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Automatic and fast classification of barley grains from images: A deep learning approach

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ABSTRACT

Australia has a reputation for producing a reliable supply of high-quality barley in a contaminant-free climate. As a result, Australian barley is highly sought after by malting, brewing, distilling, and feed industries worldwide. Barley is traded as a variety-specific commodity on the international market for food, brewing and distilling end-use, as the intrinsic quality of the variety determines its market value. Manual identification of barley varieties by the naked eye is challenging and time-consuming for all stakeholders, including growers, grain handlers and traders. Current industrial methods for identifying barley varieties include molecular protein weights or DNA based technology, which are not only time-consuming and costly but need specific laboratory equipment. On grain receival, there is a need for efficient and low-cost solutions for barley classification to ensure accurate and effective variety segregation. This paper proposes an efficient deep learning-based technique that can classify barley varieties from RGB images. Our proposed technique takes only four milliseconds to classify an RGB image. The proposed technique outperforms the baseline method and achieves a barley classification accuracy of 94% across 14 commercial barley varieties (some highly genetically related).

1. Introduction

Barley is the fourth largest grain crop in the world after wheat, maize, and rice. It is commonly used in breads, soups, stews, and health products, though it is primarily grown as animal fodder and as a source of malt for alcoholic beverages. Barley is Australias second-largest crop in volume after wheat. Australian growers annually produce around 2.3 million tons of malting barley and 6 million tons of feed barley. Australian grain accounts for approximately 60 per cent of the total crop exported each year [1].

The Australian barley industry currently performs a visual inspection to classify barley in the field for variety purity and at receival stations for segregation. Grain that meets industry standards for receival as malt barley is segregated by variety. Barley is required for a minimum of 95 per cent of variety purity to be traded as malt barley. However, manual identification of the barley crop is slow and subjective and can vary from one technician to another based on their experience. Furthermore, visual identification cannot quantify the variety or the purity of the load on receival in real-time. Therefore, there is a need to develop an automatic and reliable method for classifying and identifying the barley grain with an objective quality assessment [2].

Current lab-based barley classification methods such as protein molecular weight and DNA fingerprinting technology are time-consuming and require specialised equipment for barley classification (variety identification). The protein molecular weight approach, for example, can take 12 to 14 hours to produce the desired barley classification. If implemented on receival, it would create a bottleneck in delivering barley to a bulk handler. There is, therefore, a need for the development of efficient and portable techniques for barley classification at grain receival points in real-time.

This paper addresses those challenges by developing an automatic technique for barley classification using RGB images. Machine learning has progressed dramatically in recent years, from laboratory implementation to practical technology in widespread commercial use [3]. Machine learning has emerged as the most appropriate for developing functional software for computer vision, speech recognition, natural lan-

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guage processing, robot control, and other applications [4–6]. In addition, artificial neural networks have emerged as one of the popularly used techniques for cereal grain classification and identification [7–9]. Artificial neural networks have emerged as one of the most used techniques for cereal grain classification and identification tasks [11].

Inspired by the advent and performance of machine learning for image classification, we propose a deep learning method for barley classification. Deep learning has shown unprecedented performance for several natural image processing tasks, including object recognition, segmentation and detection. Some of the recent deep learning systems have achieved comparable performance to humans for recognition and classification [12–14]. Our proposed system can classify different barley types with high accuracy. Our grain image dataset consists of 1432 RGB images of thirteen Barley Australia accredited malt barley varieties (Bass, Baudin, Buloke, Commander, Compass, Flinders, Granger, La Trobe, Litmus, RGT Planet, Scope CL, Spartacus CL and Westminster) and one Barley Australia accredited food barley variety (Hindmarsh). Details of the dataset are provided in Section 3.

The contributions of this paper are summarised as follows:

- A deep learning approach for the automatic and efficient classification of barley grain images has been proposed.
- A barley dataset containing RGB images of 14 different barley varieties with data augmentation to increase the number of images.
- Extensive evaluation of the proposed technique on our barley dataset.

The rest of this paper is organised as follows. Literature review is provided in the next section. Our dataset is introduced and discussed in Section 3. Proposed methodology is described in Section 4. Experimental results are reported in Section 5 and the paper is concluded in Section 6.

2. Related work

2.1. Traditional approaches

Barley is traded as a variety-specific commodity on the international food, brewing and distilling markets as the intrinsic quality of the variety determines the market value. The varieties of barley have a genealogical structure that makes it hard to identify with the human eye. The barley supply chain in Australia typically applies lab-based analyses to determine variety type, but this cannot be done in real-time.

2.1.1. Protein molecular weight

Protein molecular weight has been the traditional way of identifying barley varieties. The approach relies on one or a very limited number of carefully selected proteins, whose molecular weights are measured by traditional molecular approaches, such as sedimentation equilibrium ultracentrifugation [15,16].

The variety identification is achieved then by evaluating the difference in their molecular weights. This is because morphological characterisation of barley varieties is genetically separate and thus lead to variation in molecular weights of the associated proteins [16]. However, identification based on molecular weight is not reliable and becomes rather difficult in distinguishing between closely related varieties. The other drawback is such identification involves complicated experimental procedures and time-consuming.

A study on genetic and morphological characterisation of barley variety shows that the genetic analysis indicated that there are genetically separate but not distinct regulatory controls on vegetative and inflorescence axillary development [17]. Therefore, with the level of molecular weights, it is possible to identify or determine the relationship between varieties of barley likewise other cereal crops, but it does not guarantee accurate results it has difficulty in distinguishing between closely related varieties and time-consuming. These methods have difficulty to distinguish closely-related barley varieties.

2.1.2. DNA Fingerprinting technology

DNA fingerprinting technology currently developed by Western Barley Genetics Alliance indicated that the newly developed technologys molecular test would lead to fast and accurate results thereby providing growers, plant breeders, seed companies and marketers with more confidence in the identity and purity of Australian barley varieties [1]. However, it was indicated that the test takes less than two hours, compared with days or weeks for the traditional test, and the cost was less than $100 per sample [1].

This lengthy process and cost are also seen as significant flaw about the new technology while with machine learning, a user can take pictures of the barley at the receival points and automatically the barley variety can be identified, which is the essence of this research and implementations.

2.2. Computer vision approaches

Artificial neural networks are regarded as one of the machine learning algorithms that gained acceptance for cereal grain classification and identification problems.

Szczypinsik et al. [18] developed a technique to separate varieties of barley using computer vision and an artificial neural network (a three-layer network) as the classification reference method. The study aims to identify barley varieties based on shape, colour, and texture of the grain in the images. They were able to get 67 to 86% accuracy with the neural network classifier [18].

Visen et al., [11] proposed a four-layer back-propagation neural network to classify cereal grain and dockage. Their proposed method achieved an accuracy of 90% and they used a combination of morphological, colour, and texture as the feature of the model.

Kozowski et al. [19] proposed a technique for varietal classification of barley for malting. They used convolutional neural networks (CNNs) and compared their method with other existing techniques. Their experimental results demonstrate the superior performance for the recognition of individual kernel variety. Their proposed methods achieved an improvement of 40% in classification accuracy.

Based on the previous works, it can be noted that CNNs have achieved superior performance for the task of image classification. Machine learning, especially deep learning, has become more popular because of its compelling performances in the various task. For image classification tasks, CNN has been the most extensively studied algorithm. CNN is a deep learning architecture inspired by the natural visual perception mechanism of living creatures [20]. CNN uses multiple hidden layers, such as the convolutional layer, the pooling layer, and the fully connected layer.

Based on all those studies, it is hypothesised that CNN and its variants will perform barley image classification with greater accuracy.

3. Barley dataset

3.1. Image data

Our barley grain dataset was developed at The Western Crop Genetic Alliance at Murdoch University. The samples include 13 Barley Australia accredited malt barley varieties including Bass, Baudin, Buloke, Commander, Compass, Flinders, Granger, La Trobe, Litmus, RGT Planet, Scope CL, Spartacus CL, and Westminster, and one Barley Australia accredited food variety, Hindmarsh. There was a degree of genetic relatedness in the varieties imaged (Fig. 2). For example, Scope CL was developed through mutagenesis of Buloke and is agronomically similar to Buloke, except it is tolerant of the imidazolinone group of herbicides. Commander represents three-quarters of the parentage of Compass, while Baudin is a parent of Flinders. The other four varieties are genetically different to each other.

RGB images of grain were taken in a controlled environment. The grains were captured from the back and the front side. There were 1432

Table 1
Number of samples for each barley variety.

Variety Name	Bass	Baudin	Buloke	Commander
Number of Samples	624	636	696	612
Variety Name	**Compass**	**Flinders**	**Granger**	**Hindmarsh**
Number of Samples	600	612	612	600
Variety Name	**La Trobe**	**Litmus**	**RGT Planet**	**Scope CL**
Number of Samples	612	600	600	600
Variety Name	**Spartacus CL**	**Westminster**	-	-
Number of Samples	600	600	-	-

Table 2
Accuracy for each experiment.

Classifier/Architecture	Train Accuracy (%)	Validation Accuracy (%)	Test Accuracy (%)
SVM (Back)	-	-	12
SVM (Front)	-	-	8
CNN with VGG16 (Back)	85	75	73
CNN with VGG16 (Front)	64	53	59
Feature Extraction + CNN (Back)	76	88	80
Feature Extraction + CNN (Front)	77	89	83
Feature Extraction + SVM (Back)	-	-	94
Feature Extraction + SVM (Front)	-	-	92

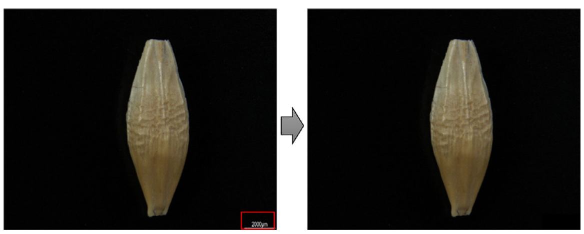

Fig. 1. Pre-processing of barley images. Removing watermark from the original image. Watermark is first detected and cropped from the image by replacing that region by black pixels.

high-quality RGB images, 716 for the back and 716 for the front side of the barley grains. Each variety had 600 to 696 images taken (Table 2). The images taken had a resolution of 1440 x 1220 pixels with 144 DPI and could be zoomed up to 2000 µm in length. Every image had a watermark on its bottom right. Therefore, all the images in the dataset are pre-processed as discussed in the following.

3.2. Data acquisition

The seed images were taken by Nikon DS-Fi 3 camera coupled with Research Stereo Microscope SMZ18, DS-L4 control unit and Schott AG Easy LED Double Spotlight. The camera was set as below: shutter speed 1/17 sec; iso 800; white balance 5500k; exposure compensation 0; shooting mode standard; metering mode average. For each variety at least 50 seeds with uniform shade and plumpness were selected to take images. For each seed, two images were taken, one from the front and the other from the back.

3.3. Data pre-processing

Image pre-processing is a common practice in image classification tasks. We perform two step pre-processing in this paper. Details are as follows:

3.3.1. Noise removal

Images of an object might be affected by the noise. We removed the noise from each image by first detecting the text, as shown in Fig. 1 (red box), and cropping the area which contains the watermark. This process was done automatically for every image.

3.3.2. Data augmentation

Next step in data pre-processing is the data augmentation. In situations, where data collection is expensive and time consuming; data cannot be collected from other resources, or the collected data is not well represented; data augmentation can be performed to generate diverse examples from the available data. This is particularly helpful if dataset size is very small and also helps to avoid overfitting of machine learning models. The efficient and the most common approach for data augmentation is to apply transformations such as translation, zoom, flips, shears, mirrors and colour perturbation on existing data [21].

We perform data augmentation on our dataset and generate new and diverse images with different kind of transformations (as above) for each image as shown in Fig. 3. We increased the sample size from 1432 to 8592 or by five folds.

4. Proposed methodology

4.1. Proposed deep learning technique

In this section, we describe our proposed deep learning technique for barley classification. Because we had a relatively small number of samples, we use a pre-trained deep learning model. All of the pre-trained models have been trained and tuned on the large-scale ImageNet dataset and are good for image classification, feature extraction, as well as transfer learning. The latter learning involves the reuse of knowledge from another related domain in the current domain, and deep learning has been very successfully utilised for various computer vision tasks, such as object identification, using transfer learning on different CNN architectures [22,23].

AlexNet, ResNet and VGG16 are widely used CNN architectures because these networks have achieved very good performance on different benchmarks for object recognition tasks [24]. In this paper, we use the pre-trained VGG-16 architecture [25] and perform transfer learning for the task of barley classification. In the following, we briefly describe VGG for completeness.

Visual Geometry Group (VGG) is a convolutional neural network model proposed by K. Simonyan and A. Zisserman in 2014 [25]. It has achieved one of the top performances in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2014. It utilises smaller filters of 3x3 with stride of 1 in convolution layer and uses same padding in pooling layers 2 x 2 with stride of 2 to provide better features extraction

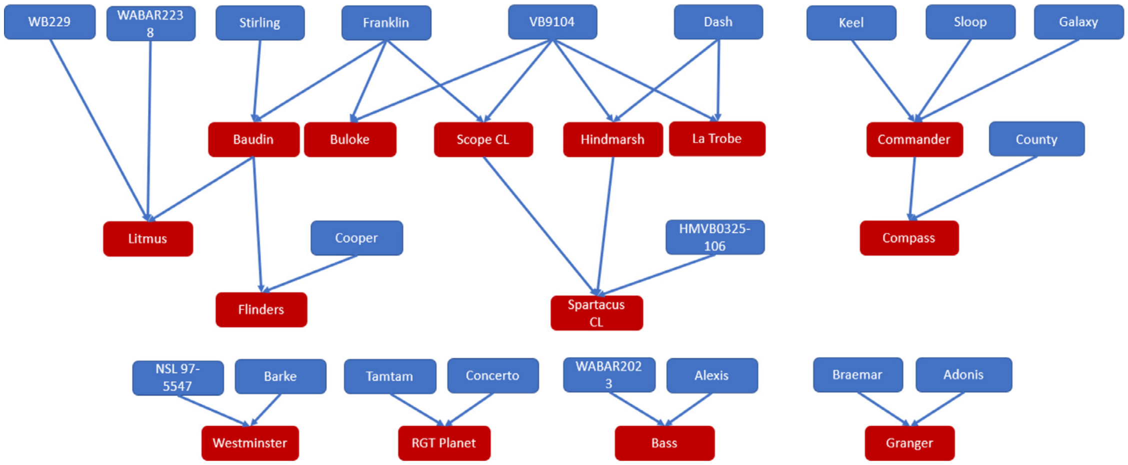

Fig. 2. Pedigrees of varieties imaged.

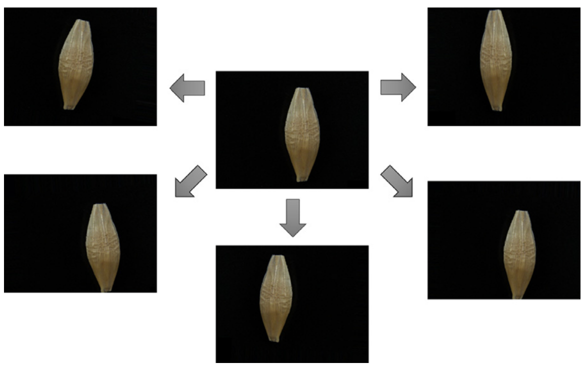

Fig. 3. Data augmentation to increase the number of samples in the dataset.

from images, using much lower filters to increase the depth of network instead of its width plays a critical role in gaining higher performance.

The network consists of 13 convolutional layers and 5 max pooling layers followed by three dense layers. We perform transfer learning, which requires modification of the final layer of this model. To demonstrate the effectiveness of the proposed model, we use two different types of classifiers including support vector machine (SVM) and the traditional softmax layer (details in Section 5). With transfer learning (VGG), the only pre-processing required is to subtract the mean RGB value, computed on the training set, from each pixel [26].

4.2. Baseline method

We used support vector machine (SVM) as our baseline method. SVM is one of the most used machine learning algorithms. It has been used in a broad range of classification problems such as recognition and detection [27]. However, to perform well in different situations, SVM must be tuned with a suitable kernel. Karamizadeh, et al. [27] mentioned that SVM could handle both linear and non-linear patterns but with different types of kernel.

5. Results and discussion

In the first experiment, the model was trained using Radial Basis Function (RBF) kernel SVM as the classifier. The dataset with raw images was split into two, for training and as the test dataset. Hyperparameters were left with default settings, i.e., C = 1 and gamma was set to auto depreciate. The RBF SVM model was run twice for each back and front images. The SVM achieved an accuracy of 12% for the back images model and 8% for the front image model. This was anticipated because SVM is not the best classifier to use when dealing with image classification problem. However, the model predicted only up to five varieties from the confusion matrix while leaving the other nine with zero predictions.

Table 3
Accuracy of fusion models.

Classifier/Architecture	Test Accuracy (%)
Feature Extraction + CNN	74
Feature Extraction + SVM	94
Feature Extraction + SVM (10-folds)	94

In the second experiment, the pre-trained VGG16 was used, split for training, testing, and validation with a proportion of 80, 10, and 10 per cent, respectively. The proposed model was fine-tuned separately for the back and front barley images. The proposed model achieved 75% accuracy for the validation set (back images) and 73% accuracy for test images (back) as reported in Table 2. For front images, 53% and 59% validation and test accuracy were achieved compared to the baseline SVM classifier.

In the third experiment, the model for feature extraction allowed dropping of the last layer of the model, with the features extracted from the last dense layer. Next, two different classifiers were trained to predict the class of input barley images using the extracted deep features. The extracted features were given as an input to a one-layer CNN with SoftMax. As a result, model accuracy increased, with a validation accuracy of 88% and test accuracy of 80% for the back image, with 89% validation and 83% test accuracy for the front image. Next, the SVM classifier was used as the last layer of the network. SVM is a good classifier and suitable for several problem domains. The features extracted from the deep learning model were fed to the SMV classifier. As a result, the enhanced model achieved 94% accuracy for back images and 92% for front images (Table 2).

In the fourth experiment, the output of the back-model (trained on back images) and front-model (trained on front images) were fused by concatenating the features extracted from each model (Table 3). The model achieved 74% accuracy with a soft-max layer. The model then achieved 94% with an SVM classifier. These results demonstrate the effectiveness of fusing the front and the back model features. To further validate the effectiveness of our model, we ran our experiments tenfold with a random selection of the training and test datasets, with an average accuracy of 94%.

Table 4 shows the confusion matrix. It can be noted that almost every variety has been classified with an accuracy of over 90%. Flinders had the lowest classification accuracy of 87%. The confusion matrix also

Table 4
Confusion Matrix for the fusion model. (% Accuracy) .

True/ Prediction	Bas	Bau	Bul	Cmr	Cps	Fli	Gra	Hin	LaT	Lit	RGT	Sco	Spa	Wes
Bass	**92**	-	-	1	-	2	-	-	-	-	4	2	-	-
Baudin	-	**99**	-	-	-	-	-	-	-	-	-	1	-	-
Buloke	-	-	**97**	1	-	-	-	1	-	-	-	1	-	-
Commander	-	-	1	**98**	-	-	-	-	-	-	1	-	-	-
Compass	-	-	-	-	**90**	1	-	-	-	-	-	3	3	2
Flinders	9	-	-	-	-	**87**	1	-	1	-	1	1	-	-
Granger	2	-	-	-	1	2	**91**	-	-	4	1	-	-	-
Hindmarsh	-	-	-	-	1	-	-	**98**	-	-	-	-	1	-
La Trobe	-	-	-	-	-	1	-	-	**94**	-	-	-	5	-
Litmus	-	-	-	-	1	1	1	-	-	**95**	-	1	2	-
RGT Planet	3	-	-	-	-	3	-	-	-	-	**92**	2	-	-
Scope CL	1	-	-	-	-	-	1	-	-	-	-	**96**	1	1
Spartacus CL3	-	-	-	-	1	-	-	-	7	-	-	-	**92**	-
Westminster	3	-	-	-	-	2	-	-	-	1	1	-	-	**93**

demonstrates several misclassifications. As many of the varieties were products or derivatives of another variety imaged (Fig. 2), they may have similar morphological characteristics and textures. The genealogical structure of the variety, therefore, limits the accuracy of any visual model. Surprisingly, Hindmarsh and La Trobe were rarely misclassified, while La Trobe and Spartacus CL were more often misclassified. Spartacus CL was predicted as La Trobe 7% of the time, and La Trobe was predicted as Spartacus CL 5%. While Flinders and Bass share a semi-dwarf heritage, their genetics are not similar, but Flinders was predicted as Bass 9% of the time. The genealogical structure of the variety limits the accuracy of the model.

Computation Time: Our experiments were run on Intel Corei5 computer with 16GB RAM. The average testing time for our proposed deep learning model is around $4ms$ per image that makes it suitable for real-time applications e.g., automatic barley variety recognition using mobile phone.

6. Conclusion and future directions

In this paper, we propose a deep learning technique for barley classification. The paper aims for an automatic image-based solution to identify 14 different barley varieties. The current methods in the field/industry are either time-consuming or expensive. The proposed method provides an efficient and cost effective solution. The results showed that the baseline SVM did not perform well compared to the deep learning algorithms. This is expected because the deep learning model learns more distinctive features compared to SVM. For the deep learning algorithm, we use pre-trained VGG16 architecture. We modified the model by using feature extraction and also performed transfer learning by replacing the last layer of the CNN.

The model performed well with a high overall accuracy and 94% of accuracy and consistent performance throughout ten folds cross-validation. Our proposed model outperforms the baseline model and achieves an average accuracy of 94% when both the front and back models are fused.

To enhance the accuracy and reduce the misclassification of the model, a larger RGB image dataset is required for the training of deep neural networks. In addition, for the model to be useful on receival, it would need to be assessed in uncontrolled environments; work with lower resolution images produced from mobile devices like a mobile phone; and detect more than one grain in an image. Other deep learning classification method and advanced preprocessing methods also need exploring. Another important research direction is to assess the ability of the model to predict the purity of barley grain in a sample. The purity of barley grain is essential for malting purposes and seed sale. In our future work, we intend to address this challenge by enhancing our current deep learning technique and by proposing new methods.

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