Fully Convolutional Networks for Weed Detection in Precision Farming

Anagha M B, Darsana K M, Fathima Pareed, and Gladis M S

Federal Institute of Science and Technology, Ernakulam, Kerala, 683577, India
Department of Computer Science and Engineering, APJ Abdul Kalam Technological University, India

ABSTRACT Weeds can be defined as any plant or vegetation that interferes with farming or forestry purposes, such as planting crops, grazing animals or planting forests. Weeds compete with plants for one or more aspects of plant growth such as mineral nutrients, water, solar energy and environment and inhibit plant performance. Therefore, weed control is very important for plant growth. Traditional weed control methods are cultural weed control, mechanical weed control, biological weed control, and chemical weed control. Traditional methods of weed control do not work effectively and the use of accurate farming plays a role. The next problem is finding the family of weeds and the right herbicide to spray the weeds. To overcome this difficulty, an android or iOS app named “Kisan Ki Dhosth (KKD)” is designed. This application clearly identifies the weed and identifies the appropriate herbicide. This can be achieved by using the photograph taken by the farmer. The dataset consists of weeds which are widely seen in Kerala, making it more user-friendly for farmers. Since persistent use of herbicide remains active in the environment for a long period of time, potentially causing soil and water contamination, home remedies like salt, vinegar, newspaper, and boiled water can be used.

INDEX TERMS Herbicides, Machine learning, Weed detection.

I. INTRODUCTION

A weed is an undesirable plant growing at the wrong place. They tend to degrade the quality of the desired plants. Competition with the desired crops for the most needed resources for the plant, i.e., direct sunlight, soil nutrients, water, and (to a lesser extent) growth space. As a result, weed control is important for agriculture. Methods include plowing, cracking or sunburn, deadly wilting at high temperatures, heat, or chemical attack with herbicides.

Among the mentioned methods, the simplest one to implement is to use herbicides. Mostly, a single herbicide would be sprayed in the entire plot. This may be effective on a few weeds but not on all. So exact identification of the weeds must be done and also the method to eliminate it as well.

To tackle this problem, an android/iOS app named “Kisan Ki Dhosth (KKD)” is designed which clearly identifies the weed using the photograph taken by the farmer. The appropriate herbicide would also be advised. The dataset consists of weeds which are widely seen in Kerala, making it more user-friendly for farmers. Since sustainable agriculture is of vital importance, use of herbicides must be reduced. Hence more reliable solution such as home remedies are also provided to eliminate weeds, if possible.

II. LITERATURE REVIEW

Most common approach in weed detection is using a robot to collect the pictures [1]. A mechanical approach to crop classification without segmentation is proposed in the paper "Plant classification system for crop/weed discrimination without segmentation" [2]. The system can distinguish crops and weeds from fields where they tend to grow together. This can help in finding different strategies to eliminate weeds in a more cost-effective way and also with less impact on the environment. The architecture is a six-stage pipeline in which there are online and offline steps. The first step is to collect the pictures for the input. The next step is background removal, which is done to segment the vegetation from the soil. In the third, computations are done on the image tiles or image patches. Later the features are extracted from the images generated in the preceding step. The Random Forest (RF) Classifier is chosen to train and classify the images. The classifier training is done offline. The Markov Random Field (MRF) approach is used for smoothening the images and finally interpolation of the sparse results is done. The method was tested using a database of photographs taken from a live carrot farm with an independent field robot under field conditions. The average classification accuracy was found to be 93.8%. The limitation is that intra class overlap is not split into different plant regions in the final image. Hence the spatial arrangement of crop and weed could be used as a priori information in the future.

According to a work from 2016, Deep Convolutional Neural Networks (DNN) for semantic segmentation (or pixel-wise separation) of dense classes in RGB images were tested in the event of crop capture and voluntary barley [3]. RGB images from a plot trial using oil radish as catch crops in barley. The images were captured using a high-end consumer camera mounted on a tractor. The images were manually annotated in seven classes: oil radish, barley, weed, stump, soil, equipment, and unknown. To artificially increase the size of the dataset, data argumentation was done. Images were flipped and rotated. A modified version of VGG-16(also called OxfordNet) DNN was used. First, the last fully connected layers were transformed into a convolutional layer and the depth was adjusted to accommodate the number of our classes. Second, a deconvolutional layer with 32 strides was added between the fully integrated end layer and the SoftMax partition layer to ensure that the output layer has the same size as the input. The network was supposed to be trained for 40 epochs, but 10 epochs later it started to overflow so it was disconnected after 23 of them. The network model stored after 10 epochs has been used to produce results. A pixel accuracy of 79% was shown initially.

Low cost Unmanned Aerial Vehicles (UAVs) are used [4] to address the problem of detecting value crops and typical weeds using a camera installed on an UAV. The main purpose of the proposed plant classification is to identify sugar and weed plants in UAV images to provide an accurate monitoring tool for the planting of real fields. The installation of the system is as follows: either 4-channel RGB + NIR images or standard RGB images, depending on the UAV sensor setup. They used and tested their system using UAVs in pairs farms, one German and the other in Switzerland and show that their method allows for the analysis of the field and the separation of individual plants. The three steps of their approach are: First, they apply a pre-processing to remove the background i.e., mostly the soil and get the resultant vegetation. Second, they extract features from vegetation with a combination of an object-based and a keypoint-based approach. Third, they apply a multi-class Random Forest (RF) classification and obtain a probability distribution for the predicted class labels. The evaluation metrics are Receiver Operating Characteristic (ROC) curves and Precision-Recall (PR) plots and the datasets are JAI, MATRICE and PHANTOM.

There is a growing interest in agricultural robots and precision farming. For such domains, appropriate data sets are difficult to find, as dedicated fields require care and data collection time is important. Nived Chebrolu, Philipp Lottes, Alexander Schaefer, Wera Winterhalter, Wolfram Burgard, and Cyrill Stachniss [5] presented a large database of agricultural robots for crop differentiation and landscaping and mapping including appropriate crop growth phases to interfere with robots and weed control. On average, they compiled data three times a week, starting with the emergence of crops and ending in a state where the field was no longer available on the machine without damaging the crops. The robot was attached with four camera channels and an RGB-D sensor for capturing more information on the field. Many lidar sensors as well as the global positioning system and wheel encoders provided measurements related to location, navigation, and mapping respectively. All sensors were limited before the data acquisition campaign. The agricultural robot platform is BoniRob. The BoniRob platform is a multi-purpose robot by Bosch DeepField Robotics. Multiple sensors are used to provide visibility, depth, 3D laser, GPS and odometry data. It has a removable Personal Computer (PC) with i7 core processor and 6 GB Double Data Rate 3(DDR3) memory and Ubuntu 14.04.

A Self-Supervised framework for weed detection using hyperspectral data was presented by Alexander Wendel and James Underwood [6]. High resolution hyperspectral imagery is used which is captured by an autonomous mobile ground vehicle. The proposed method is an eight-step process. The first step is Hyperspectral Imaging (HSI) Data collection which is gathered by the ground vehicle. The next step is Normalized Difference Vegetation Index (NDVI) Vegetation Segmentation. It is a technique used to separate the vegetation pixels from background pixels. After segmentation, manual data labelling was done along with automatic generation of training data to make a comparison between the performance. For automatic generation, the segmented data is given as input to Hough transform. In this way, the training dataset is generated. Spectral Preprocessing was done on this data to mitigate the effects of varying environmental illumination at different times of the day. Then normalization was done using principal component analysis (PCA) for feature extraction and dimensionality reduction on the data. Both linear discriminant analysis (LDA) and support vector machine (SVM) were used as classifiers and implemented using the scikit-learn package [7]. Both SVM and LDA performed similarly. SVM is a complex but well-known classifier, which has been employed with HSI in the past [8]. The method gives highly accurate per pixel classification. This technique is also adaptable to changes in seasons, geography, illumination, and so on. Further testing is required to confirm and demonstrate how robust the system is to changing conditions compared to static training data.

The problem of creating large agricultural datasets with pixel-level annotations was addressed in another paper [9]. The paper also put forwards an approach to decrease the manual labour required to train a visual model classification system. The strategy is to develop a visuals-based classification system which can distinguish crops from weeds. Large training datasets are created routinely by giving arbitrary values to the important features of the farm land such as crop and weed species, soil type, light conditions, and so on. They are required for more accuracy in precision farming and creating them is a huge task. The method makes use of an open image engine as a solution to the problem, that is by structuring data systematically. For the procedural dataset generation, Unreal Engine 4[2] was used as a graphic engine. A clear-cut model of the target environment was generated and using few real-world textures. It creates a large variety of annotated data of plant species using a procedural method. Two datasets are used and both were collected from a BOSCH Bonirob farm robot moving on a sugar beet field. The first dataset contains 100 images and it has been gathered during the first growth stage of the plants i.e., when both the crop and weeds have not developed completely. The second dataset contains 400 images and it has been gathered after 4 weeks when the plants have developed and are in their advanced growth stages. The performance and quality of the synthetic databases are evaluated using an effective pixel-wise classification Convolutional Neural Network (CNN), SegNet [10]. The results showed that a virtual dataset containing all the weeds has the same level of accuracy as real-world images.

A novel and practical DNN architecture for semantic pixel-wise segmentation termed SegNet was presented by Vijay Badrinarayanan, Alex Kendall and Roberto Cipolla [11] in 2017. This core trainable segmentation engine consists of an encoder network, a corresponding decoder network followed by a pixel-wise classification layer. They evaluated the performance of SegNet on two scene segmentation tasks, CamVid road scene segmentation and SUN RGB-D indoor scene segmentation. The final decoder output is fed to a multiclass soft-max classifier to produce class probabilities for each pixel independently. The cross-entropy loss is used as the objective function for training the network. To compare the quantitative performance of the different decoder variants, three performance measures were used: global accuracy, class average accuracy, and mean intersection [12]. The best performance is achieved when encoder feature maps are stored in full. When memory during inference is constrained, then compressed forms of encoder feature maps can be stored and used with an appropriate decoder to improve performance. They analyzed SegNet and compared it with other important variants to reveal the practical trade-offs involved in designing architectures for segmentation. Those architectures which store the encoder network feature maps in full perform best but consume more memory during inference time. SegNet on the other hand is more efficient since it only stores the max-pooling indices of the feature maps and uses them in its decoder network to achieve good performance.

Another approach for training neural networks that allows us to trade off complexity and accuracy to learn lightweight models suitable for robotic platforms were put forward by Chris McCool, Tristan Perez, and Ben Upcroft [13]. The proposed approach is achieved through a three-step process. First step is to adapt a pre-trained model, the Inception-v3 [14] model and refer to this adapted model as Adapted-IV3. Second, by using an adapted model and employing model compression techniques. Third is by combining a set of K-lightweight models. This mixture model further enhances the performance of the lightweight models. To enhance the performance of the compressed models they combine multiple lightweight models as a mixture model of Mix-Agent and Mix-mini Inception. This approach leads to impressive results for weed segmentation. The Adam Optimizer [14] was used with a learning rate=le-4, a batch size of b=60 and a dropout rate of 50 percent. Weed segmentation is key to enabling integrated weed management for intra-row weed management [15]. The downside to this highly accurate model is that it is currently not able to be deployed for real-time processing on a robotic system as it can only process 0.12 frames per second.

IV. PROPOSED METHODOLOGY

The primary objective of our proposed approach is to robustly identify weed and predict accurate herbicide or home remedy. An android or iOS application is designed to help farmers to identify the category of the weed and reduce the use of herbicides. Herbicides and home remedies for weed removal are advised to the farmers
with the help of a dataset. Dataset includes the details of weeds and their corresponding treatment solution (amount of herbicide required). When the farmer takes the picture of a weed, the details of the weed and the required herbicide is shown.

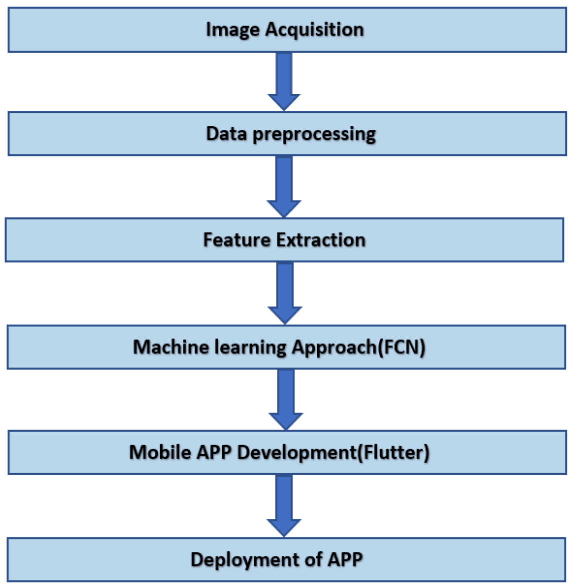

FIGURE 1. Proposed Flow diagram

There are mainly six steps in our proposed system (see figure 1). The first is Image acquisition, we used mobile cameras, the internet, common datasets and articles to collect images. Images are collected in different luminous intensities. Second is Data preprocessing, which includes importing libraries, importing datasets, splitting dataset into training and test set and feature scaling. Third is Feature selection, dimensionality reduction is done here to extract important features from an image. Fourth is a machine learning approach, we used Fully Convolutional Neural Network (FCN) and Random Forest (RF) classifier to train the model. Fifth is Mobile App development, the flutter framework is used to develop the application. Sixth is Deployment of developed application. Our application is named as "Kisan Ki Dhosth (KKD)". Level zero data flow diagram (see figure 2) and level one data flow diagram (see figure 3) gives more information about our proposed system.

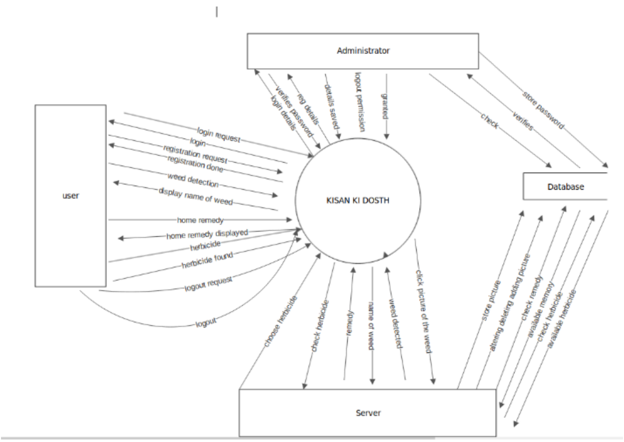

FIGURE 2. Level 0 Data Flow Diagram

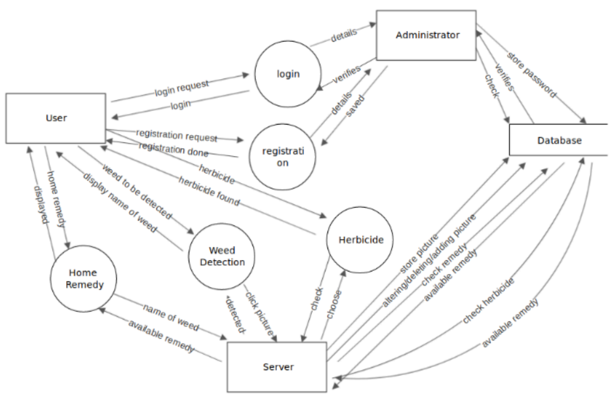

FIGURE 3. Level 1 Data Flow Diagram

VI. CONCLUSION

Among the species that endanger agricultural production are weeds that, when invading crops, can cause high losses in yield and quality of yield. Therefore, in order to improve crop production and quality, agricultural weed removal is essential. Considering that the use of agrochemicals, such as herbicides, has caused significant environmental pollution, due to its widespread use, it has become increasingly important to conduct toxicity testing of these compounds so that its use can be reduced.

An android and iOS application for the classification of weeds is generated. It also gives information about the herbicide to be used against the weeds. The dataset contains pictures collected from various sources like the internet, cameras etc. Those pictures are processed and the model is trained. This model correctly classifies the photograph of the weed clicked using a smartphone. It may also suggest any organic remedies existing. The project aims to support sustainable agriculture and hence less use of herbicide is preferred.

References:

[1] P. Lottes, J. Behley, A. Milioto and C. Stachniss, "Fully convolutional networks with sequential information for robust crop and weed detection in precision farming," in IEEE Robotics and Automation Letters, vol. 3, no. 4, pp. 2870-2877, Oct. 2018, doi: 10.1109/LRA.2018.2846289.

[2] S. Haug, A. Michaels, P. Biber and J. Ostermann, "Plant classification system for crop/weed discrimination without segmentation", Proc. IEEE Winter Conf. Appl. Comput. Vis., pp. 1142-1149, 2014.

[3] A.K. Mortensen, M. Dyrmann, H. Karstoft, R.N. Jorgensen, and R. Gislum. Semantic Segmentation of Mixed Crops using Deep Convolutional Neural Network. In Proc. of the International Conf. of Agricultural Engineering (CIGR),2016

[4] P. Lottes, R. Khanna, J. Pfeifer, R. Siegwart and C. Stachniss, "UAV-Based crop and weed classification for smart farming", Proc. IEEE Int. Conf. Robot. Autom., pp. 3024-3031, 2017.

[5] N. Chebrolu, P. Lottes, A. Schaefer, W. Winterhalter, W. Burgard and C. Stachniss, "Agricultural robot dataset for plant classification localization and mapping on sugar beet fields", Int. J. Robot. Res., vol. 36, no. 10, pp. 1045-1052, 2017.

[6] A. Wendel and J. P. Underwood, "Self-Supervised weed detection in vegetable crops using ground based hyperspectral imaging", Proc. IEEE Int. Conf. Robot. Autom., pp. 5128-5135, 2016.

[7] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine Learning in Python," ´ The Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.

[8] R. J. Murphy, S. T. Monteiro, and S. Schneider, "Evaluating classification techniques for mapping vertical geology using field-based hyperspectral sensors," Geoscience and Remote Sensing, IEEE Transactions on, vol. 50, no. 8, pp. 3066–3080, 2012.

[9] M. D. Cicco, C. Potena, G. Grisetti and A. Pretto, "Automatic model based dataset generation for fast and accurate crop and weeds detection", Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst., pp. 5188-5195, 2017.

[10] K. A. B. Vijay and R. Cipolla, "Segnet: A deep convolutional encoder-decoder architecture for image segmentation," arXiv preprint arXiv:1511.00561, 2015.

[11] V. Badrinarayanan, A. Kendall and R. Cipolla, "SegNet: a deep convolutional encoder-decoder architecture for image segmentation" in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 12, pp. 2481-2495, 1 Dec. 2017, doi: 10.1109/TPAMI.2016.2644615.

[12] M. Everingham, S. A. Eslami, L. Van Gool, C. K. Williams, J. Winn and A. Zisserman, "The pascal visual object classes challenge: A retrospective", Int. J. Comput. Vis., vol. 111, no. 1, pp. 98-136, 2015.

[13] C. S. McCool, T. Perez and B. Upcroft, "Mixtures of lightweight deep convolutional neural networks: Applied to agricultural robotics", IEEE Robot. Autom. Lett., vol. 2, no. 3, pp. 1344-1351, Jul 2017.

[14] D. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in ICLR, 2015.

[15] C. Szegedy, V. Vanhoucke, S. Ioffe, and S. Shlens, “Rethinking the inception architecture for computer vision,” in arXiv, 2015.