Classification of Wheat Species Using Convolutional Neural Networks: A Comparative Study

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Abstract. This paper introduces a novel image dataset tailored for evaluating machine learning solutions, particularly focusing on deep neural networks. Derived from X-ray images of wheat grains, the dataset encompasses three distinct species: Kama, Rosa, and Canadian. We provide a comprehensive overview of the dataset's structure and conduct experiments using ten pretrained deep neural networks to classify wheat species. The *Seeds Image* Data Set offers a competitive alternative to established object recognition benchmarks such as CIFAR-10, CIFAR-100, SVHN, and ImageNet. Its compact size streamlines computational processes, making it an efficient resource for exploratory data analysis. The dataset will be publicly available, serving as a foundational resource for future research endeavors in the field.

Keywords: data set · algorithm validation · deep learning · convolutional neural network · prediction ability · benchmark

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1 Introduction

The advent of machine learning (ML) techniques, particularly deep learning, has catalysed significant advancements across diverse domains, including agriculture and food science. In this era of technological innovation, the application of ML algorithms for crop classification and monitoring holds immense promise for enhancing agricultural productivity and sustainability. One of the key challenges in agricultural research is the accurate identification and classification of crop species, which is crucial for tasks such as crop management, disease detection, and yield prediction.

The primary objective of this study is to explore the efficacy of CNNs in classifying wheat species using high-resolution X-ray images of wheat grains. X-ray imaging offers a non-destructive and highly informative approach to visualise internal grain structures, enabling the extraction of discriminative features for species identification. Leveraging a novel dataset, derived from X-ray images of wheat grains, we aim to assess the performance of pretrained CNN models in accurately classifying three distinct wheat species: Kama, Rosa, and Canadian. By scrutinising the capabilities and limitations of various CNN architectures, we seek to provide insights into the feasibility and practicality of automated wheat species classification in real-world agricultural settings.

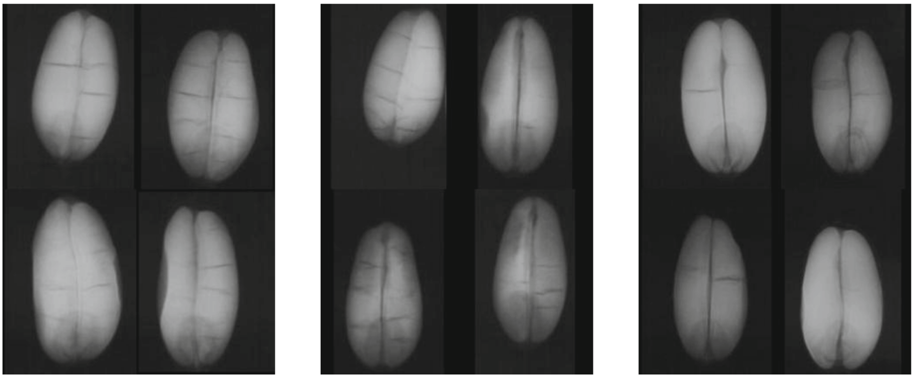
In recent years, the availability of large-scale image datasets, coupled with advancements in deep learning architectures, has propelled the field of computer vision to new heights. The success of deep learning-based approaches in tasks such as object recognition, image segmentation, and facial recognition underscores the potential of these techniques for agricultural applications. However, the adaptation of deep learning models to agricultural contexts presents unique challenges, including limited data availability, domain-specific variability, and the need for interpretability and explainability in model predictions.

To address these challenges, this study adopts a transfer learning approach, wherein pretrained CNN models, initially trained on large-scale image datasets such as ImageNet, are fine-tuned on our wheat species classification task. Transfer learning offers a practical solution for leveraging existing knowledge encoded in pretrained models and adapting it to domain-specific tasks with limited labeled data. By systematically evaluating the performance of pretrained CNN models on our dataset, we aim to elucidate the factors influencing classification accuracy and identify avenues for future research and improvement.

2 Seeds Image Data Set and Its Purpose

The *Seeds Image* dataset consists of X-ray images of wheat grains, originally shared in the UCI Machine Learning repository [8], as a multivariate dataset [1][1]. The dataset encompasses three wheat species: Kama, Canadian, and Rosa, each characterized by seven geometric kernel parameters. Images were captured using an X-ray apparatus, and preprocessing was performed to standardize image dimensions and enhance uniformity.

[1] Data set available on the website https://archive.ics.uci.edu/dataset/236/seeds.



(a) Kama (b) Canadian (c) Rosa

Fig. 1. X-ray images of three species of wheats

In this manuscript, we introduce a novel and competitive dataset that encapsulates authentic biological data. Positioned within a public repository, this dataset is poised to contend with existing benchmark data, enhancing the breadth of available resources. Our objective is to furnish readers with comprehensive insights into the inherent nature and structural intricacies of this dataset, while also presenting baseline experiments employing prevalent discriminative methodologies.

The *Seeds Image* dataset, while not voluminous, offers notable advantages, particularly for researchers lacking access to substantial computational resources. Its modest scale renders it easily deployable, catering to a broader spectrum of investigators. Moreover, this dataset serves as a valuable tool for scrutinizing the nuanced interplay between algorithmic parameters, facilitating a deeper understanding of their mutual dependencies-an endeavour often encumbered by the exigencies of time.

3 Data Partitioning and Cross-Validation

To ensure robust evaluation of ML models, the *Seeds Image* dataset was partitioned into train and test sets using a five-fold cross-validation strategy [3]. This approach not only mitigates the impact of data imbalance but also enhances the generalization ability of trained models. Table 1 provides an overview of the data distribution across cross-validation sets, highlighting the consistency and reliability of the dataset.

4 Deep Neural Networks Used as Baseline Classifiers

The convolutional neural network (CNN) emulates the human visual analysis process, with neurons in the brain's visual cortex responding exclusively to stimuli within their receptive fields. These overlapping fields collectively form the

Table 1. Number of elements in each cross validation subset

class	set	cross validation subsets				
		0	1	2	3	4
Kama	train	57	56	59	55	61
	test	15	16	13	17	11
Canadian	train	81	77	69	84	73
	test	15	19	27	12	23
Rosa	train	83	88	93	82	86
	test	25	20	15	26	22

visual domain, with larger ones adept at detecting intricate patterns. This biological architecture inspired the development of CNNs, wherein neurons detecting objects within their receptive fields transmit signals to subsequent layers for complex pattern recognition. CNNs can comprise tens or even hundreds of layers, each specialising in detecting distinct image features.

In practical applications, constructing CNN models from scratch is rare due to resource limitations, necessitating the use of pretrained models on extensive image datasets. Transfer learning, a prevalent approach, involves adapting only the final layers of pretrained models to specific tasks, significantly expediting model development. Therefore, this research delves into deep neural networks applied to RTG figure recognition, leveraging transfer learning for efficient model deployment.

We evaluated ten state-of-the-art CNN architectures pretrained on ImageNet [7] for classifying the *Seeds Image* dataset. Transfer learning was employed, adapting pretrained models for wheat species recognition. Notable architectures included DenseNet 121 and DenseNet 201 [5], Inceptionresnet V2 [11], InceptionResNetV2 [12], ResNet50 V2 [13] and ResNet152 V2 [14], VGG 16 [10], MobileNet V2 [9] [4], and Xception [2].

The training parameters were kept consistent across all networks, and the experiments were carried out using the five cross-validation partitions. Training outcomes, comprising both loss and accuracy metrics, were meticulously documented and subjected to a detailed analysis. In the classification task, convolutional neural networks were used, employing SoftMax activation in the final layer and categorical cross-entropy as the loss function [6]. This function is formally expressed as follows:

$$loss_{CE} = -\sum_{c=1}^{C} y_c log(\hat{y_c}), \tag{1}$$

where C is a number of output classes, $\hat{y_c}$ is the c-th element of SoftMax output prediction and y_c is the c-th element of target output.

5 Computational Results

Training and testing results for each CNN architecture are presented in Table 2. While all networks achieved high training accuracy, performance on test data varied. The standard deviations of test accuracy ranged from 1.86% to 6.5%, highlighting the impact of data partitioning on model generalisation.

In particular, networks such as MobileNetV2, VGG19, and InceptionV3 exhibited superior stability in test accuracy across cross-validation sets. Conversely, networks such as VGG16 demonstrated higher variability in performance.

Table 2. Results of application well-known pretrained convolutional neural networks for *Seeds Image* Data Set classification task.

CNN type	train set				test set			
	loss	loss std	acc	acc std	loss	loss std	acc	acc std
DenseNet 121	0.1852	0.0207	0.9619	0.0110	0.3087	0.0499	0.8912	0.0186
DenseNet 201	0.1272	0.0143	0.9946	0.0038	0.2662	0.0347	0.9094	0.0223
Inceptionresnet V2	0.2158	0.0241	0.9547	0.0092	0.4029	0.0631	0.8440	0.0337
Inception V3	0.0888	0.0098	0.9964	0.0059	0.3295	0.1134	0.8876	0.0553
MobileNet V2	0.1536	0.0116	0.9810	0.0118	0.3130	0.0867	0.8947	0.0650
ResNet50 V2	0.0689	0.0117	0.9991	0.0020	0.2317	0.0730	0.9165	0.0421
ResNet152 V2	0.0687	0.0145	**1.0000**	0.0000	0.2518	0.0769	0.9058	0.0326
VGG16	**0.0002**	0.0000	**1.0000**	0.0000	**0.1927**	0.2205	**0.9419**	0.0395
VGG19	0.0014	0.0007	**1.0000**	0.0000	0.3856	0.2272	0.8910	0.0576
Xception	0.1635	0.0084	0.9783	0.0049	0.3466	0.0659	0.8803	0.0402

6 Conclusions

The *Seeds Image* dataset serves as a valuable benchmark for evaluating ML models in real-world scenarios. Despite its small size and class imbalance, the dataset presents challenges akin to practical applications. Our experiments demonstrate the efficacy of CNNs in classifying wheat species, with test accuracies approaching 90%. Cross-validation proved crucial in assessing the robustness of the model, highlighting the importance of data partitioning strategies.

In conclusion, this study presents a comprehensive analysis of wheat species classification using pretrained CNN models. The introduction of the *Seeds Image* dataset provides a valuable resource for benchmarking ML algorithms in real-world scenarios. Our experiments highlight the efficacy of transfer learning in adapting pretrained models to domain-specific tasks, with VGG16 emerging as the top-performing architecture.

Future research may explore additional preprocessing techniques and alternative model architectures to further enhance classification performance. Moving forward, future research could explore alternative data augmentation techniques and model architectures to further improve classification accuracy. Additionally, the *Seeds Image* dataset and its cross-validation sets will be publicly available, encouraging collaborative efforts in advancing ML solutions for agricultural applications.

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