Classification of *Trifolium* Seeds by Computer Vision Methods

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Abstract: - Traditional machine learning methods have been extensively used in computer vision applications. However, recent improvements in computer technology have changed this trend. The dominance of deep learning methods in the field is observed when state-of-the-art studies are examined. This study employs traditional computer vision methods and deep learning to classify five different types of *Trifolium* seeds. *Trifolium*, the leading food for nutritious dairy products, plays an essential role in livestock in some parts of the world. First, an image data set consisting of 1903 images belonging to five different species of *Trifolium* was created. Descriptive and quantitative morphological features of each species are extracted using image-processing techniques. Then a feature matrix was created using eight different features. After feature selection and transformation, unnecessary and irrelevant features were removed from the data set to build more accurate and robust classification models. Four common and frequently applied classification algorithms created a prediction model in the seed data set. In addition, the same dataset was trained using VGG19, a convolutional neural network. Finally, the performance metrics of each classifier were computed and evaluated. The decision tree has the worst accuracy among the four traditional methods, 92.07%. On the other hand, Artificial Neural Network has the highest accuracy with 94.59%. As expected, VGG19 outperforms all traditional methods with 96.29% accuracy. However, as the results show, traditional methods can also produce results close to the deep learning methods.

Key-Words: - Classification, Computer Vision, Machine Learning, Deep Learning, *Trifolium*

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1 Introduction

Computer vision is extracting valuable information from digital images or videos acquired from an electronic camera to decide and perform an action based on that information. Due to the latest developments, it has been widely used in various applications, such as autonomous vehicle systems [1, 2], health care treatments [3, 4] and quality control processes on production lines [5, 6]. A traditional computer vision application requires the following procedures: image acquisition, prepossessing, segmentation, feature extraction, recognition and knowledge base. In the feature extraction stage, some high-dimensional quantitative data of the image is collected for use in the following steps. These features are edges, corners, blobs and ridges. They should not be sensitive to rotation, scale, translation, and contrast changes. The selected features must contain relevant information so that the requested task succeeds. For example, a face recognition system measures the distinctive organs of a human face, such as the nose, eyes and eyebrows [7].

When applying traditional computer vision methods to a problem, much of the time is spent preparing the data and extracting feature sets that require expert knowledge of the problem domain. In addition, these human-crafted features can be incomplete and specific. The cycle is repeated until the desired accuracy and consistency are achieved. However, deep learning has wholly altered the time distribution of the learning process. Deep learning applications spend most of their time modelling data with neural network architectures that automatically convert raw inputs into valuable features.

Precision farming can be defined as applying the latest technology and science in agriculture. Technologies such as Machine Learning, Cloud Computing, Big Data, and the Internet of Things (IoT) help farmers make more accurate and conscious decisions about the consequences of their actions [8, 9]. Thanks to the sensors placed in the fields, critical choices such as irrigation time and amount, the need for pesticide use and when to start harvesting can be automated by eliminating the human factor. Moreover, data such as the type, quality and quantity of crops harvested in the coming season can be obtained using digital images from satellites. Thus, administrations can take necessary precautions against problems in the food market [10]. In addition, studies based on image processing and computer vision methods try to detect crop diseases as early as possible to improve product efficiency.

The genus *Trifolium* includes more than 200 species, some of which are rich in calcium, phospho-

rus and various vitamins, so they are important in the livestock economy [11–13]. A study conducted in 1976 revealed that *Trifolium* species are among the most valuable forage legumes in all parts of the world except the tropics [14]. *Trifolium* species are important nitrogen fixers in temperate regions that improve pasture quality in both natural and cultivated meadows. The species with the highest agricultural value are *T. alexandrinum*, *T. fragiferum*, *T. incarnatum* *T. pratense* and *T. repens* [15].

Choosing high-quality and suitable seed species suitable for land and climate conditions is necessary to obtain high yield efficiency. Human experts often control the grading of seeds according to quality and type [16]. This process is susceptible to errors and subjective because it depends on visual inspection. Choosing objective and quantitative methods to classify seeds will satisfy both the producer and consumer. For this purpose, many studies in the literature [17–19]. Recent studies have shown that state-of-the-art solutions can successfully achieve the desired output.

This study aims to classify five different *Trifolium* seeds depending on the features obtained by using image processing and computer vision methods. There are many classification techniques in the literature. These are divided into statistics-based, rule-based, neural network-based, ensemble learning and instance-based categories according to different mathematical concepts used in classification. Naïve Bayes, Decision Tree, Artificial Neural Networks (ANN), Random Forest and k-Nearest-Neighbour(k-NN) techniques, which are widely used in each category, were used in this study. In addition, the data set was trained with deep learning and results were obtained. Thus, it was possible to compare two different approaches. Section 2 gives detailed information about the techniques.

2 Materials and Method

2.1 Image Acquisition

The computer vision process's first stage is obtaining the necessary digital images. The following steps' success depends on the image set's relevance and quality. We have captured 1903 images of five different species. A digital microscope acquired digital images of seed samples with a spatial resolution of 0.01 mm/pixel, a colour depth of 24 bits and a scanning area not exceeding 1600 x 1200 pixels. The seeds were placed on a whiteboard. Thus, the background colour is different from the seed colours to ensure that the segmentation process is more successful. A sample image of each *Trifolium* type is presented in Figure 1. The colour images were then converted to a grey scale to be able to apply the next image processing methods. A flowchart showing the order of each operation is depicted in Figure 2.

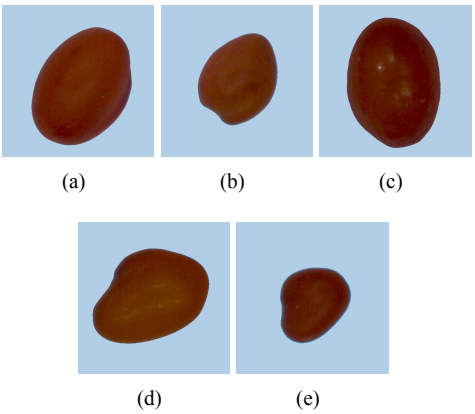


Figure 1: Sample images of different species of *Trifolium* (a) *T. alexandrinum* (b)*T. fragiferum* (c)*T. incarnatum* (d) *T. pratense* (e) *T. repens*

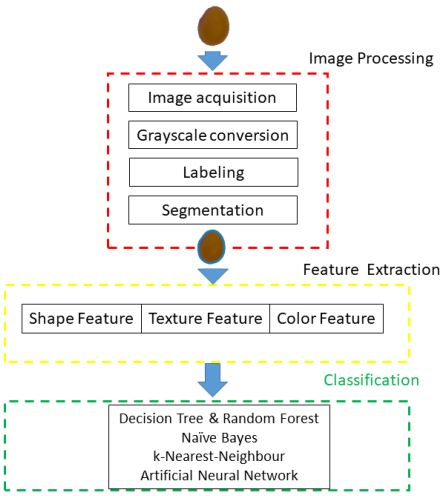


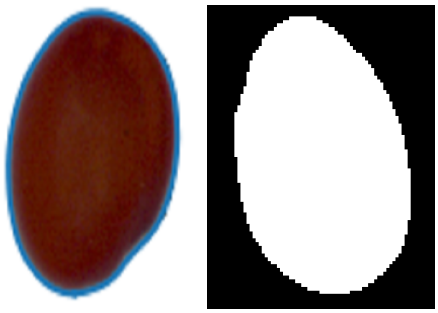
Figure 2: Flowchart of *Trifolium* seed classification

2.2 Image Segmentation

Image segmentation separates the object of interest from other parts of the image [20]. There are various image segmentation methods, such as region-based methods [21], morphological operation [20] and thresholding [22]. The choice of the algorithm used in segmentation usually depends on the properties of the problem solved. In this study, Otsu's threshold-based segmentation algorithm, which maximizes the inter-class variance parameter, was applied to determine the threshold value.

Image segmentation identifies mutually exclusive regions to find distinct elements that constitute an image. These regions have either a common colour or

texture. The goal of segmentation is to find objects or their boundaries. Segmentation plays a crucial role in subsequent feature extraction and classification tasks. There are two groups of segmentation methods—the first one search for the edges, which display sharp differences between the two contrasting regions. The second one tries to discover related areas according to defined similarity metrics. Thresholding is a simple but effective way of finding the contrast between foreground and background objects. The basic idea of thresholding is giving a specific intensity value for the region with less than a predefined intensity value. Pixels outside the area get a higher value. The threshold value is decided depending on the outcome of histogram analysis. In some cases, the local threshold method produces better results than the global threshold method since the relationship between the pixels is unrelated to the location. Therefore, the local method uses multiple threshold values in different segments.



(a) (b)

Figure 3: Segmentation of *Trifolium* seeds (a) convex hull (b) binary image after thresholding

2.3 Feature Extraction

A feature is defined as an essential part or aspect of something. Feature extraction methods analyze the entire or part of the image to determine the attributes that can be stored as a quantitative value required by classification methods. Identifying more relevant features to solve a specific problem can improve the accuracy of classification models. Many image-processing methods identify images or videos' shape, colour, motion, and texture features. Table 1 presents the morphological features and their descriptive statistics.

		T. ale.	*T.fra.*	*T. inc.*	*T. pra.*	*T. rep.*
Count		346	410	348	407	392
Area	μ	3.17	2.08	3.85	2.97	1.35
	σ	0.27	0.14	0.42	0.22	0.14
	min	2.69	1.82	3.09	2.56	1.11
	max	3.70	2.36	4.65	3.38	1.61
Perimeter	μ	6.80	5.46	7.49	6.63	4.38
	σ	0.30	0.19	0.41	0.26	0.22
	min	6.18	5.06	6.66	6.08	3.97
	max	7.41	5.86	8.36	7.19	4.83
BBoxArea	μ	4.16	2.72	5.07	3.97	1.76
	σ	0.38	0.21	0.55	0.32	0.19
	min	3.42	2.29	3.90	3.32	1.40
	max	5.05	3.25	6.24	4.72	2.18
ConvexArea	μ	3.18	2.10	3.86	3.00	1.36
	σ	0.27	0.15	0.42	0.22	0.14
	min	2.70	1.83	3.10	2.58	1.12
	max	3.71	2.38	4.67	3.43	1.63
Diameter	μ	2.01	1.63	2.21	1.94	1.31
	σ	0.09	0.06	0.12	0.07	0.07
	min	1.85	1.52	1.98	1.81	1.19
	max	2.17	1.73	2.43	2.07	1.43
F. Area	μ	3.17	2.08	3.85	2.97	1.35
	σ	0.27	0.14	0.42	0.22	0.14
	min	2.69	1.82	3.09	2.56	1.11
	max	3.70	2.36	4.65	3.38	1.61
Major	μ	2.37	1.80	2.62	2.29	1.40
	σ	0.14	0.07	0.16	0.13	0.08
	min	2.06	1.59	2.25	1.93	1.22
	max	2.73	2.03	3.03	2.63	1.68
Minor	μ	1.70	1.48	1.87	1.67	1.24
	σ	0.10	0.06	0.13	0.09	0.07
	min	1.44	1.28	1.54	1.38	1.04
	max	1.96	1.62	2.21	1.95	1.40

Table 1: Descriptive statistics of *Trifolium* species

2.4 Classification Methods

Machine learning is based on the idea that the computer can learn without being programmed explicitly. Machine learning requires the following tasks: selection of sample data, pre-processing and transforming data, model building and evaluation. Machine learning methods are generally categorized into three main subgroups. These are supervised, unsupervised and reinforcement learning methods. Supervised (predictive) learning methods use historical data to predict future events. They are intended to estimate class labels by using inputs (features). Classification, Anomaly Detection and Regression belong to supervised learning. On the contrary, unsupervised (descriptive) learning methods do not have class labels in the data sets. These methods use similarity or distance metrics to find groups of objects that exhibit common behaviours. Clustering and Association Rule Mining methods are two generally preferred unsupervised methods. Lastly, the reinforcement learning method determines its behaviour according to the reward and punishment it receives in response to its actions. This type of learning is widely preferred in digital games, autonomous cars and robot programming.

The classification methods use some data (training set) to determine the class boundaries. After the edges are located, the class of an object whose label is unknown is decided according to its position. This process is defined as classification. The most common classification algorithms are as follows: Decision trees, Naïve Bayes, Logistic regression, k-Nearest Neighbours(k-NN), Support Vector Machines(SVM)

and Artificial Neural Networks(ANN). In this study, we will use four extensively preferred classification methods.

2.4.1 Decision Trees and Random Forest

Decision trees are a non-parametric supervised learning method. Decision trees, which can process quantitative and categorical data, are widely used because they are easy to build and interpret. In addition, they are resistant to outliers. There are three types of nodes in decision trees, root, leaf and internal. Decision tree algorithms such as ID3, C4.5 and CART are based on a divide-and-conquer approach. They start from the root node and grow to the leaf node with a greedy strategy. The leaf node at the end of the path starting from the root determines the class label of an unlabeled object. Decision trees are prone to overfitting, mainly when the tree is fully-grown. A pruning or random forest approach can be adopted to overcome this problem. The pruning cut down less significant branches to create simpler trees. Random forest builds multiple trees using sampling with replacement methodology. If there is a conflict in the predictions of the trees, the final class label is determined by evaluating the majority of the decisions made by each tree.

2.4.2 Naïve Bayes

The Naive Bayes method based on the Bayes theorem employs the assumption of independence between predictors. It calculates the probability of past observations using training data set. Then it uses probability values to estimate the likelihood of future events. For each class, the Naive Bayes classifier computes the posterior probability using Eq. 1. The labels of the test data are determined as the label of the class with the highest probability.

$$p\left(class \mid feature\right) = \frac{p\left(feature \mid class\right) p\left(class\right)}{p\left(feature\right)} \tag{1}$$

- p(class | feature) : posterior probability of class given evidence
- p(class) : prior probability of class
- p(feature | class) : prior probability of predictor given class
- p(feature) : the prior probability of predictor

2.4.3 k-Nearest-Neighbour

Classification methods are divided into two categories as eager and lazy learners. Eager learners produce a prediction model using historical data before classifying the new instance. Lazy learners do not make a similar preparation before the prediction process. Whenever a new unclassified object arrives, it repeats the necessary steps defined by the algorithm each time. k-Nearest-Neighbour (k-NN) is a lazy learner. It finds the nearest k neighbours around the unclassified object and decides the class label based on the class labels of the neighbours. It determines its closest neighbours using distance metrics. However, one of the most important disadvantages is the determination of the k value that generates the best prediction accuracy. For this purpose, a sequence of experiments is carried out, and the k value that gives the best result is chosen.

2.4.4 Artificial Neural Networks

Artificial neural networks, which are highly robust and learn very quickly, simulate how the human brain processes information. Artificial neural networks are created by intensely interconnecting a series of neuron-like simple units. Each unit converts the input value it receives into an output. The generated output is forwarded to the next layer. The output value delivered from the last layer is used as a result. The connection between units is called edges, which have weights initialized randomly. The learning process is defined as tuning these weights to enhance the accuracy of the network. There is a wide variety of network types defined to handle different problems. Feedforward, Radial Basis Function, Multilayer Perceptron, Convolutional and Recurrent Neural networks. Figure 4 illustrates the network architecture used in our study.

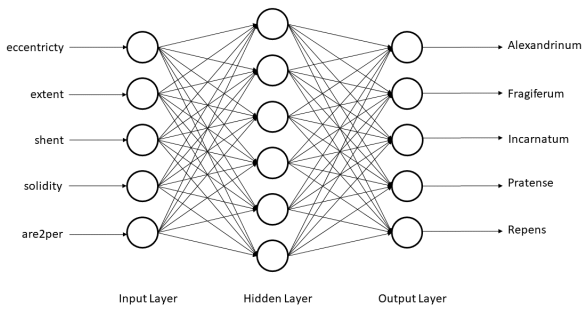


Figure 4: The Feedforward ANN structure

2.4.5 Convolutional Neural Networks

Deep learning is used to solve many different complex problems in digital image processing. Deep learning methods, such as Convolutional Neural Networks (CNNs), enhance the accuracy of classification models by using a large data set and sufficient computing power. CNNs consist of various layers: input, convolution, pooling, fully connected, softmax

and output. In a deep learning architecture, the first layer that receives raw pixels of input data learns how to represent simple features. Each successive layer learns the complex features of the previous layer as they collect and recombine the features of the earlier layers. Adding more layers to the network allows it to handle higher dimensional data.

Although VGG was not the winner of the 2014 ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) competition, it has been used in many applications due to its modular and simpler architecture [23]. Unlike other CNNs, VGG prefers smaller kernel sizes, which helps increase its expressibility. VGG architecture has several variations according to the number of layers it contains. The smallest one (VGG-11) has 11 layers and 133 million parameters. The largest one (VGG-19) consists of 19 layers and requires 144 million parameters to be tuned. The architecture of the VGG is displayed in Figure 5.

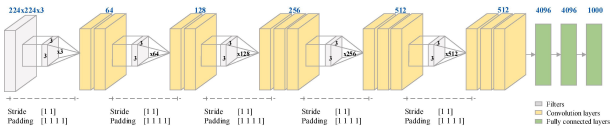


Figure 5: The architecture of VGG [24]

2.5 Model Evaluation

At the final stage of the machine learning process, each classification model should be evaluated with test data they do not encounter during the building phase. Thus, it can be foreseen how accurate they can produce a prediction for objects whose label is not specified. Besides, the best model can be distinguished among different ones. There are two widely used evaluation methods.

2.5.1 Holdout Method

Before the model-building process, this method divides the data into two disjoint sets. Generally, two-thirds of the data is called training data used for model building. The remaining portion is used for evaluation purposes. If there is less training data, a model with inadequate generalization capability can be developed. In this case, the accuracy of the test data may not exceed a certain threshold. If the test data is insufficient, an unreliable and unstable model emerges. Repeating the holdout method with different training and test data sets can reduce deviations caused by specific sample data. The overall error rate is computed using the average error rates obtained for each data set.

2.5.2 k-fold Cross-Validation

Unlike the Holdout method, the data set is divided into k independent sets of almost equal size. The testing process is repeated k times in total. For each round, *k-1* sets are considered the training set and the model is built using them. The model is tested with the excluded set that is different each time. The error rate is calculated by dividing the total number of incorrectly predicted objects by the total number of objects in the data set. The advantage of this method is that it allows testing of each object in the data set. Choosing k is practically suitable between 5 and 10. In that case, the test set consists of at least 10% of all data.

3 Results and Discussion

A digital image consists of a collection of pixels representing an intensity value stored in a multidimensional array. Naturally, raw image data is high dimensional. Therefore, feature selection and transformation play an essential role in the accuracy of image classification applications. Irrelevant and redundant attributes should be verified and removed from the data set before the model building phase.

Raw features are converted to the following feature set:

- eccentricity: Eccentricity is the ratio of the focal length of an ellipse to the major axis length. It gets values in the range of zero and one. As the value approaches zero, it is more like a circle.
- extent: It is computed as the ratio of the number of pixels in the area to the number of pixels in the total bounding box.
- shent: Entropy shows variability in data.
- solidity: It is expressed as the ratio of pixels in the region to the pixels of the convex hull of the image.
- minor_axis_length: The width of bounding box
- major_axis_length: The length of bounding box.
- maovermi: The value obtained by dividing the major axis length by the minor axis length.
- are2per: It is computed by dividing the area into the perimeter.

There are two different approaches to achieving feature selection. The first one calculates either correlation or chi-squared values between features. Highly correlated features are eliminated. The second approach uses a brute force search strategy to find the optimal feature combination that results in the best accuracy value. We utilized the first approach. Figure 6 presents the correlation matrix between features.

As seen from the correlation matrix, *maovermi* attribute is highly correlated with *eccentricity* and

Figure 6: Correlation matrix of features

are2per (correlation value of maovermi between eccentricity and are2per is -0.98 and -0.82, respectively). Therefore, *maovermi* is removed from the data set. Then, four classification algorithms are applied. We use the scikit-learn Python library to run each classifier for two different evaluation methods. The accuracy percentage, weighted ROC area and F1 score values of each classification algorithm are presented in Table 2.

	10-Fold Cross-Validation			Holdout		
	Accuracy	ROC	F1	Accuracy	ROC	F1
Decision Tree	92.07%	0.97	0.92	93.20%	0.98	0.92
Random Forest	93.12%	0.99	0.93	93.66%	0.99	0.92
k-NN	92.28%	0.99	0.92	92.73%	0.99	0.93
Naive Bayes	91.96%	0.99	0.90	92.12%	0.99	0.92
ANN	93, 17%*	0.99	0.93	94.59%*	0.95	0.99

Table 2: Performance of classifiers

Among the classification models produced, Naïve Bayes has the lowest accuracy values for the 10-fold cross-validation and holdout method. ANN has the highest accuracy values for both methods. The weighted ROC area and F1 score values of all models are close to one, which indicates that each model convincingly distinguishes objects of different classes. According to two different evaluation methods, the confusion matrices of ANN that have the highest accuracy values are given in Table 3 and 4.

		Actual Class				
		T. ale.	*T. fra.*	*T. inc.*	*T. pra.*	*T. rep.*
Predicted	***T. alexandrinum***	87	0	19	5	0
	T. fragiferum	0	151	0	0	0
	T. incarnatum	5	0	102	3	0
	T. pratense	2	0	1	131	0
	T. repens	0	0	0	0	141

Table 3: Confusion matrix of ANN for Holdout

		Actual Class				
		T. ale.	*T. fra.*	*T. inc.*	*T. pra.*	*T. rep.*
Predicted	***T. alexandrinum***	272	0	52	22	0
	T. fragiferum	0	410	0	0	0
	T. incarnatum	29	0	316	3	0
	T. pratense	22	0	2	383	0
	T. repens	0	0	0	0	392

Table 4: Confusion matrix of ANN for 10-fold-Cross-Validation

		Actual Class				
		T. ale.	*T. fra.*	*T. inc.*	*T. pra.*	*T. rep.*
Predicted	***T. alexandrinum***	95	0	13	3	0
	T. fragiferum	0	151	0	0	0
	T. incarnatum	4	0	104	2	0
	T. pratense	1	0	1	132	0
	T. repens	0	0	0	0	141

Table 5: Confusion matrix of VGG19

All of the instances of *T. fragiferum* and *T. repens* are correctly classified. However, prediction models incorrectly classify some instances that belong to classes *T. alexandrinum*, *T. incarnatum*, and *T. pratense*. We can conclude that *T. fragiferum* and *T. repens* have more distinctive features than other classes. The accuracy and loss of training and validation sets for the VGG19 are shown in Figure 7. The accuracy of both the training and validation data sets converges to their final values at approximately epoch 30.

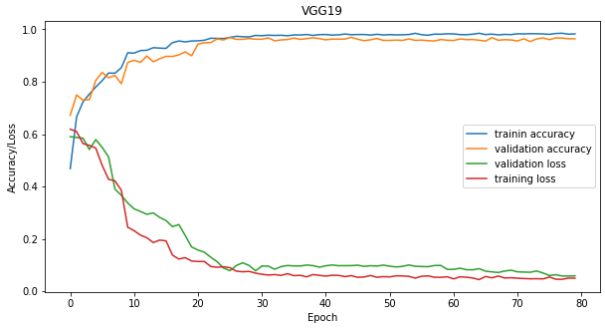


Figure 7: Accuracy and loss of training and validation sets

4 Conclusions

This study proposes a method that automates the classification process of *Trifolium* seed. An image data set of five different species of *Trifolium* has been created that can be used in future studies. After the necessary prepossessing methods were applied to the images, they were forwarded to different classification methods, including Decision tree, Naïve Bayes, k-NN and ANN. The outcome of each classifier was analyzed and discussed. It is realized that ANN produces the best performance values among the four

methods. Furthermore, the results demonstrate that species of *T. fragiferum* and *T. repens* have distinct quantitative features than the other ones. In addition to the old-school methods mentioned above, we obtained results by applying the VGG19 architecture to the same data set. The performance of VGG19 is slightly better than theirs. In conclusion, it has been shown that traditional methods can produce prediction models as accurate and reliable as deep learning methods in cases where the dataset size is small and computational power is low.

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