvement could be the training of the neural network in a workstation different from the one to be used for grain analysis. Thus, GPU clustering could be exploited to increase the number of classes and images used in network training without the processing time

required to make the process unfeasible. In addition to the six models explored in this paper other models presented in the literature can be evaluated. Although we have selected the most representative models available, a different model could bring some relevant results for our tests. Another approach would be the development of a specific model for grains considering their specific characteristics.

Finally, the most valuable contribution is that the SeedFlow methodology could be used for other oat cultivars or for other grain crops.

4 Conclusion

In this study, six CNN models were compared using our methodology in order to use as a classifier of oat grains in a controlled environment. The obtained accuracy of the evaluated methods have shown that it is feasible to classify grains as species and as cultivar using such methods. For the case of oat species, *Avena sativa* and *Avena strigosa*, the accuracy reached 99.7% using the DenseNet model. For the case of oat cultivars, the accuracy reached 89.7%. In a preliminary study, it was identified that this result is superior to a human inputted one when tested against the

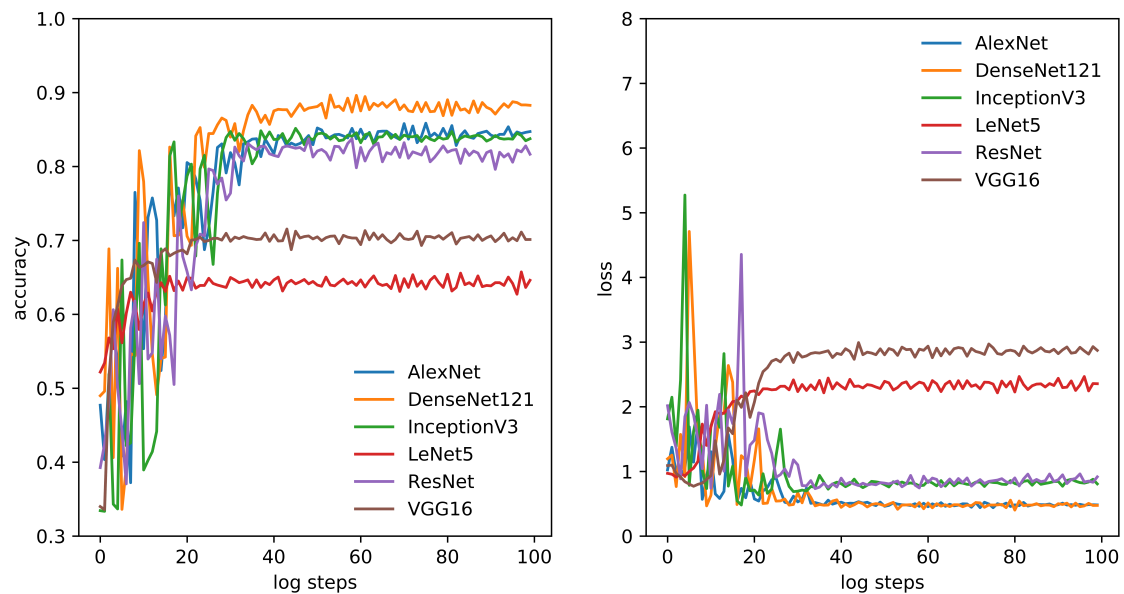


Figure 5: Identification results between UPFA Ouro $\times$ UPFA Fuerza $\times$ UPFA Gaudéria.

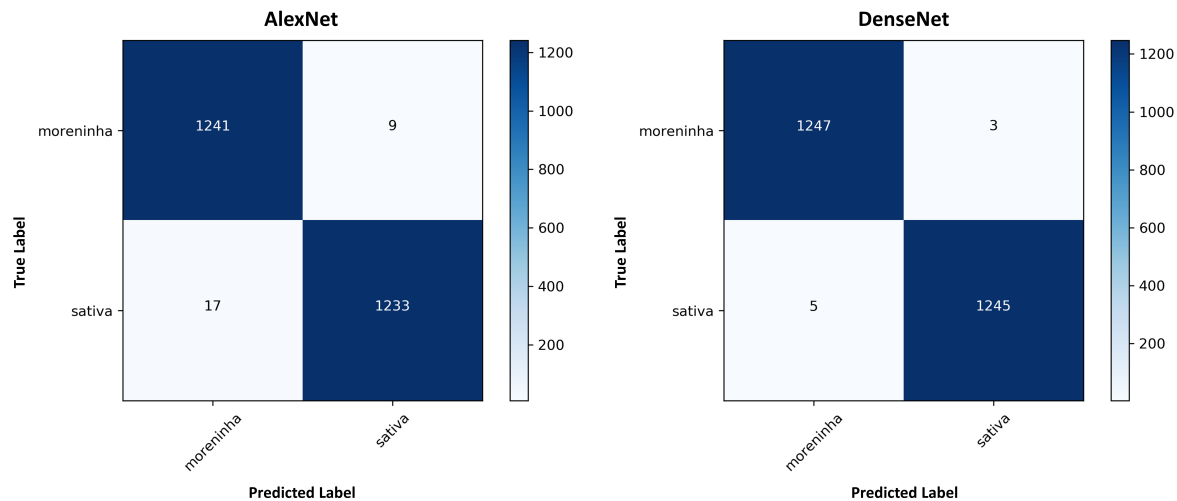


Figure 6: Confusion matrix of oat species identification - UPFA Moreninha $\times$ Avena sativa.

oat species classification case.

The main contribution of this work was SeedFlow, a computational methodology for oat cultivars classification using computer vision and deep learning. The application design considered its use in a workstation using low-cost hardware and a graphical interface that facilitates the use of the software without extensive prior training of users. However, we highlight that it is still necessary to evaluate the use of our tool considering a larger sample of subjects.

CNN models are a vast area of knowledge, and several improvements are released frequently. Future studies of SeedFlow must evaluate newer architectures, such as Spatial Networks, YOLO, and Vision Transformers,

to improve seed classification accuracy. Furthermore, another species can be tested in order to produce a more robust neural network capable of use within the industry. The same process presented in this study can be used for other grain crops. Other future works could include developing an embedded device equipped with small single-board computers that can be used outside of the laboratory environment. Such a device could then be coupled to a conveyor belt and be used when the industry receives the product in a pre-screening phase of oat grain processing.

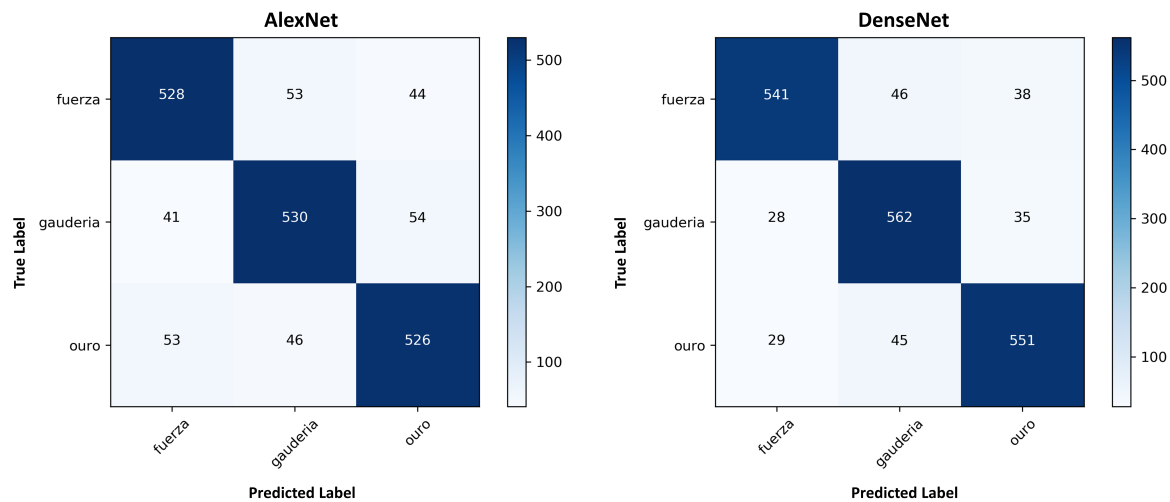


Figure 7: Confusion matrix of oat varieties identification - UPFA Ouro × UPFA Fuerza × UPFA Gaudéria.

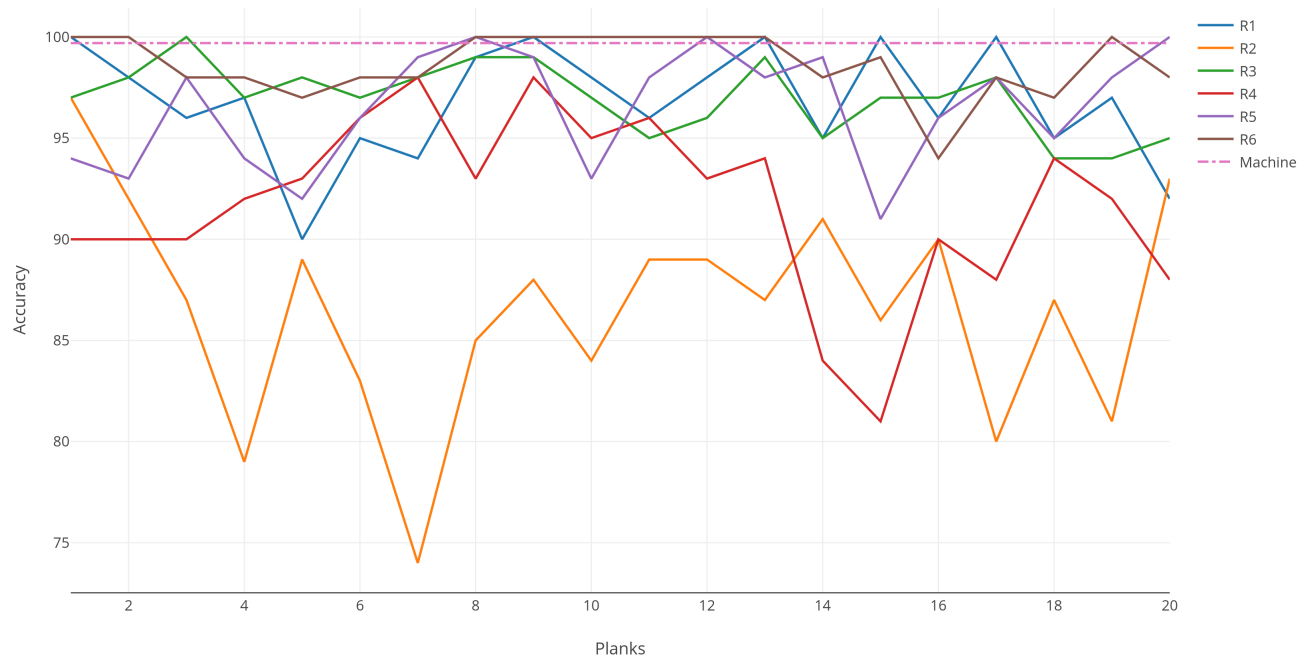


Figure 8: Comparison of accuracy for oat species identification task considering experiment volunteers (R1 to R6) and the proposed method (Machine).

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