WEED IDENTIFICATION USING VEGETATION INDICES AND MULTISPECTRAL UAV IMAGING

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ABSTRACT: Weeds are undesirable plants in a field that compete with desirable plants. This competition results in a significant reduction in the expected yield. Depending on the nature of weeds, different chemical herbicides are used to avoid this reduction in the yield. However, excessive use of chemical herbicides can be hazardous for the environment. Therefore, effective site-specific use of the herbicides is desirable to minimize the negative impacts on the environment. Multiple existing studies have proposed methods to identify weed concentration regions from the field images. These studies are primarily focused on the identification of weeds at early phenological stages. However, as far as we know, there is no study to identify the weeds at later phenological stages for the maize field as high similarity in the weeds and the crop makes it difficult to distinguish them. Therefore, this study proposes a novel pipeline to identify and mask weed concentration regions in the images, collected through UAV at the later phenological stage. The image dataset is collected on three different days and at three different altitudes. The proposed pipeline uses U-Net for precise and fast semantic segmentation in the image. Moreover, instead of generating ground truth images manually or from software, we used two vegetation indices GNDVI and NDRE images as ground truth images. GNDVI-based pipeline successfully identified weeds with a 0.81 IOU score whereas NDRE could achieve only a 0.75 IOU score.

1. INTRODUCTION

Precision agriculture stands out from the application of the latest developments in intelligent systems. The motivation behind the introduction of such systems is to increase the quality and effectiveness of treatments, cost reduction and improve the quality and quantity of agricultural products. Weeds are undesirable plants that compete with plants or crops for light, water, and nutrients and interfere in their growth. The weeds also provide breeding places or shelters for various pests [1]. In past years, weeds have been responsible for most of the crop loss. To overcome this threat, farmers apply uniform herbicide spraying to their fields. This method doesn't only require a large number of herbicides but has an impact on human health and the environment. To reduce environmental impact and cost, appropriate doses of herbicides should be distributed properly at the right spot. Unmanned aerial vehicle (UAV) is a great acquisition system for the location and management of weeds because of its ability to capture photos of the entire field with low cost and high spatial resolution. But instead of significant advances in unmanned aerial vehicles, automatic weed identification remains a difficult problem due to their strong resemblance to crops [2]. With a rapidly growing world population of almost 1.09% per year, demand for additional feed, food, fuel, and fiber needs to increased accordingly, resulting in a higher demand for agriculture to ensure ever-higher yields. The population of the world is projected to the extent of 9 billion by 2050, so the agricultural production should be double to meet rising demand [3]. But, agriculture is having enormous challenges, including climate change, the severe depletion of farmland and water resources, and the threat of diseases, weeds, and pests [4]. For decades, scientists and farmers have made great efforts in weed control to meet the difficult challenges that weeds pose. Weeds appear randomly in the field and use the water, sunlight, and nutrients of crops, which can negatively affect the yield and quality of the crop if not properly controlled [5]. Many studies have shown a solid correlation between weed competition and crop loss [5]–[7]. Various weed control measures have been taken, including manual weed removal or the use of hand tools that have been used for eras and are still used in small fields [7]. But manual weeding consumes more time, is ineffective and labor-intensive, which makes this method impossible for modern weeding. So with the development of mechanization and automation of agriculture, methods of mechanical weeding by plowing or cultivating orchards and row crops have been largely adopted [8]. Compared to manual weeding, the mechanical methods are less labor-intensive and more efficient but can barely remove weeds in a row without the aid of a target sensing module, and can cause the damage of crops, although many efforts have been made to construct complex mechanical hoes [5]. The use of chemical sprays for weed control before or after weed emergence is widespread worldwide. Research is ongoing into combating weeds with organic methods, such as the use of natural insects or microorganisms that eat weeds to decrease the negative effects of chemicals on the environment and crops. Another problem with the use of herbicides is that overuse can cause weeds to become resistant to such chemicals [1]. Like all other crops maize is also affected by weeds. In maize, weed has been detected at the early stages of crops but has not been detected at different stages of crops. A lot of vegetation indices like GNDVI and NDRE have been introduced but have not been used in weed identification in Maize. So our main goal is to identify weed in maize at different stages with different vegetation indices. Moreover, to analyze the effect of weed identification on the productivity of the maize.

2. RELATED WORK

Author O. Barrero [9] projected and tested an image classifier that is based on the BOVW structure for mapping the weeds using a small UAV with a commercial camera at a low altitude. Image Classifier had been trained using SVM after creating a visual dictionary of the local features from multiple collected UAV images. In-window processing was used to map the presence of weeds in the UAV images. The UAV flight campaign had been conducted in a wheat field infested with weeds and photos were taken at an altitude of 1 to 6 m. From the UAV images, 25,452 plants of weeds as well as wheat and soil were described as baseline classes for training and model validation. Results indicated that the BOVW model permitted the differentiation of individual plants with the high precision of 88.60% (Matricaria recutita L.), 89.08% (Papaver rhoeas L.), 87.93% (Viola arvensis M.), and 94.09% (winter wheat) on generated maps. For site-specific control of the weed, UAV classified images would allow the selection of an appropriate herbicide based on the predicted distribution of the weed species.

RGB images based on UAS, which were recorded at two different test locations in the early stage of wheat growth are used to develop predictive models [10]. DNN in combination with an advanced method of feature selection was used for identifying ryegrass in the wheat and measure canopy cover. Predictive models had been developed by following the coverage of ryegrass at the beginning of the season with biomass at end of the season (at the time of wheat maturation) and the ryegrass yield seeds, and the decrease in grain yield of wheat. The Italian ryegrass has been identified with high precision using the best model with four features: saturation, hue, ExG, and VARI. The ryegrass biomass at the end of the season had been predicted with a high accuracy i.e R2 = 0.87, while the remaining variables were of a level of moderate to high accuracy for ryegrass 0.73 for the reduction of wheat biomass and 0.69 yields of wheat grain. The methodology presented in this study shows an excellent potential for quantifying and mapping the infestation of ryegrass and for predicting the competitive response to wheat to allow timely decision-making.

The aim of the study [11] was to create geo-referential infestation maps of weed seedlings in two fields of sunflower by analyzing overlapping aerial images of near-infrared and visible spectra (using multispectral or visible cameras) received from a UAV flying at an altitude of 30 m and 60 m. In the first stage of image analysis, rows of sunflowers were correctly aligned with orthomosaic images, which allowed for precise image analysis using OBIA. OBIA algorithm developed for mapping weed seedlings with orthomosaic images, it was possible to classify sunflower rows in both fields with 100% accuracy for all altitudes of flights and types of camera. This indicates the analytical and computational robustness of an OBIA. Early mapping and detection of johnsongrass in maize are major the challenge in real field scenarios as both species belong to Poaceae family and share similar spectral patterns, remarkably similar appearance and parallel phenological development. To solve the problem, an automatic OBIA method was developed that can be applied to orthomosaicked images with visible RGB and multispectral cameras collected by a UAV that flew 30m, 60m, and 100m over two fields of maize [12]. The rows of maize were mapped and distinguished with an accuracy of 100% using the OBIA method for all flight altitudes and both types of cameras.

O. Barrero and S. A. Perdomo [13] presented a new method of combining RGB images with high resolution and multispectral images with low resolution to identify Gramineae in fields of rice at 50 days of post-emergence. Photographs are taken by UAVs at an altitude of 60 meters and 70 meters. The method combines texture information provided by the high-resolution RGB image with reflection information provided by the low-resolution multispectral image creating a merged RGB-MS image. After NDVI and the NGRDI for weed identification, NGRDI was found to have better features. Both the indices were assessed in four areas of validation using three NN detection systems that are based on three images types namely RGB, RGB-NGRDI combined, and RGB + NGRDI. Author J. Rasmussen [14] describes a method for detecting green weeds in crops before harvesting using commercial drone images and RGB cameras. All the images which had been used for developing and testing the identification process were taken from Cirsium arvense-infested fields of barley and wheat. The procedure is known as the thistle tool. The development of an automatic weed identification tool by using CNN has been proposed in [15]. The dataset used in this study includes 1,500 images, of which 770 images are negative (having no weeds) and 730 images are positive (having weeds). The validation set consists of 575 images, 203 images of which are negative images (having no weeds) and 186 images are positive (having weeds).

S. Abouzahir [16] used histograms on basis of colors indices to distinguish three classes: soybean, soil, and weeds. This representation of features has been tested with the two classifiers, the BPNN, and the SVM. This approach gained the highest efficiency with the accuracy of 95.078% SVM and 96.601% for BPNN. The photos are taken with the DJI Phantom3 Quad-Copter and fly 4m above the soybean crop. The proposed method in [17] is to collect unsupervised data and use a single-class classifier to train the model. Along with the Hough transform, the method identifies lines of crops through skeletons. when the crop lines are detected, the image is split into superpixels. Then all the superpixels on the crop lines are gathered to create a training dataset. The feature extraction is then performed on the training dataset. SVM was selected for training the model. In [18] a method is proposed for discriminating crops and weeds using images of UAV. It is based on, Hough transform, vegetation skeleton, and SLIC. The blend of spatial relationships of the superpixels and their position on the detected lines of crop allows the detection of interline weeds. The photos used in this study were taken with the SenseFlyR eBee drone. The flight height is approximately 100 m above the ground. The experiments were carried out in two maize and beet fields.

According to [15], SVM doesn't work very well if the dataset contains more noise (The target classes overlap) and SVM is not appropriate for big datasets. As they also plan to build a large database, CNN would be a good solution. The main disadvantage of the method used in [16] is that the color indices are sometimes sensitive to changes in outdoor lighting that affect system performance. More research is needed to prove the suitability of this under different lighting conditions, different types of crops, and real-time constraints. To enhance background segmentation for the identification of weeds in maize crops, authors of [2], [18] planned on using multispectral images because NDVI can improve background segmentation. The limitation of the research proposed in [19] was the problem of sunlight intensity because the variation of the recorded image was high. It can be remedied if similar studies are performed in a controlled environment. A better camera should be used to take a better photo with different sensors to overcome the issue that occurs due to the sunlight and shadow variations.

Study [10] has several limitations: 1- Only ANNs have been tested to detect weeds where many machine learning classifiers are available, such as SVM and random forest, and has been used in the past for weed identification and mapping. Future research is needed to check these classifiers individually or perhaps with advanced deep learning models such as CNN. 2- A wider application of the classification model is presented in wheat fields but environmental and geographies conditions are unknown. Varieties of wheat can differ significantly in leaf composition and color and may have various spectral signatures. The model can be empowered and generalized with various training patterns. 3- Competition models developed in this study were based on this only above the area of ryegrass canopy as estimated from aerial photographs. This research did not try to use/evaluate existing competing weed models based on variables such as biomass, leaf area index, and weed density. The performance of ground and canopy prediction as compared to previous approaches is not known. Future research is needed to test and consolidate these approaches to enhance the feasibility and accuracy of weed and crop interaction assessments. 4- adapting this model to a huge production field can be difficult because of high computational requirements. In [20], the effectiveness of pixel-based classification had been limited in the early stages of growth because of the strong similarity between the weed species.

Studies mentioned above are only capable of identifying weeds in the early phenological stages of maize but not in the later phenological stages of maize. Farmers need multispectral cameras for better identification of weeds that is cost-consuming. Moreover, in Pakistan maize is infested with different weeds that are not mentioned in the above studies.

3. DATA ACQUISITION

We grew maize at our university campus in the area of 5 Marlas. The crop of maize was sown on 10 March 2021 in rows. The emergence of maize plants started after 15 days of sowing. The area of the study was infested naturally with Purple nutsedge (deela), Swine cress (jangli haloon), and Horsepurslane (itsit). We collected data at three different stages and three different altitudes. Images have been collected after 29 days, 43 days, and 52 days after sowing. These stages are chosen because at these later stages an efficient control of weeds is very difficult to get. Images have been collected at 5m, 8m, and 10m. We collected images at these three altitudes on all three stages. At 5m 80 images are collected, 42 images have been collected at 8m and 32 images are collected at 10m. Our dataset contains GNDVI, NDRE, and RGB images. We have used DJI phantom P4 in our experiment. The P4 Multispectral solidifies the way toward capturing information that gives understanding into crop wellbeing and vegetation management. It provides 27 min time of max flight. Farming imagery collection is presently more straightforward and more proficient than before with an implicit settled imaging framework that gathers complete informational collections. Access data gathered by a multispectral camera and 1 RGB camera cluster with 5 cameras that cover Green, Red, Blue, Near Infrared, and Red Edge bands. The camera and its wavelengths are shown in Figure 3.2. It captures all bands at 2 megapixels with the global shutter and on 3-axis balanced out gimbal.

4. METHODOLOGY

We introduce a novel approach to identify the weeds in the Maize crop. The methodology use advantages of Deep learning for weed identification.

4.1. Data Preprocessing

The size of our images collected by UAV is 1300*1600. We resized it into 1024*1024. We split our data into training, testing, and validation. As our dataset is too small so we increase our training dataset by using the data augmentation technique. We increase the dataset by rotating, horizontal flipping, and vertical flipping. We did not use testing and validation datasets in data augmentation and training. For weed identification with NDRE, folders of training, testing, and validation contain two subfolders named input and output. Input folder contains RGB and output folder contain NDRE images. For weed detection with GNDVI, we used GNDVI images in the output folder and RGB images in the input folder.

4.2. Image Segmentation

To perform semantic segmentation on images, we used U-Net architecture to create binary segmented masks. Semantic image segmentation is a key problem in the field of computer vision. It has been solved by using methods of clustering. However, recently deep neural networks have shown to be excellent at dealing with a variety of problems of computer vision because of the ability to learn automatically large representations of features from data. It aims to better understand the scene by assigning the label of object category to every pixel in the image. With advances in computer vision, this problem is solved with encoder-decoder-style architecture that involves CNN.

The U-Net architecture consists of two paths: contracting path and expansive path. The Contracting path consists of typical convolutional network architecture. It contains two convolutions of 3x3 followed by ReLU and a max-pooling of 2x2 with the Stride of 2 for the downsampling. With every downsampling step, feature channels are doubled [21].

Each step in expansive path contains upsampling of feature map which is followed by 2x2 convolution which halves a number of the features channels, concatenation with correspondingly cropped feature map from contracting path, and two convolutions of 3x3, each followed by ReLU. Cropping is important due to the loss of the border pixels in each convolution. In a final layer, one convolution of 1x1 is used for mapping each feature vector of 64- components to the required number of classes.

Ground truth of images has been created by using GNDVI/NDRE images instead of generating ground truth images manually or from software. we perform thresholding on GNDVI/ NDRE images to get the ground truth images. We set the threshold value to 100. Then predicted mask using U-NET has been created. The predicted mask is then deployed on the input RGB image. Then we can see where weeds are present in an RGB image.

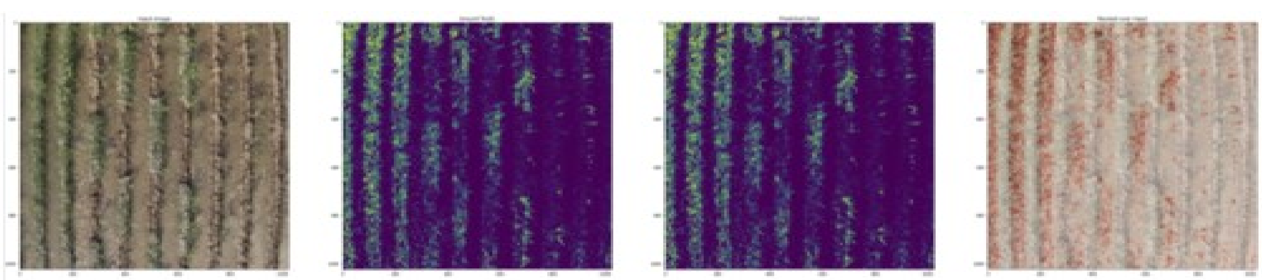
4.3. Evaluation Metric

The evaluation metric taken for semantic segmentation is IOU [22]. It measures the number of pixels that are common between the prediction mask and target mask divided by the total amount of pixels that are present in both masks.

$$IOU = \frac{Area\ of\ Intersection}{Area\ of\ Union}$$

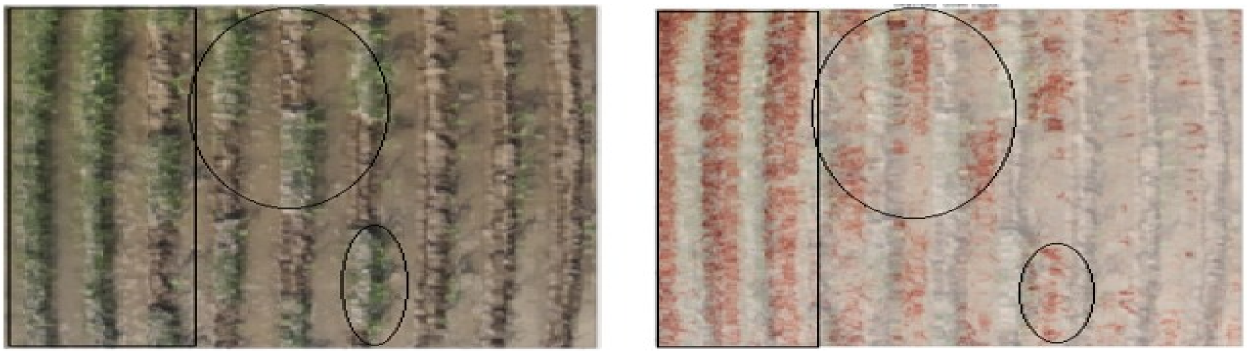
5. RESULTS AND DISCUSSIONS

Figure 1 (a) shows the RGB image, (b) shows the ground truth image created by applying a threshold on the GNDVI image, then (c) shows the predicted mask created by U-NET, and then in (d) the predicted mask has been shown on RGB image. Figure 2 (a) clearly shows the weed in the highlighted part of the RGB image and then the mask of weed is shown on the RGB image in (b).



(a) (b) (c) (d)

Figure 1: RGB, Ground Truth, Predicted Mask, Mask over RGB



(a) (b)

Figure 2: RGB, Mask over RGB

We calculated the IOU score of all the three altitudes of all three days. Table 1 shows that from NDRE we got an average IOU score of 0.66 on the 29th day at 5m, an average IOU score of 0.74 on the 43rd day, and an average IOU score of 0.69 on the 52nd day at 5m. At 8m we got an average IOU score of 0.69 on the 29th day, an average IOU score of 0.70 on the 43rd day, and an average IOU score of 0.67 on the 52nd day. At 10m we got an average IOU score of 0.68 on the 29th day, an average IOU score of 0.69 on the 43rd day, and an average IOU score of 0.65 on the 52nd day. On the 29th day, the results are not good because the height of maize is similar to the height of weed. On the 43rd day, we got maximum results from NDRE because the height of maize is larger than weeds. As the crop has become larger so NDRE had not given maximum results on the 52nd day.

Table 1: IOU scores of NDRE

Altitude	**29th day**	**43rd day**	**52nd day**
5m	0.66	0.74	0.69
8m	0.69	0.70	0.67
10m	0.68	0.69	0.65

We calculated the IOU score of all the three altitudes of all three days. Table 2 shows that from GNDVI we got an average IOU score of 0.78 on the 29th day at 5m, an average IOU score of 0.80 on the 43rd day, and an average IOU score of 0.77 on the 52nd day at 5m. At 8m we got an average IOU score of 0.78 on the 29th day, an average IOU score of 0.80 on the 43rd day, and an average IOU score of 0.78 on the 52nd day. At 10m we got an average IOU score of 0.79 on the 29th day, an average IOU score of 0.81 on the 43rd day, and an average IOU score of 0.77 on the 52nd day. On the 29th day, the results are not good because the height of maize is similar to the height of the weed. On the 43rd day, we got maximum results from GNDVI because the height of maize is larger than weeds. As the crop has become larger so GNDVI had not given maximum results on the 52nd day.

Table 2: IOU scores of GNDVI

Altitude	**29th day**	**43rd day**	**52nd day**

5m	0.78	0.80	0.77
8m	0.78	0.80	0.78
10m	0.79	0.81	0.77

On the 29th day, we got maximum results of 8 meters from NDRE i.e 0.69. On the 43rd day, we got maximum results of 5 meters i.e 0.75. On the 52nd day, we got maximum results of 5 meters i.e 0.70. Maximum results of NDRE are shown graphically in Figure 4.19.

On the 29th day, we got maximum results on 10 meters from GNDVI i.e 0.81. On the 43rd day, we got maximum results of 10 meters i.e 0.81. On the 52nd day, we got maximum results of 8 meters i.e 0.77. Maximum results of GNDVI are shown graphically in Figure 4.20.

6. CONCLUSION

Weeds compete with the crops causing a significant reduction in the expected yield. Automated control of weed is a growing research area in precision farming. Weeds compete with the crops and reduce yield with losses of more than 30%. Chemical herbicides are the most common methods of weed control, but because of their negative environmental impact, farmers are under pressure to regulate the number of herbicides used. To gain this, farmers would have to manually check the fields before applying herbicides, which is very time-consuming and laborious. So, an automatic process for weed presence detection is required, which can reduce the farmer's workload. UAV imaging has great potential in developing site-specific weed control. With a high-resolution image, farmers can accurately and quickly spot weeds and use a minimal amount of pesticides to eliminate them. Using high-resolution cameras, UAVs can detect weeds and specifically spray the herbicide. It can save up to 90 percent of chemical herbicides. In this research, we have built a pipeline to identify the weeds and create a mask where weeds are located in an image by using U-NET architecture. We used RGB, NDRE, and GNDVI images. We got better results when GNDVI was used. On the 29th day, we got an average IOU score of 0.79 and an average F1 score of 0.79 at 10m. On the 43rd day, we got a 0.81 average IOU score and an average F1 score of 0.81 at 10m. On the 52nd day, we got a 0.79 average F1 score and 0.78 IOU score at 8m. In the future, the results can be improved by training the model on a relatively larger dataset, collected in a controlled environment. We believe that this technology offers a huge scope in the agricultural sector. It can help the farmers reduce losses by suppressing the identified weeds, hence improving the quality of yield. Moreover, farmers do not have to buy multispectral cameras, they will give RGB images as input instead. We hope to use this pipeline with automatic vehicles/robots to spray herbicides in the future, thus automating the entire weed control process.

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