COMPARISON OF SUPPORT VECTOR MACHINES AND DEEP LEARNING FOR PLANT CLASSIFICATION IN SMART AGRICULTURE APPLICATIONS

Esmael Hamuda[1], Ashkan Parsi[2], Martin Glavin[2] and Edward Jones[2]

[1]Department of Electrical and Computer Engineering,
Elmergib University, Al Khums, Libya
[2]Department of Electrical and Electronic Engineering,
University of Galway, Galway, Ireland

ABSTRACT

*In this paper, we investigate the use of deep learning approaches for plant classification (cauliflower and weeds) in smart agriculture applications. To perform this, five approaches were considered, two based on well-known deep learning architectures (AlexNet and GoogleNet), and three based on Support Vector Machine (SVM) classifiers with different feature sets (Bag of Words in L*a*b colour space, Bag of Words in HSV colour space, Bag of Words of Speeded-up Robust Features (SURF)). Two types of datasets were used in this study: one without Data Augmentation and the second one with Data Augmentation. Each algorithm's performance was tested with one data set similar to the training data, and a second data set acquired under challenging conditions such as various weather conditions, heavy weeds, and several weed species that have a similarity of colour and shape to the crops. Results show that the best overall performance was achieved by Deep learning models.*

KEYWORDS

Deep Learning, BoWs, SURF, Data Augmentation, Plant Classification and Smart Agriculture.

1. INTRODUCTION

While machine vision technology has made great inroads in smart agriculture, according to [1], [2],[3],[4] it is still not fully capable of handling certain real-world issues such as weather variability, the presence of shadows in sunny conditions, natural similarities between the target object (weed or crop) and the background, and unexpected changes in camera parameters.

Recent research has attempted to increase performance by applying deep learning technology, with promising results [5],[3]. In [6] McCool et al. applied deep convolutional neural networks (pre-trained model) to perform crop and weed segmentation and reported an accuracy of nearly 94%. In [7] Milioto et al. applied the NDVI color index for vegetation detection and then used a Convolutional Neural Network (CNN) classifier to classify the detected plants into crops and weeds. The algorithm was tested on early and late (two weeks later) growth stages and achieved 99.42 and 99.66% precision on weeds, respectively. In [8] Yalcin et al. used a pre-trained CNN to classify sixteen kinds of plant species. Their approach was tested on acquired images under natural outdoor illumination and compared with an SVM model with different features such as Local Binary Pattern (LAP) and Generalized Search Tree (GIST), and with different kernels such

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as Radial Basis function (RBF) and polynomial. The CNN achieved good performance (classification accuracy of 97.47%) compared to the SVM model (RBF kernel with LBP and GIST features: 74.92 and 83.88%, respectively; polynomial kernel with LBP and GIST features: 69.81 and 82.29%, respectively). Other researchers have implemented CNNs for plant disease detection and achieved excellent results. In [9] Sladojevic et al. conducted experiments to detect plant diseases based on leaf image classification using deep neural networks. Their model showed precision between 91% and 98%, for separate class tests, while the overall accuracy of the trained model was 96.3%. In [8] Mohanty et al. investigated the feasibility of using a deep convolutional neural network for the detection of plant disease. They used a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions with 14 crop species and 26 diseases. The trained model showed an accuracy of 99.35%. They also used the well-known AlexNet and GoogleNet architectures on different image types (RGB color, Gray scale, leaf segmented), with different training approaches (transfer learning and training from scratch), and different choices of training-testing set distribution (train: 80%, test: 20%; train: 60%, test: 40%; train: 50%, test: 50%). Overall, Googlenet with RGB color images, transfer learning, and 80% of the dataset for training and 20% for testing achieved an accuracy of 99.3% while Alexnet with the same conditions achieved an accuracy of 99.2%.

For plant classification, in [10] Pawara et al. investigated the use of AlexNet and GoogleNet trained from scratch or using pre-trained weights. They used different datasets in their experiments, including original datasets and data-augmented image datasets for three plant classification problems: Folio [11], AgrilPlant [12], and the Swedish leaf dataset [13]. They also used six different Data-Augmentation (DA) techniques such as Rotation, Blur, Scaling, Contrast, Illumination, and Projective to investigate the classification performance on both pretrained and fully trained CNNs. The results show that data augmentation methods are important to obtain higher accuracies for CNN models trained from scratch. For AlexNet and GoogleNet architectures, the combined effects of rotation and illumination, or rotation and contrast are very beneficial, whereas the blur operation does not help to obtain higher accuracies. For AlexNet architecture refined by transfer learning, the scaling DA technique was somewhat helpful, whereas the transfer learning GoogleNet benefits from DA with illumination, but most other DA techniques are not helpful to obtain higher accuracies with the pre-trained CNN architectures.

In most previous work, the dataset used generally contains a single class such as fruit (apple, banana, grape, jack fruit, orange, papaya, persimmon, pineapple, sunflower, and tulip) or a single plant leaf. In this work, more challenging problems with more than one class, and with images under different illuminations, are investigated. In addition, two well know deep neural networks (AlexNet [14] and GoogleNet [15]) are compared with an SVM model with Bag of Words feature sets based on different approaches: L*a*b colour space, HSV color space, and Speeded-up Robust Features (SURF) were applied and investigated their impact on the classification results as well as compared with AlexNet and GoogleNet.

The rest of the paper is organized as follows: Section 2 gives details on the SVM model with the different features and the used deep neural networks. Section 3 describes the testing framework and performance metrics. The results and discussion are given in Section 4. Finally, Section 5 gives the conclusion of this work.

2. MACHINE LEARNING ALGORITHMS AND FEATURES

2.1. SVM model

Support Vector Machines (SVMs) [16], and [17] are supervised learning models with associated learning algorithms that analyze data and recognize patterns. They are used for classification and regression analysis. SVM can perform both linear classification and non-linear classification. SVMs are used with features extracted from the input data; in this work, the Bag of Words (BoWs) approach is used with different base features.

2.2. Bag of Words (BoWs)

The BoWs [18]features of images can be obtained by using the K-Means clustering algorithm on features extracted from those images. The features may be shape or structure features, or colour features. The algorithm iteratively groups the descriptors into k mutually exclusive clusters. The resulting clusters are compact and separated by similar characteristics. Each cluster center represents a feature or visual word. Three separate features are considered here to create individual BoWs representations: one based on feature descriptors (SURF [19]) and two colour features (L*a*b and HSV colour spaces). To create Bag of Words features from the colour information, the following steps are used.

1. Convert RGB images to the L*a*b* or HSV colour space.
2. Compute the "average" L*a*b* or HSV colour within 16-by-16-pixel blocks. The average value is used as the colour portion of the image feature.
3. Reshape L*a*b* or HSV average values (features) into a Kx3 matrix, where K is the number of features.
4. Normalize each channel to the root mean squared value of the channel.
5. Augment the colour feature by appending the [x y] location within the image from which the colour feature was extracted. This technique is known as spatial augmentation. Spatial augmentation incorporates the spatial layout of the features within an image as part of the extracted feature vectors. Therefore, for two images to have similar colour features, both the colour and the spatial distribution must be similar.
6. Normalize pixel coordinates to handle different image sizes.
7. Concatenate the spatial locations and colour features.
8. Add the variance of each channel as an additional feature.

2.3. Deep learning approaches

In this work, two common deep-learning approaches were used for plant classification: Alex Net [14], GoogleNet [15]. These were applied individually on raw images (RGB colour images), and the ones that had preprocessing.

2.3.1. AlexNet

AlexNet [14] is a neural network model with 60 million parameters in 8 layers and is available pre-trained on the Image net database which contains more than a million images in 1000 categories. Specifically, it consists of five convolutional layers followed by three fully connected layers as illustrated in Figure 1.

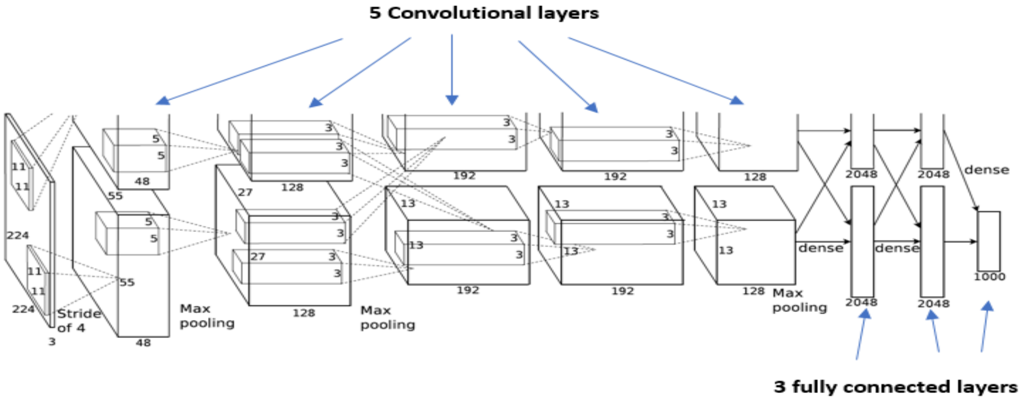

Figure 1. An illustration of the architecture of AlexNet [14].

The main purpose of the convolutional layer is to extract features from the input images while the fully connected layers are used to classify the extracted features to the desired class.

2.3.2. GoogleNet

GoogleNet [15] has 22 layers, with fewer parameters than AlexNet (about 7 million) [20]. GoogleNet has a different architecture to AlexNet, and uses combinations of inception modules, each including some pooling, convolutions at different scales and concatenation operations. It also uses 1x1 feature convolutions that work like feature selectors. The advantage of using 1x1 convolutions is to reduce the number of parameters. These components are shown in Figure 2.

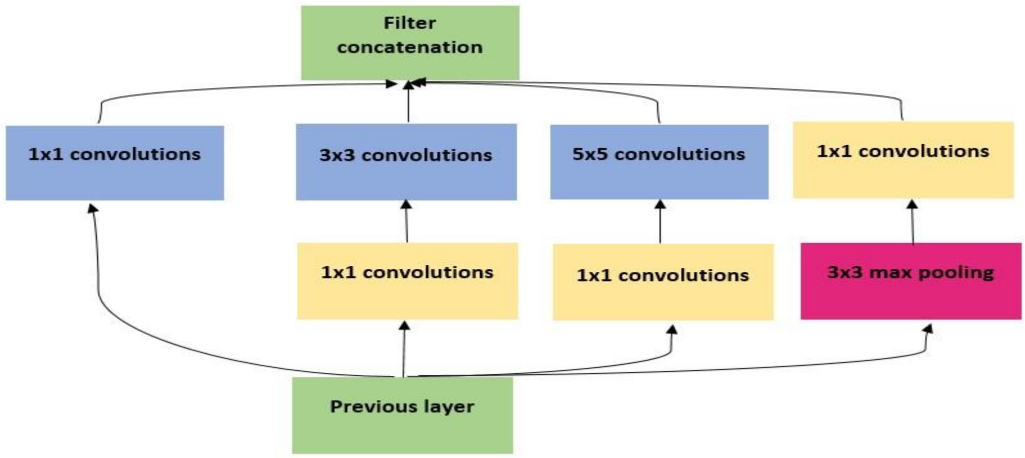

Figure 2. The inception module of GoogleNet [15] with dimension reduction.

3. Testing Framework and Performance Metrics

3.1. Image acquisition

A digital camera (GoPro Hero 4 Silver with maximum video resolution of 3840 2160 pixels, Effective Photo Resolution of 12.0 MP, and memory card max supported size of 64 GB) was used to acquire cauliflower images under a variety of illuminations: cloudy, partially cloudy, and sunny days for different stages of growth (from June until the end of September 2015).

Additionally, various circumstances such as partial occlusion between crop and weeds light changes, motion caused by the wind, different types of shadows, and various backgrounds (soil, nylon, stones, and other residues) were included. The images were captured in the west of Ireland. A top-view camera position was adopted to capture the images with a resolution of 2704 x1520 pixels. A standard desktop computer with an Intel i7-4790 CPU running 64-bit Windows 7 and 32 GB of RAM with Matlab installed was used for developing and executing each given algorithm.

In this paper, there are two types of training data: One is the original dataset (raw images) and the second data is Data augmentation (preprocessing images).

3.2. Training set

The datasets used in this work consisted of images converted to size 227x227 for training and testing purposes; the size conversion is necessary to match the expected input size of the neural networks employed for classification. A set of 800 cauliflowers images and a set of 1000 weed images were used. 80% of the dataset (randomly chosen) was used for training [21](referred to as the training set), and the remaining (20%) for testing (referred to as the test set). The characteristics of the training and testing sets were broadly similar. Figure 3 shows examples of the training set.

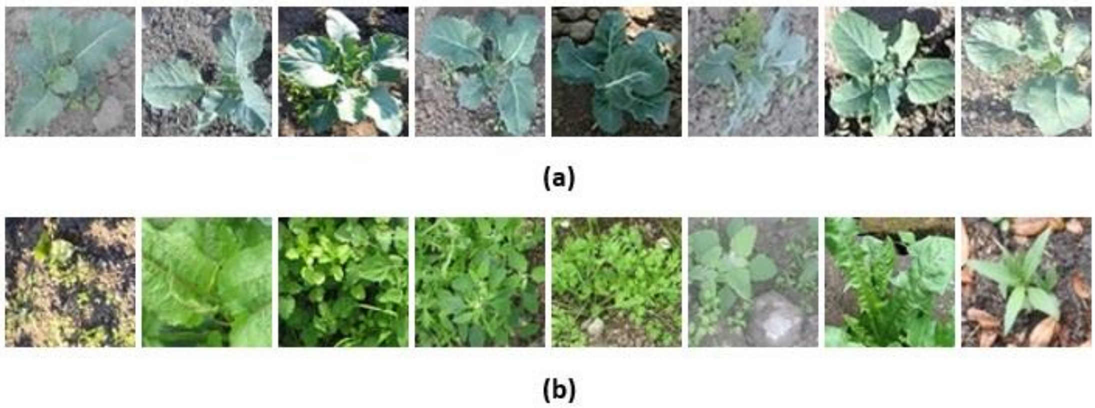

Figure 3. Sample images from training set. Figure (a) represent the positive set (cauliflowers),while figure (b) represents the negative set (weeds).

3.3. Data Augmentation (DA)

Since there is a relativity small original dataset and to perform better classification accuracy, this dataset needs to increase. That can be achieved by augmenting the original images via several random transformations (pre-processing) to generate new training samples (more data) without changing the class labels. This process is called Data augmentation. In this project, seven image transformations are done on the original dataset. These operations are:

1. **The rotation range** is a value in degrees (0-180), a range within which to randomly rotate pictures. The used value is 40.
2. **Width-shift and height-shift** are ranges (as a fraction of total width or height) within which to randomly translate pictures vertically or horizontally. The value of 0.2 is used for both shifts.

3. **Rescale** is a value which is used to multiply the data before any other processing. The used value is 1/255.
4. **Shear-range** is for randomly applying shearing transformations. The used value is 0.2
5. **The zoom range** is for randomly zooming inside pictures. The used value is 0.2.
6. **Horizontal flip** is for randomly flipping half of the images horizontally.
7. **Fill mode** is the strategy used for filling in newly created pixels, which can appear after a rotation or a width/height shift.

Thus, the total generated data is 12600 images (5600 images for cauliflower and 7000 for weeds). 80% of the DA (randomly chosen) was used for training and the remaining (20%) for testing.

3.4. Challenge set

In addition to the test set described above, a further 200 images (100 images for cauliflowers and another 100 images for weeds) were selected for evaluating the algorithms. These images were selected carefully with more challenging conditions than used in the original training and test sets, and include cauliflowers surrounded by heavy weeds, leaves of cauliflowers turned over or otherwise distorted, shadows, sunshine, weeds with similar colour and shape to cauliflowers, and blurred images etc. This data set is referred to as the challenge set. Figure 4 shows examples from this set.

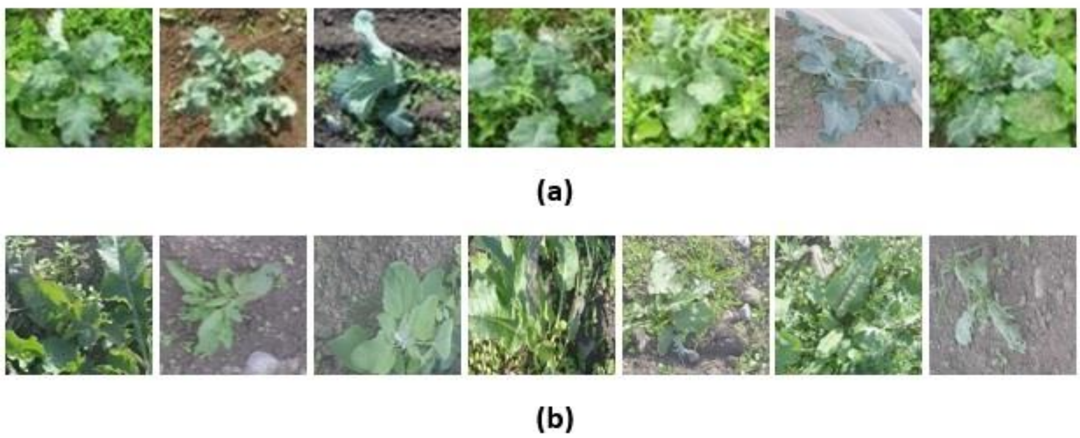

Figure 4. Sample images of the Evaluation set. Figure (a) represents the positive set (cauliflowers), while figure (b) represents the negative set (weeds).

3.5. Performance evaluation

To evaluate the crop vs. weed accuracy of the given algorithms, the primary metric used is classification accuracy, defined as follows:

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \quad (1)$$

where T_P is True Positive, T_N is True Negative, F_P is False Positive, and F_N is False Negative.

For precision agriculture, it is important to keep the number of False Negatives small, which means keeping the number of crops classified as weeds (and thereby removed) as small as possible.

4. RESULTS AND DISCUSSION

4.1. Parameter Selection

For GoogleNet (144 layers) and AlexNet (25 layers), pre-trained networks were used, with transfer learning using the training set to retrain the output layers. To retrain GoogleNet to classify new images, the last three layers of the original network was retrained to produce three new layers (a fully connected layer, a softmax layer, and a classification output layer). A similar approach was taken to apply transfer learning with AlexNet. The AlexNet training parameters were as follows: Number of iterations: 1400, train batch size: 10, base learning: 0.00001, Epoch: 10. The GoogleNet training parameters were as follows: Number of iterations: 890, train batch size: 10, base learning: 0.00001, Epoch: 10. In adaptation, a new layer was added to the layer graph in GoogleNet: a dropout layer with a probability of 60% dropout. The advantage of this layer is that it can prevent Neural Networks from overfitting and improve the quality of features [9], [1].

For all of the SVM+BoWs feature combinations, the parameters were set to the same values. The features from the training images were processed by K-Means clustering to create a 500-word visual vocabulary. Once the features are extracted, the SVM classifier is applied. SVM parameters were empirically optimized to obtain the best performance, with the following parameters used: the SVM kernel was chosen as 'RBF', the cost parameter (c) is set to 1.8, and Gamma (the kernel width) is set to 0.09.

4.2. Results From the Test Set

Table 1 illustrates the accuracy of each algorithm for the test set on the test dataset. Two versions of the test set were used for evaluation: the original test set, and a version of the test set to which data augmentation techniques were applied. Data augmentation [22], [23], [24] is commonly used in deep learning applications and involves increasing the size and variability of a dataset through transformations of the original data. These transformations typically include e.g. blurring, rotation and translation operations. These transformations generated 12600 images (5600 images for cauliflower and 7000 for weeds). The columns marked "Cauliflower" and "Weed" give the detection rate on those subsets of the test set, while "Overall" accuracy is the overall performance on the database.

Table 1. Average test accuracy on test set.

Model	Without Data Augmentation			With Data Augmentation		
	Cauliflower	Weed	Test accuracy	Cauliflower	Weed	Test accuracy
AlexNet	100%	99.44%	99.72%	100%	99.58%	99.79%
GoogleNet	97.62%	100%	98.81%	100%	99.66%	99.83%
SVM+BoWs(HSV)	96.00%	99.00%	97.50%	99.00%	99.00%	99.00%
SVM+BoWs (L*a*b)	97.00%	99.00%	98.00%	99.00%	100%	99.50%
SVM+BoWs (SURF)	97.00%	86.00%	91.50%	94.00%	92.00%	93.00%

From Table 1, it can be seen that the deep learning approaches gave the highest average test accuracy for dataset without Data Augmentation (99.72% and 98.81% for AlexNet and GoogleNet, respectively) and for dataset with Data Augmentation (99.79% and 99.83% for AlexNet and GoogleNet, respectively), whereas the SVM+BoWs of SURF features has the lowest performance at 91.50% and 93.00% for dataset without Data Augmentation and dataset with Data Augmentation, respectively. The SVM+BoWs of HSV and L*a*b colour features show good performance (97.5 and 98.0%, respectively) for dataset without Data Augmentation, and (99 and 99.5%, respectively) for dataset without Data Augmentation.

In total, all models achieved higher classification accuracy when they applied on the test set of the dataset with Data Augmentation than the one without Data Augmentation. The next sub-section discusses performance on the more difficult challenge set. From Table 1, it can be seen that the deep learning approaches gave the highest average test accuracy (99.72% and 98.81% for AlexNet and GoogleNet, respectively), whereas the SVM+BoWs of SURF features has the lowest performance at 91.50%. The SVM+BoWs of HSV and L*a*b colour features show good performance (98.0%). In total, all models achieved high classification accuracy on the test set. The next sub-section discusses performance on the more difficult challenge set.

4.3. Results From the Challenge Set

Table 2 summarises the performance of each algorithm and the overall test accuracy on the Challenge Set by using the output of the training phase for both variants of the challenge dataset (without and with Data Augmentation) for all models tested.

Table 2. Overall results on the challenge set.

Model	**Without Data Augmentation**			**With Data Augmentation**		
	Cauliflower	Weed	Test accuracy	Cauliflower	Weed	Test accuracy
AlexNet	95.00%	100%	97.50%	100%	98.80%	99.40%
GoogleNet	96.00%	99%	97.50%	100%	97.62%	98.81%
SVM+BoWs(HSV)	94.00%	93.00%	93.50%	97.00%	94.00%	95.50%
SVM+BoWs (L*a*b)	89.00%	98.00%	93.50%	95.00%	98.00%	96.50%
SVM+BoWs (SURF)	82.00%	95.00%	88.50%	88.00%	95.00%	91.50%

According to the results in Table 2, all of the models without Data Augmentation have higher accuracy on the weed images than cauliflower images, except for the SVM+BoWs based on the HSV colour space. For images correctly classified as cauliflowers, GoogleNet demonstrated the highest classification accuracy without Data Augmentation and GoogleNet and AlexNet demonstrated the highest classification accuracy with Data Augmentation, whereas the SVM+BoWs of SURF gave the lowest classification accuracy in both types of dataset. AlexNet demonstrated the second highest classification accuracy for the dataset without Data Augmentation. The SVM+BoWs of HSV colour space achieved the third highest classification accuracy for the dataset without Data Augmentation, whereas the SVM+BoWs of L*a*b colour achieved the third highest classification accuracy when the dataset with Data Augmentation was used. The SVM+BoWs of L*a*b and HSV colour gave similar classification accuracy when they used the dataset without Data Augmentation and with Data Augmentation.

In terms of overall test accuracy (the last column in Table 2), AlexNet demonstrated the highest overall accuracy results (99.40%) and GoogleNet demonstrated the second-highest overall accuracy results (98.81%) with Data Augmentation, whereas AlexNet and GoogleNet demonstrated the highest overall accuracy results (97.5%) without Data Augmentation. The SVM+BoWs of SURF features gave the lowest performance at 88.5% and 91.50% for the dataset without and with Data Augmentation, respectively. The SVM+BoWs of HSV and L*a*b colour features achieved a performance of 93.5% on the dataset without Data Augmentation, whereas when the dataset with Data Augmentation was used, the SVM+BoWs of L*a*b demonstrated higher classification accuracy (96.5%) than SVM+BoWs of HSV (95.5%).

In conclusion, deep learning approaches outperformed the other systems in terms of accuracy on the two types of datasets. Although both used deep learning approaches with different network architectures (AlexNet has 25 network layers and a greater number of parameters, while GoogleNet has greater network layers and fewer parameters), they demonstrated similar classification accuracy on the dataset without Data Augmentation. However, when the dataset increased, AlexNet demonstrated higher classification accuracy than GoogleNet.

The SVM classifier has shown results that are competitive with the more sophisticated methods like AlexNet, especially with BoW of L*a*b and HSV colour spaces for the two types of datasets. Moreover, SVM+BoWs of HSV colour space gave the highest correct classification of cauliflower (as can be seen in Table 2) for the two types of datasets. This may be because HSV is an intuitive colour space that is aligned with the human colour perception [25] and is somewhat robust to the illumination variation [26]. The SVM+ BoWs of SURF features exhibited lower accuracy than other features with SVM for the two types of datasets. One reason for this may be that SURF is not robust to illumination variation [27].

In total, all models achieved higher classification accuracy when they were applied to the challenge set of the dataset, especially when trained on the dataset with Data Augmentation.

5. CONCLUSIONS

In this paper, a number of approaches were applied to the task of plant classification to distinguish between cauliflowers and weeds. Two types of datasets were used in this project, one without Data Augmentation and the other with Data Augmentation. In addition, the approaches were tested on two different test data sets, one with similar characteristics to the training data, and one with more challenging characteristics (the challenge set). The results show that most of the systems tested are capable of achieving good performance on the challenge set. In addition, with help of Data Augmentation, all systems increased their classification accuracy compared to the ones without Data Augmentation. AlexNet, based on deep learning, demonstrated the highest plant segmentation accuracy (97.50% and 99.40%) on the dataset without Data Augmentation and with Data Augmentation, respectively. The SVM+BoWs of L*a*b and HSV colour space also demonstrated good performance, comparable to the more sophisticated CNN-based AlexNet and GoogleNet.

In conclusion, deep learning-based approaches are the better choice for plant classification. Thus, a high plant classification performance is required for smart agriculture applications, particularly precision chemical applications, and with good performance, the volume of herbicides that are applied to the fields can be minimised.

Overall, this study demonstrated the utility of a range of approaches for plant and weed classification. Future work will include further testing with a larger database with more plant species, in similarly challenging conditions, and comparison with other deep learning architectures.

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AUTHORS

Esmael Hamuda received the B.E. degree in Electrical and Computer Engineering from Elmergib University, Libya in 2002 and the M.E. degree in Electrical, Electronics, and Telecommunication Engineering from University Technology Malaysia (UTM) in 2006. He received his Ph.D. degree in Electrical and Electronic Engineering from the National University of Galway (NoG) in 2019. His PhD research topic was on Signal and Image Processing Technology for Smart Agriculture Applications. From January 2008 to December 2013, he served as a Lecturer Assistant in Electrical and Computer Engineering at Elmergib University. He also held the head of the Electrical and Computer Engineering Department (2012-2013). While he was pursuing his PhD at the NoG, he worked as a lab supervisor/ instructor in the Electrical & Electronic lab at the undergraduate level (2014-2017) and a Lecturer Assistant of Advanced Image Processing at the postgraduate level (2018-2019). From June 2019 to December 2020, he served as Postdoctoral Research Fellow at ADAPT Centre at Trinity College Dublin(TCD). Esmael has recently joined Irish Centre for High-End Computing (ICHEC) as a Machine Learning and Data Scientist to work with academic researchers, Irish start-ups and SMEs as a part of the EuroHPC National Competence Centre (EuroCC).

Ashkan Parsi received his B.E. degree in computer software and his M.Sc. degree in artificial intelligence from the Shahrood University of Technology, Shahrood, Iran, in 2010 and 2013, respectively, and his Ph.D. degree in electrical and electronic engineering from the University of Galway, Ireland, in 2021, for which he has been awarded the Government of Ireland Postgraduate Research Scholarship (IRC). From 2012 to 2016, he was working as a software developer, senior researcher, and technical project manager on several national projects with Iran Telecommunication Research Center (ITRC). He is currently leading and conducting research in the development of signal and image processing for advanced sensors and machine vision technologies for in-cabin monitoring systems at Xperi Inc. His research interests include signal processing, machine learning, and algorithm design.

Martin Glavin received the B.E. degree in electronic engineering and the Ph.D. degree in the area of algorithms and architectures for high-speed data communications systems from the National University of Ireland (NUI), Galway, Ireland, in 1997 and 2004, respectively, and the Higher Diploma in Third Level Education in 2007. He was a Lecturer (fixed term contract) from September 1999 to December 2003 and became a permanent member of an academic staff in January 2004. He is currently the Joint Director of the Connaught Automotive Research (CAR) Group, NUI Galway. He is also a Funded Investigator in Lero, the Irish Software

Research Centre. He currently has a number of Ph.Ds and Post-Doctoral Researchers working in collaboration with industry in the areas of signal processing and embedded systems for automotive and agricultural applications

Edward Jones (Senior Member, IEEE) received the B.E. (Hons.) and Ph.D. degrees in electronic engineering from the National University of Ireland at Galway. His Ph.D. research topic was on the development of computational auditory models for speech processing. He is currently a member of faculty in electrical and electronic engineering, NUI Galway. From 2009 to 2010, he was a Visiting Researcher with the Department of Electrical Engineering, Columbia University, New York, NY, USA, and has been appointed as a Visiting Fellow with the School of Electrical Engineering and Telecommunications, University of New South Wales, Sydney, Australia. From June 2010 to December 2016, he served as the Vice-Dean of the College of Engineering and Informatics, NUI Galway, with responsibility for performance, planning, and strategy. He also has a number of years of industrial experience in senior positions, in both start-up and multinational companies, including Toucan Technology Ltd., PMC-Sierra Inc., Innovada Ltd., and Duolog Technologies Ltd. He also represented Toucan Technology Ltd., and PMC-Sierra Inc., on international standardization groups ANSI T1E1.4 and ETSI TM6. He is also a Chartered Engineer and a fellow of the Institution of Engineers of Ireland.