Crop and Weeds Classification in Aerial Imagery of Sesame Crop Fields Using a Patch-Based Deep Learning Model-Ensembling Method

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Abstract*—Sesame (Sesamum indicum L.) is an important commercial and food crop, and its yields is limited by many insects, pests, diseases, and weeds. Autonomous aerial agrochemicals spray application on sesame fields using a drone aims to save crop from these yield limiting factors and in addition agrochemicals application quantity and site could be controlled, and human health is expected to be protected. For accurate and selective spray application, autonomous systems would need some parameters to distinguish between crop, weed and background. In this research an aerial sesame field dataset has been collected with the focus to classify patch areas of sesame and weeds present in the field. Dataset was captured using Agrocam. We have developed a patch image-based classification approach along with a novel SesameWeedNet convolutional neural network (CNN) inspired by the layer's configuration of VGG networks and depth-wise convolutions of the MobileNet. The small model contains 6 convolutional layers, and it runs faster and accurately on small patch images. Our approach breaks 1920×1080-pixel images into smaller patch images of size 45×45 pixels. After that, these small patch images are fed to a relatively small CNN for training, validation, and finally for classification. Patch based model ensemble and dataset grouping are two major parts in our methodology. Our system recommends the dataset grouping according to vegetation present in the images to enhance classification results. We have achieved accuracy up to 96.7% with our proposed method. We have tested our system under sunlight variation, in wet and dry soil conditions and at different growth stages. To the best of our knowledge, no attempt has been made to classify and treat crop and weeds in sesame fields at the post-emergence stage previously. In this research we have made the contribution of aerial sesame-weed dataset and a complete deep learning-based approach to classify weeds in sesame fields under variable lighting conditions.

Keywords—crop-weed classification using deep learning, sesame weed dataset, patch classification, sesame weed classification.

I. INTRODUCTION

Sesamum indicum is named as the queen of oil crops due its high-quality oil. Another property of sesame is drought resistance due to which it is popular in water scarce areas in the world. In 2018-19 Pakistan exported 366 million tons of sesame worth ~$56 million according to Federal Bureau of Statistics [1]. In early crop stage, sesame is very sensitive to weeds and therefore weed control is important for yield increase. Grasses like baroo and khabbal, and broadleaf weeds like tandlla, bakhra, hazardani and cholai compete with sesame [2]. Sesame yield is also limited by many kinds of insects, pests [3], and diseases. Sesame yield in Pakistan is 418 kg/hectare [4] while world average is 512 kg/ha, China has highest average sesame yield of 1223 kg/ha [5]. Pakistan yield potential of sesame is up to 2000 kg/ha. Better control of weeds and pests in sesame will result in increased sesame yield in the world especially in developing countries.

For automatic pest/weed management and spraying systems, the first important and most challenging step is correct detection and classification of crop and weeds [6]. Crop-weed classification is challenging as both classes have similar textures, shapes, and colors. Other problems in classification of crop and weeds include lighting conditions based texture and color variations, different growth stages of crop and weeds, and soil conditions [7]. Autonomous agrochemicals spray application could help save water, agrochemicals, human health, and soil pollution. For autonomous agrochemicals spray, weed must be classified separately from the crop. Autonomous spraying drone units are being used in fields for spraying weeds. Spraying using aerial spraying drone is time efficient as compared to spraying with ground-based robots. Commercially available drones spray agrochemicals using GPS on complete field without distinguishing between weeds, crop and background. Crop/weeds must be classified, and their location should be given to the autonomous drone to effectively and selectively spray in the agricultural field.

Two types of learning-based techniques are seen in literature to classify between weeds and crops i.e., classical machine learning-based and deep learning-based techniques. In vision tasks, the performance of deep learning-based techniques improve with more data plus these techniques are easily adaptable and transferable to different applications [8].

This research is funded by Higher Education Commission of Pakistan and National Centre of Robotics and Automation under grant number PSDP – 261, DF 1009-0031.

As crops and weeds are very much similar, discriminative feature selection and extraction is difficult with classical machine learning. Strong feature learning capabilities of deep learning makes it ideal to be applied in crop-weed classification tasks. The performance of classical machine learning methods like SVM and k-means clustering etc. become saturated and does not improve with increase in the dataset after a limit, while on the other hand, deep learning perform well with small datasets, and its performance increases with improvement and increase in datasets [9].

Espejo-Garcia et al. [10] did weed detection using transfer learning by fine tuning previously trained models like Xception, Inception-Resnet, VGGNets, Mobilenet and Densenet. The approach worked well on segmented individual plants however the approach is tested on a non-cluttered individual plants environment, and it would fail on datasets in which crop and weeds would be overlapping. Another problem with these state-of-the-art models is, they could not be applied on small patch images, due to a greater depth of network and heavy down sampling. Le et al. [11] did image classification of 4 classes i.e. canola, corn, radish and background using dataset taken under laboratory conditions and achieved good performance however there are few problems in this research. The dataset is taken under laboratory conditions under controlled environment, this situation changes in field where weeds could be overlapping with crops posing difficulty in separating crop and weed plants. Andrea et al. [12] also did similar plant based classification of weeds in maize using LeNET, AlexNet, cNET and sNET at early stage of crop. Greenness is segmented and individual green blobs are passed to neural network for classification. The approach is applicable at early stage of crop when weed plants did not overlap with crop however the approach will have difficulty in separating individual plants at later stages when weeds will cover the ground and overlap with crop. Gao et al. [13] did weed detection in sugar beet field using YOLO-v3 and tiny YOLO-v3. The crop and weed plants in the used dataset were easily segment able and without overlap. This approach could fail when two crop and weed plants are in close proximity and overlapping, in such scenario the model will confuse those two plants as one and the classification would not be accurate. Some researchers [14-16] have done crop/weed classification using semantic segmentation, which classifies every pixel in image, however it is difficult and computationally expensive instead patch-wise classification would be a good choice for patch-wise spray application. Patch-wise classification is expected to be efficient than pixel-wise classification. A better alternative of existing techniques is possible if we could apply a small semantic segmentation model to classify vegetation first, and then after that a neural network trained on crop and weed patch images is deployed.

In this paper, we propose a complete deep learning based approach that relies on dataset grouping and model ensembling, in which vegetation is classified and extracted using a small semantic segmentation model and then a small patch-image based classification model is used to classify crop and weeds patches in sesame fields. The purpose of semantic segmentation model in first stage is to classify and extract vegetation only. After vegetation is extracted, small patch images of size 45×45 pixel are cropped for classification at the places where vegetation is detected. At this stage dataset grouping is done in such a way that all patches are divided into three groups, according to the vegetation present in them. Model ensembling is used after that, in which each dataset group is used to train a model. The results of three models trained on three different dataset groups is combined to generate full results. For the classification of smaller patch images, we are also proposing SesameWeedNet, a smaller convolutional neural network constructed by us using layer style of VGG architecture and depth wise convolutions of MobileNet. It has total 13 layers (consisting of 6 convolutional layers) that can classify sesame and weeds more accurately and faster.

We have found no attempt of sesame-weed classification in the literature although sesame is a very valuable crop and that's why this research has a novelty of addressing crop/weed classification in sesame crop in postemergence stage.

In this research, we have made three main contributions.

1. An improved patch-wise method to enhance sesame / weed classification for autonomous spray application using drones
2. A convolutional neural network capable of classifying small patch-images and
3. A new aerial sesame-weed dataset

The rest of the paper is divided into four sections i.e. dataset, system architecture & implementation, results and discussion, and conclusion.

II. DATASET

We have captured a new aerial sesame-weed dataset using Agrocam NDVI using Phantom 3 standard. Agrocam is especially designed to monitor crop health, here we have deployed it to capture dataset to classify sesame crop and weeds. The fields where we imaged sesame crop are in Ballo Shahabal village near Jhang, Punjab, Pakistan under geographical coordinates of latitude 31.391394 and longitude of 72.373489. The captured sesame fields are shown in Fig. 1. Fig. 2. shows experimental setup for dataset capture.

Two fields of approximately 0.927-hectare area of sesame crop are imaged in August 2020 at different growth stages. Four campaigns of aerial images dataset collection are done on these two fields at approximate crop age of 16 and 28 days. Table I lists four drone fly campaigns on 2 sesame fields.

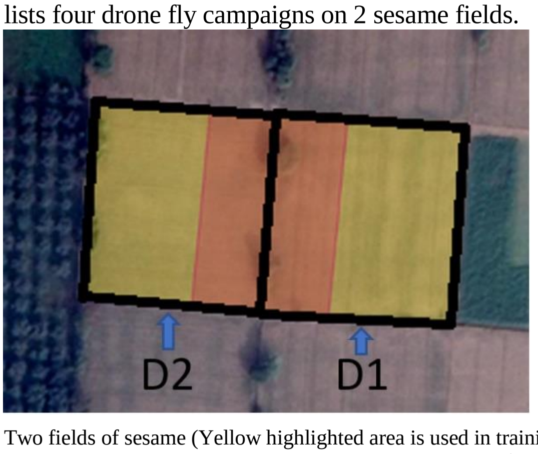


Fig. 1. Two fields of sesame (Yellow highlighted area is used in training and Red highlighted area is used in testing, black line separate two fields).

Fig. 2. Experimental Setup (Agrocam attached with Phantom 3 drone).

Flight time of the campaigns is 10-20 minutes. While flying snapshots are taken every 5 seconds automatically and video is captured continuously. The images are captured automatically however the drone is flown in a manual mode using remote control at an average altitude of 15 feet which corresponds to ground sampling distance of 0.33 cm/pixel.

TABLE I. DRONE FLY CAMPAIGNS

Field No.	Timing Around	Soil Condition	Sunlight Condition	Date Captured
D1	8:30am	Dry	Sunny	09 August 2020
D1	11:30am	Dry	Cloudy	10 August 2020
D1	6:00pm	Dry	Near Sunset	19 August 2020
D2	2:00pm	Wet	Sunny + Cloudy	21 August 2020

Agrocam provide NGB images, the three channels of the camera are NIR, G and B. As R (red channel) is not present in Agrocam so the green vegetation appear orange in the images obtained from Agrocam.

These four campaigns on two sesame fields D1 and D2 have various natural conditions like sunlight variation, wet and dry soil conditions, crop shadows in different positions and different growth stage conditions which makes these datasets ideal for deep learning processing.

We have labelled images manually with Image labeler app of MATLAB. The app generates a uint8 grayscale image of labels. Background, crop and weed get pixel value 0, 1 and 2 respectively in the labeled image. This new aerial sesame weed dataset is made public [17] freely to support further research on sesame crop.

III. SYSTEM ARCHITECTURE & IMPLEMENTATION

Flow diagram of our proposed system is shown in Fig. 3. Our system takes input NGB (NIR+G+B(3-channel)) images from Agrocam NDVI sensor. To extract vegetation and remove background we have applied semantic segmentation. UNet with vanilla mini neural network backbone is applied to classify the input image content into two classes i.e. background and vegetation. UNet with vanilla mini backbone is a simple semantic segmentation network with encoder size of two, which is enough to extract all vegetation present in an image. Through experimentation we know that higher encoder size at this step will only be an increase in computational complexity. Vegetation extraction using UNet with vanilla mini backbone is shown in Fig. 4. Various natural conditions and weed overlapping with sesame crop plants are also obvious in Fig. 4. After this preprocessing which itself is based on deep learning, our system crops 45×45-pixel patch images where vegetation is detected. Using labeled data sesame and weed patch images are separated for training. In labelled data, soil background has label value of zero, sesame crop has label value of one and weeds has label value of two. With every vegetation patch cropped, its corresponding labels are analyzed. Based on label values, the sesame and weed patches are separated from each other.

An existing patch-based method is already published in [18], using different sugar beet datasets and a deep learning model, here in this paper we have proposed a patch-based method based on model ensembling and dataset grouping. We have applied both existing [18] and our proposed method on our acquired sesame dataset.

Our proposed patch-based approach is an improvement of existing [18] patch based approach. We have improved that research by a neural network ensembling technique and grouping the cropped patches according to the vegetation present in them. Neural network ensemble is a learning method to solve a problem where multiple neural networks work jointly. After vegetation extraction step, dataset grouping is shown in Fig. 3. In our proposed approach, after separation of patches of both classes, these patches are grouped into three categories according to vegetation pixels present in them. The patch images are analyzed, vegetation pixels in the patches are counted and based on the number of detected vegetation the patch images are separated into three groups. Group 1 contains patches with 1-25 % vegetation (patches having 20-500 vegetation pixels in them). Group 2 contains patches with 25-50 % vegetation (patches having 500-1000 vegetation pixels in them). Group 3 contains patches with 50-100 % vegetation (patches having 1000-2025 vegetation pixels in them).

Separate training is done using these three dataset groups by ensembling three neural networks with proposed SesameWeedNet CNN and validation is done with cross validation data. Some cropped patches with different percentage of vegetation present in them are shown in Fig. 5.

For testing we do vegetation detection with semantic segmentation and then we crop 45×45-pixel patch images from unseen test data where vegetation is detected. We count number of vegetation pixels in each 45×45-pixel patch images and separate them into respective three groups as done in the case of training. The three dataset groups are passed from respective trained model for prediction. Patches of group 1 of test data are passed through SesameWeedNet trained on 1-25 % vegetation, patches of group 2 of test data are passed through SesameWeedNet trained on 25-50 % vegetation, and patches of group 3 of test data are passed through SesameWeedNet trained on 50-100 % vegetation and predictions are saved. After prediction of these patch images labeled test data is consulted for quantitative evaluation.

Our proposed SesameWeedNet is inspired by layers configuration of VGG and depth wise convolutions of MobileNet and it is smarter than both networks. It contains 6 convolutional and 1 fully connected layer (total 13 layers) and is shown in Fig. 6.

Cropped crop and weed patches of size 45 × 45 pixels used in training are 10,71,542 patches. Validation split is kept at 0.2 i.e. 5th part of training data is used in cross validation. Deep learning is applied using Keras with Tensorflow-GPU backend. Our system specifications are i5 eighth generation, NVIDIA GTX 1050 graphics card and 16 GB RAM. A learning rate of 0.0001 is applied.

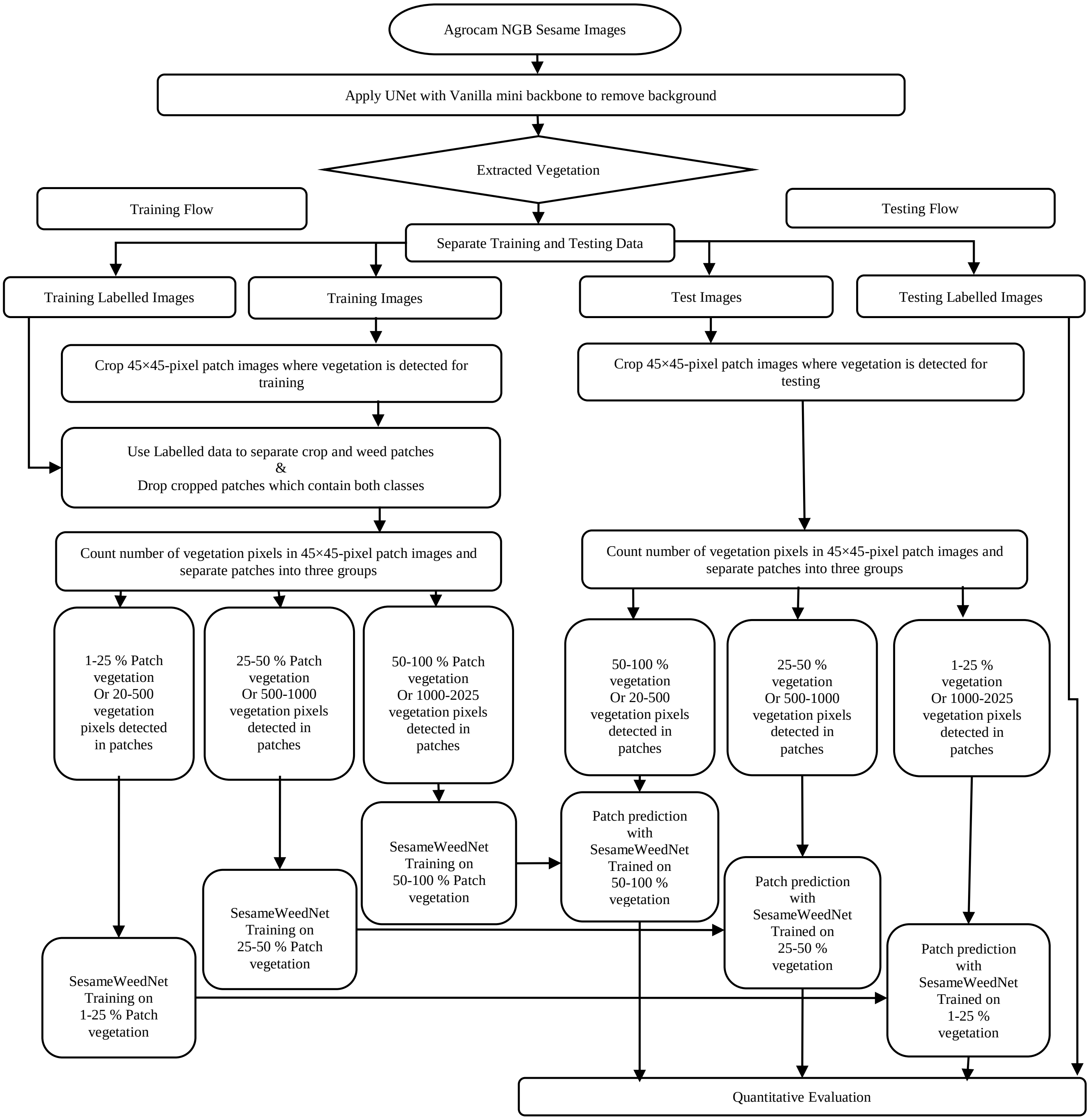


Fig. 3. Patch based system flow diagram showing dataset grouping and model ensembling

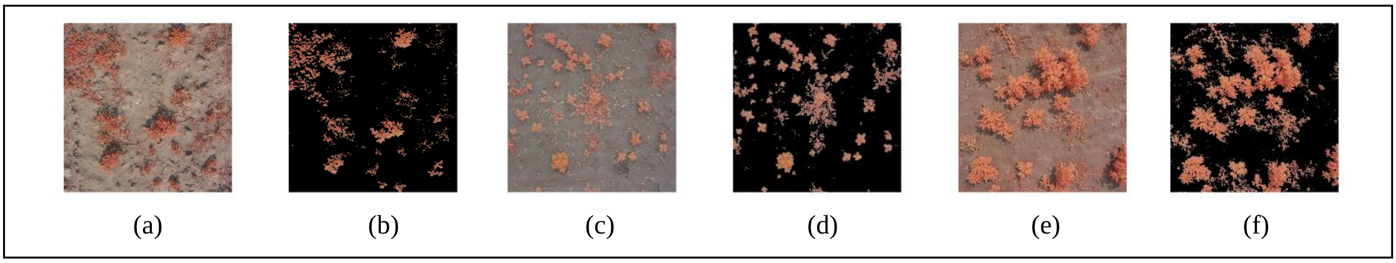


Fig. 4. Vegetation extraction and various natural conditions: (a) An image from field D1 with Sunny and Dry soil Conditions; (b) Detected vegetation by applying semantic segmentation on (a); (c) An image from field D2 with Cloudy and Wet soil Conditions; (d) Detected vegetation by applying semantic segmentation on (c); (e) An image from field D2 with Sunny and Wet soil Conditions; (f) Detected vegetation by applying semantic segmentation on (e)

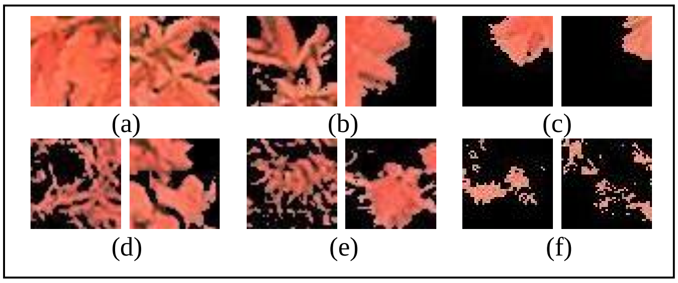


Fig. 5. Some cropped patches with different percentage of vegetation present in them: (a) Two sesame patch images having 50-100% vegetation in them; (b) Two sesame patch images having 25-50% vegetation in them; (c) Two sesame patch images having 1-25% vegetation in them; (d) Two weed patch images having 50-100% vegetation in them; (e) Two weed patch images having 25-50% vegetation in them; (f) Two weed patch images having 1-25% vegetation in them.

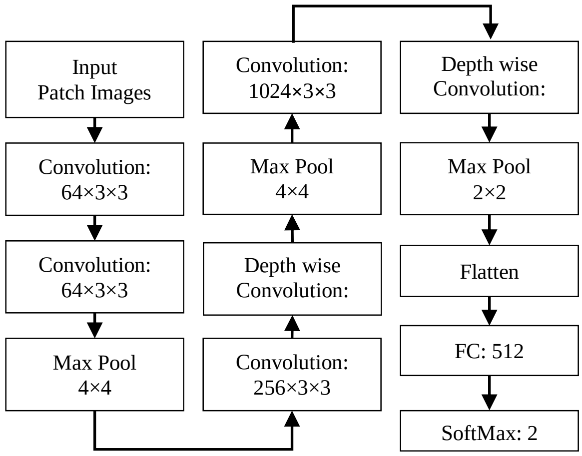


Fig. 6. Proposed SesameWeedNet Flow Diagram

Adam and binary cross-entropy are selected as optimizer and loss function respectively. Data augmentation of vertical and horizontal flips are applied. Epoch with minimum validation loss is used to save the best-trained model. We have used accuracy (ACC) and area under precision recall curve (AUC) as evaluation metrics.

IV. Results and Discussions

Table II shows labelled test patches cropped and achieved quantitative results when patch images are divided into three groups according to the vegetation concentration present in them. In experiment no. (1) 97 test images from field number D1 are used. This field have dry soil and sunny weather conditions. In experiment no. (2) 91 test images from field number D2 are used. This field have wet soil and sunny weather conditions. In experiment no. (3) 18 test images from field number D2 are used, these images have wet soil and cloudy weather conditions.

We have observed in Table II that patches of group 2 and 3 have higher classification accuracy as compared to group 1. This is due to more vegetation presence in group 2 and 3 patch images, as a result good features are learned while training, which in turn increase classification accuracy.

In case of test dataset D1, ninety-seven 1920×1080-pixel images have 11149 vegetation patches which corresponds to 115 average vegetation (sesame+weed) patches per 1920×1080-pixel image. Testing time for 11149 patches is 43.1 seconds with our system with our 3-bin approach, this implies that in one second over 258 patches are tested on average. These facts lead to a conclusion that in 1 second approximately 2.2, 1920×1080-pixel images are processed on average. This makes our work suitable for real-time processing.

Fig. 7. shows qualitative results achieved on an image from test dataset. Fig. 7(a) shows automatically cropped patches which are input to the system. All those patches where vegetation (crop or weed) is detected are cropped. Note that there are few locations where weed is visible but are not detected and cropped automatically, that weed is almost dead, it has very dull color and that's why it is not detected as vegetation. Fig. 7(b) shows prediction of patches, red color patches are predicted as weeds while green color patches are predicted as sesame, Fig. 7(c) shows connected weed patches in a binary image (white color patches are predicted as weeds while black color patches represent sesame or background, this is simplified classification of weed which could be used to perform autonomous activities on weeds in the sesame farms.

Crop and weed have similar features while background have more distinct features as compared to crop and weed. This fact leads to another problem and that is sometimes crop and weed classes are confused into each other while background is efficiently classified. The probability output of background class is distinct while output probabilities of crop and weeds are much closer which leads to confused prediction of crop and weed. In our patch-based approach this problem in handled more suitably as background class is already detected separately and now the competing classes are only crop and weed.

Patches containing background would not pass through the system, as we have already detected vegetation in first step so only those patches go through system which contain some kind of vegetation (crop or weed). This way our approach converts a 3-class (background + crop + weed) problem to a 2-class (crop + weed) problem. This practice in our approach leads to less testing time as no time will be wasted to classify background patches.

The quantitative comparison between our proposed and an existing [18] patch-based method is shown in Table III, more accuracy and less testing time is obvious using dataset grouping and parallel model ensembling.

There is a limitation of our work. The network is trained and tested on 0.33cm/pixel dataset GSD at the height of 15 feet. If any new test dataset will be tested with much different lower or higher GSD, then classification could become less accurate. In this case, new training data with similar GSD can be used to finetune the network and improve results.

V. Conclusion

We have proposed a new methodology for weed detection in sesame crop; a complete deep learning-based approach that is more realistic for real-time intelligent aerial spraying systems.

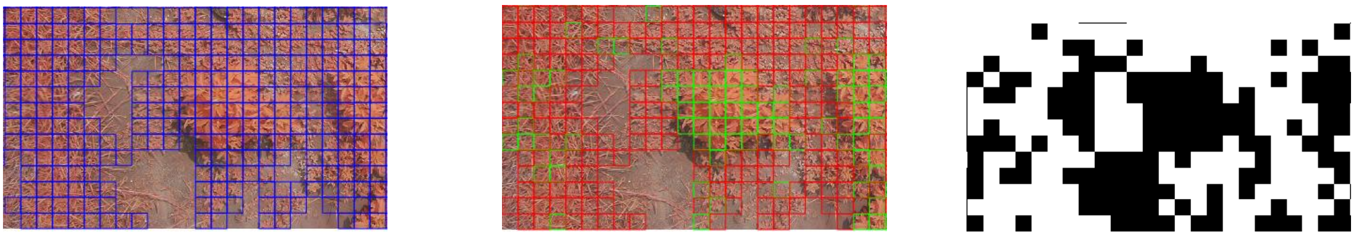
Our method uses semantic segmentation as a first step to extract vegetation, this way our method gets rid of problems introduced by variable lighting conditions and different soil colors. After that, to classify crop and weed, our method makes use of model ensembling and dataset grouping. This approach has shown more robustness as compared to previous patch-based deep learning application.

TABLE II QUANTITATIVE RESULTS OF 3 BINS OF DIFFERENT FIELDS WITH DIFFERENT FIELD CONDITIONS (N IS TOTAL NUMBER OF PATCHES IN A DATASET GROUP)

Experiments	Dataset Group 1			Dataset Group 2			Dataset Group 3		
Experiment no. (1) Dry soil + Sunny conditions Field number D1 No. of 1080P Test Images = 97	N = 7391	Sesame	Weed	N = 2531	Sesame	Weed	N = 1227	Sesame	Weed
	Sesame	2013	154	Sesame	952	26	Sesame	844	8
	Weed	177	5047	Weed	31	1522	Weed	30	345
	ACC = 95.5%	AUC = 0.980		ACC = 97.7%	AUC = 0.987		ACC = 96.9%	AUC = 0.961	
	Test Time = 26.3 seconds			Test Time = 11.2 seconds			Test Time = 5.6 seconds		
Experiment no. (2) Wet soil + Sunny conditions Field number D2 No. of 1080P Test Images = 91	N = 5763	Sesame	Weed	N = 2908	Sesame	Weed	N = 1638	Sesame	Weed
	Sesame	2152	339	Sesame	1533	65	Sesame	1350	57
	Weed	86	3186	Weed	25	1285	Weed	24	207
	ACC = 92.6%	AUC = 0.946		ACC = 96.9%	AUC = 0.971		ACC = 95.1%	AUC = 0.847	
	Test Time = 24.4 seconds			Test Time = 13.4 seconds			Test Time = 7.4 seconds		
Experiment no. (3) Wet soil +Cloudy conditions Field number D2 No. of 1080P Test Images = 18	N = 2049	Sesame	Weed	N = 957	Sesame	Weed	N = 608	Sesame	Weed
	Sesame	755	101	Sesame	529	1	Sesame	507	1
	Weed	121	1072	Weed	31	396	Weed	11	89
	ACC = 89.1%	AUC =0.936		ACC = 96.6%	AUC =0.978		ACC = 98.0%	AUC =0.948	
	Test Time = 9.6 seconds			Test Time = 4.9 seconds			Test Time = 2.7 seconds		

TABLE III COMPARISON OF OUR MODEL EMSEMBLING PATCH BASED TECHNIQUE WITH AN EXISTING PATCH BASED METHOD, RESULTS OF TESTING ON COMPLETE DATA (CWA STANDS FOR CLASS WISE ACCURACY)

Method and Neural Network	Field number D1 No. of 1080P Test Images = 97				Field number D2 No. of 1080P Test Images = 91			
Patch-based method discussed in [18] without Creating Bins	Class	sesame	weed	Mean	Class	sesame	weed	Mean
	CWA	90.1%	97.3%	93.7%	CWA	89.4%	97.4%	93.4%
	Testing time = 53.8 seconds				Testing time = 49.2 seconds			
Our patch-based method with creating 3 bins and model ensembling as in Table II	Class	sesame	weed	Mean	Class	sesame	weed	Mean
	CWA Bin 1	92.8%	98.2%	95.5%	CWA Bin 1	86.4%	98.8%	92.6%
	CWA Bin 2	97.3%	98.1%	97.7%	CWA Bin 2	95.9%	97.9%	96.9%
	CWA Bin 3	99.1%	94.7%	96.9%	CWA Bin 3	95.9%	94.3%	95.1%
	3-Bins Average	96.4%	97.0%	96.7%	3-Bins Average	92.7%	97.0%	94.8%
	Testing time = 43.1 seconds				Testing time = 45.2 seconds			



(a) (b) (c)

Fig. 7. Qualitative results of Our Agrocam Sesame dataset: (a) Cropped patch images input to the system (Blue color boxes are patches which are input to the system); (b) Predicted patches output of system (Red color patches are predicted as weeds while Green color patches are predicted as sesame); (c) Connected weed patches in a binary image (white color patches are predicted as weeds while black color patches represent sesame or background, this is simplified classification of weed which could be passed to drone for spraying weed areas).

For classification, we developed a new SesameWeedNet convolutional neural network (CNN), which is inspired by VGG and MobileNet models. For experiments, we acquired a new sesame crop dataset with 3-channel multispectral sensor with a ground sampling distance of 0.33 cm/pixel and a height of 15 feet. A contribution of sharing of this dataset with researchers is also done.

We tested our system under various natural conditions like sunlight variation, wet and dry soil conditions, crop shadows in different positions and at different growth stages.

Our system recommends the dataset grouping according to vegetation present in the images to enhance classification results. We observed that if we group the images according to percentage vegetation present in them then the performance of neural network is increased. Our approach detects vegetation and classification happens between two classes, i.e. crop and weed, which, in turn, improves crop and weed classification accuracy, as the background patches do not pass through system so testing time for an image is also reduced.

The potential application and extension of this work is autonomous agrochemicals spray application on sesame crop using drone to treat weeds, pests, insects, and diseases. The research presented in this paper is a part of a big ongoing project in which autonomous drone is aimed to target weed patches. In future we aim to implement our method on NVIDIA Jetson Nano board, optimize proposed methodology, and design a special nozzle for agricultural sprayer drone which could target individual patch areas on ground. Two other important future perspectives are drone flight planning and spray nozzle control system.

ACKNOWLEDGMENT

This research is funded by Higher Education Commission of Pakistan and National Centre of Robotics and Automation under grant number PSDP – 261, DF 1009-0031.

We are thankful to Higher Education Commission of Pakistan and National Center of Robotics and Automation for funding this research.

REFERENCES

[1] A. A. research institute Faisalabad, “Oilseeds Research Institute, Faisalabad.” https://aari.punjab.gov.pk/sesame_oilseed (accessed Jan. 21, 2021).

[2] Pakistan Agriculture Research Council, “SESAME PRODUCTION PRACTICES.IN.PAKISTAN.”http://www.pakissan.com/english/allabout/crop/sesame.shtml (accessed Jan. 21, 2021).

[3] N. Dilipsundar, N. Chitra, and V. Gowtham, “Checklist of insect pests of sesame,” Indian Journal of Entomology, vol. 81, no. 4, p. 928, 2019, doi: 10.5958/0974-8172.2019.00141.x.

[4] U. Gupta, “Oilseed Crops,” What’s New About Crop Plants, pp. 465–465, 2011, doi: 10.1201/b10736-27.

[5] D. Myint, S. A. Gilani, M. Kawase, and K. N. Watanabe, “Sustainable sesame (Sesamum indicum L.) production through improved technology: An overview of production, challenges, and opportunities in Myanmar,” Sustainability (Switzerland), vol. 12, no. 9, pp. 1–21, 2020, doi: 10.3390/SU12093515.

[6] A. Wang, W. Zhang, and X. Wei, “A review on weed detection using ground-based machine vision and image processing techniques,” Computers and Electronics in Agriculture, vol. 158, no. February, pp. 226–240, 2019, doi: 10.1016/j.compag.2019.02.005.

[7] B. S. & L. F. D. Troy Arnold Jensen, “An automated site-specific fallow weed management 1017 system using unmanned aerial vehicles.,” Centre for Agricultural Engineering, University of Southern Queensland, 2020. https://grdc.com.au/resources-and-publications/grdc-update-papers/tab-content/grdc-update-papers/2020/03/an-automated-site-specific-fallow-weed-management-system-using-unmanned-aerial-vehicles

[8] “Deep Learning vs Classical Machine Learning,” 2018. https://towardsdatascience.com/deep-learning-vs-classical-machine-learning-9a42c6d48aa (accessed Jan. 21, 2021).

[9] M. Z. Alom et al., “A state-of-the-art survey on deep learning theory and architectures,” Electronics (Switzerland), vol. 8, no. 3, pp. 1–67, 2019, doi: 10.3390/electronics8030292.

[10] B. Espejo-Garcia, N. Mylonas, L. Athanasakos, S. Fountas, and I. Vasilakoglou, “Towards weeds identification assistance through transfer learning,” Computers and Electronics in Agriculture, vol. 171, no. October 2019, p. 105306, 2020, doi: 10.1016/j.compag.2020.105306.

[11] J. You, W. Liu, and J. Lee, “A DNN-based semantic segmentation for detecting weed and crop,” Computers and Electronics in Agriculture, vol. 178, no. March, p. 105750, 2020, doi: 10.1016/j.compag.2020.105750.

[12] C. C. Andrea, B. Mauricio Daniel, and J. B. Jose Misael, “Precise weed and maize classification through convolutional neuronal networks,” 2017 IEEE 2nd Ecuador Technical Chapters Meeting, ETCM 2017, vol. 2017-Janua, pp. 1–6, 2018, doi: 10.1109/ETCM.2017.8247469.

[13] J. Gao, A. P. French, M. P. Pound, Y. He, T. P. Pridmore, and J. G. Pieters, “Deep convolutional neural networks for image-based Convolvulus sepium detection in sugar beet fields,” Plant Methods, vol. 16, no. 1, pp. 1–13, 2020, doi: 10.1186/s13007-020-00570-z.

[14] P. Bosilj, E. Aptoula, T. Duckett, and G. Cielniak, “Transfer learning between crop types for semantic segmentation of crops versus weeds in precision agriculture,” Journal of Field Robotics, vol. 37, no. 1, pp. 7–19, Jan. 2020, doi: 10.1002/rob.21869.

[15] A. Abdalla et al., “Fine-tuning convolutional neural network with transfer learning for semantic segmentation of ground-level oilseed rape images in a field with high weed pressure,” Computers and Electronics in Agriculture, vol. 167, Dec. 2019, doi: 10.1016/j.compag.2019.105091.

[16] J. You, W. Liu, and J. Lee, “A DNN-based semantic segmentation for detecting weed and crop,” Computers and Electronics in Agriculture, vol. 178, no. March, p. 105750, 2020, doi: 10.1016/j.compag.2020.105750.

[17] "Sesame Aerial Dataset," 2020. [Online]. Available: https://data.mendeley.com/datasets/9pgv3ktk33/draft?a=a14f5693-fe7b-4718-b524-6066d3d46c8e

[18] S. Imran Moazzam et al., “A Patch-image Based Classification Approach for Detection of Weeds in Sugar beet Crop,” IEEE Access, vol. PP, pp. 1–1, 2021, doi: 10.1109/access.2021.3109015.