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Classification of Weeds of Paddy Fields using Deep Learning

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ABSTRACT

Weed management is one of the important tasks in agriculture. Weeds in rice fields are usually managed using three ways - chemical herbicides, mechanical weeders, and manual weeding. Manual weeding becomes a problem when there is a shortage of agricultural laborers. Mechanical weeders are not suitable for direct-seeded rice fields. Chemical herbicides are not advisable especially when farmers do not know about site-specific weed management. Site-specific weed management is using the right herbicide in the right amount. Therefore, this paper investigates computer vision-based deep learning techniques with transfer learning classifying three types of weeds in paddy fields, namely sedges, grasses, and broadleaved weeds so that the right herbicide is recommended to the farmers. This would reduce the broadcast application and the overuse of the herbicides, thereby limiting the negative impact of the chemical herbicides on the environment. This research work shows promising results with an accuracy around 90% and thus encourages the development of digital agriculture.

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1. INTRODUCTION

Agriculture, also known as farming, is the production of food, animal feed, and fiber through growing and harvesting plants. The agriculture system dates back to ancient history thousands of years ago. It is one of the cornerstones of civilization. Agriculture is practiced throughout the world. It is the backbone of several developing countries like India where 70% of the workforce is employed in agriculture-related organizations. Modern farming began in the 18th century when several changes were made to agricultural practices in a short period that witnessed a massive improvement in yield and a more efficient process. In the middle of 19th century, technology was used in agriculture. The tractor was introduced, followed by new irrigation, tillage equipment, and harvesting equipment. All these technologies led to higher yields and improved the quality of farm output. Precision agriculture can be defined as the art and science of using advanced technology to enhance crop production [1].

Precision agriculture is an information communication and technology-based data-driven agriculture system used to precisely monitor each step to maximize agricultural production and lower harmful impact on the environment without much human intervention. One of the facets of precision agriculture is site-specific crop management. It involves remote monitoring of crops in the field for pests and diseases, building decision support systems by sensing environmental factors, precise pesticide, herbicide, and fertilizer spraying, predicting crop yield and so forth. It also concerns pre- and post-production in the agricultural sector. Precision agriculture is rapidly spreading in developing nations like India, which had to explore precision agriculture to meet its ever-growing food demand.

A Wireless sensor network (WSN) is an ideal technology to provide efficient and viable solutions for different applications such as environmental monitoring, agricultural monitoring, military applications, and so forth. The primary driver of the development of precision agriculture is WSNs. Recent advancements in sensor technologies have led to the development of low-cost, small-sized, and low-powered sensor nodes which are used to monitor agricultural fields. The sensor nodes of the WSNs implemented in a farm

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field collect data in real-time. This real-time data is then forwarded to a remote station or to a cloud-based platform where it will be processed by an automated system or by human experts to make decisions [3]. The potential applications of WSNs in agriculture are many, like groundwater monitoring, greenhouse gas monitoring, predicting the occurrence of pests and diseases in crops, predicting water requirements of farm fields, helping enable the controlled use of pesticides and herbicides, and so on [4]. These WSNs sense environmental factors such as soil water content level, humidity, temperature, and other gases and send them to a server for decision-making. A Wireless image sensor network (WISN) has image or visual sensor nodes to capture images/ videos at regular time intervals and forward them to the remote station where images/videos will be processed for decision-making. In [5], a WSN was implemented with image sensors and other sensors like humidity sensors and temperature sensors. The nodes in this WSN accumulate data such as temperature, humidity, and crop growth images. The authors state that images help farmers make an accurate judgment at the right time. Similarly, in [6], a WSN was implemented with image sensors to monitor plants grown inside the greenhouse. In both [5] and [6], no image processing techniques were used for realizing automated decision-making and images had to be manually analyzed by human operators to make a decision. In [7], a WISN was implemented to monitor pest (insect) density with the help of image sensors. The images acquired by the nodes were processed using image processing techniques and when the pest density reached beyond some threshold an alarm was raised indicating the requirement for pest control. In [8], an integrated crop monitoring system was developed with the help of a WSN that consisted of image sensors and other sensors to sense environmental factors. The images acquired by the image sensors were processed to detect insects on the crops.

Soft computing techniques are being used in the agricultural domain to automate various agricultural tasks and to build decision support systems. The data input to the soft computing techniques may come from WSN, WISN, and other sources. It is used in automatic plant classification, crop and weed discrimination, crop disease identification, crop yield estimation, plant growth estimation, automatic fruit grading, etc.., [9]. An automatic weeding machine was proposed in [10] which uses soft computing techniques for its operations. WSNs with efficient communication technology along with soft computing techniques are helping farmers and agronomists to make the right decisions at the right time. Precision agriculture resulted from the advancement in WSNs and soft computing techniques [11]. This model is helping to reorganize the entire farming system with low input, high efficiency, and sustainable farming.

As a branch of soft computing techniques, machine learning has been widely used in various applications for classification tasks. WSNs are the driving forces behind precision agriculture. Together these technologies are contributing to building various decision support systems that help farmers know the conditions of soil, crops, and other environmental factors, and make important decisions like when to start sowing, spray pesticides, herbicides, apply fertilizers, and so on. This has resulted in increased crop production and yield. Weeds can be defined as unwanted or undesirable plants growing among crops and competing with crops for soil nutrients, water, and sunlight. They also contribute to lower yields and serve as hosts to many pests and parasites, which harm crops. Thus, controlling weeds is an important task in agriculture.

In precision agriculture, automated detection of weeds is a hot research area with great potential. Many interested researchers have developed a system for discriminating crops from weeds from digital images in the past. In [12], discrimination between chilli crops and five types of weeds has been done using color, size-dependent, size-independent, and moment features using a support vector machines (SVM) classifier. Real field images were used in this computer vision-based automated weed detection system. In [13], crops and weeds were discriminated using texture features extracted using a color co-occurrence matrix (CCM) and artificial neural networks (ANN). In [14], weeds were recognized based on shape features. They could also create a weed distribution map for site-specific weed management using a GPS-controlled herbicide sprayer. In [15], authors have used shape-based classification to discriminate between the seedlings belonging to two different crop species. The images were acquired under controlled lighting conditions in the laboratory. In [16], discrimination of a carrot crop from weed has been done on images acquired using a Bonirob robot. In [17], discrimination between monocot weeds and dicot weeds was done using Hu's invariant moments [18], and six geometric shape features like perimeter, major axis, minor axis, diameter, and so on. In [19], discrimination between sugar beet crops and weeds was done using different shape features. The classification was done using ANN and SVM classifiers. The performance of these two classifiers was evaluated and analyzed.

In [20], discrimination between crop and weeds was done using a fully convolutional network along with plant stem position and spatial coverage of crop and weeds. In [21], the authors give insights into various ways of identifying plant species using machine vision techniques. In [22], vegetable crop and weed classification was carried out based on color features and area thresholding. In this work, images were captured under natural lighting conditions from the farm fields. In [23], country-wise details of research work done using computer vision techniques to identify crop diseases, pests and invasive plants (weeds) is given. In [24], the authors review the development of autonomous weeding robots. They state that the main hindrance to the development of commercial weeding robots is the lack of robust weed recognition techniques. This is still the case even though research has progressed in this direction. This can be attributed to several challenges one faces when working with discrimination of crops and weeds.

One of the key challenges is to discriminate between crops and weed at an early stage when most plants look alike because they do not have their true leaves at an early stage. Another big challenge arises when crops and weeds are morphologically similar to one another. For example, paddy crop and grass-type weeds are very similar morphologically. That means grass-type weed is often mistaken as paddy crop and goes unnoticed. Other challenging factors are that some of the weed species change significantly during their growth stages making them hardly recognizable as the same plant because of less resemblance between early growth and later growth stages. Variance within weed species is also a challenge for an automated weed recognition system. Lighting conditions can also influence the automation of the weed and crop discrimination framework. The plant reflectance increases as the intensity of the light increases. This can result in reduced discrimination of crops and weeds. The increased plant reflectance could also result in distorted colors in digital images [25]. In addition to these issues, occlusion problems, that is too heavy overlapping of crop and weeds, also make it difficult to discriminate using machine vision techniques.

1.1 Deep Learning in weed classification

Deep learning has been used in many fields of agriculture and has developed into a powerful method for image classification [26]. Deep Learning is a subset of Machine Learning. It extends classical machine learning by adding more complexity or depth and makes use of deep neural networks or use of multiple layers of neurons to progressively extract features from raw input. By allowing various transformation functions to transform the data, data can be represented more hierarchically while at the same time maintaining abstraction of the data [27] [28]. By mapping the consistency of features with a feed-forward process and optimizing the regularize loss function from the backpropagation process, deep learning networks are expected to recognize the patterns hidden in a supervised dataset and to automatically create feature maps to extract those features from the dataset. The model then uses the recognized knowledge from pattern learning to perform classification. Transfer learning in deep learning uses existing models which were trained for one task for another related or unrelated task [29]. The transfer learning optimizes the model development cost by allowing rapid model development with improved performance. Transfer learning is frequently used in software defect prediction [30], sentiment classification [31], and activity recognition [32].

1.2 Motivation for the research

Paddy is one of the important crops of India. It is reported that annually India is incurring a loss of INR 1050 million because of weeds in paddy fields [33]. The standard ways of handling weeds in India are:

- Manual weeding
- Mechanical weeder
- Use of chemical herbicides

Hand weeding involves pulling the weed plants with their roots or using a tool like a sickle, hoe, or spade. Hand weeding is a time-consuming and labor-intensive job. Moreover, in the coastal Karnataka region, there is an acute shortage of agricultural laborers. Therefore, hand weeding is not preferred in these regions because of the reduced availability and high cost of laborers. Mechanical weeding is carried out using a machine called a rotary weeder. This is ineffective in paddy fields because of complex and difficult field conditions in a paddy. In addition, it seems impractical for the directly seeded paddy fields to use mechanical weeders because there are no crop rows in direct-seeded rice or paddy fields.

Herbicides are chemicals capable of killing some plants (weeds) without significantly affecting other plants (crops). Herbicides have many ill effects on the environment. Most of the farmers in India do not have primary education and they do not have any knowledge about site-specific treatment in agriculture. Therefore, most of the time any type of weed is treated with a broadcast application of herbicides. This excessive use of herbicides has resulted in the contamination of the groundwater and herbicide-resistant weeds. In addition, it has been shown that the farmer's expenditure can be reduced by 40% if the correct herbicide is used in the right amount at the right time [34]. Moreover, most automated weed recognition techniques are only able to discriminate between crop and weed.

When controlling weeds with herbicides, it is essential to know the species of the weeds so that the suitable herbicide is applied. Spraying a specific type of herbicide via site-specific weed management (SSWM) can help in reducing herbicide usage and thus results in less environmental pollution and increased profits to the farmers. Therefore, it would greatly help the farmers if there were automation of detecting and identifying weeds in paddy fields with precision agriculture. This research work shows the feasibility of an approach of detecting and identification of three types of weeds and paddy crop itself using deep learning techniques. The novelty in this research work is that we have considered directly seeded rice fields as well as transplanted rice fields for image acquisition. In addition, images were acquired from different cameras fixed at different heights and hence we are processing a diversified dataset. By grouping the dataset into two, one with paddy and three weeds and another with only weeds, we investigated how well the models discriminate between paddy crop and weeds and also discriminate among weed types.

Our main contributions are as follows:

- This paper investigates several deep learning models with transfer learning in the classification of three types of weeds in paddy fields.
- A detailed performance analysis of the models is described in the paper

2. RELATED STUDY

In this section, deep learning-based weed identification studies covering three approaches are summarized. They are:

- Image classification
- Object detection
- Semantic segmentation

In [35], the discrimination of maize crop and weed was done using a convolutional neural network (CNN). Four types of CNN models were used namely, LeNet, AlexNet, cNet, and sNet and their performance was analyzed. In addition, these models were also executed on different hardware set-ups like a normal CPU, a Raspberry Pi 3 Model B, and with a Nvidia Graphics Card. The cNet model outperformed all other models with 16 filters with an accuracy of 97%. The model, which ran on a Nvidia Graphics Card CUDA platform, executed 18 times faster than a standard CPU and 170 times faster than the model executed on the Raspberry Pi 3 Model B. Figure 1 shows the cNET architecture.

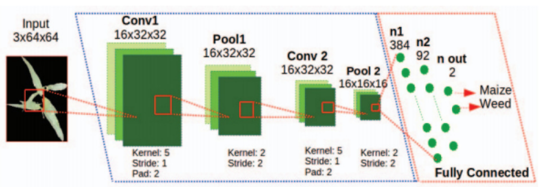


Fig.1: *Architecture of cNET [35]*

In [36], classification of weeds in various crops like wheat, maize, and sugar beets has been done using a CNN model. The plant seedlings dataset from Kaggle was used. The authors report an accuracy of 89% in classification of weeds.

In [37], classification of 12 species of crops and weeds was done using a convolutional neural network with transfer learning. A publicly available weed dataset created by Aarhus University Signal Processing group in collaboration with University of Southern Denmark [38] was used for this study. A model which was earlier trained with the ImageNet dataset with Residual Network 101 was used for transfer learning. Various techniques like progressive resizing, cyclical learning rate, and focal loss function were used to adjust the model's parameters to improve performance. The authors report an accuracy of 98% during validation and 96% on the test set.

In [39], classification of crop and weeds has was done using a CNN model. A VGG16 was used with a support vector machine algorithm. A publicly available weed dataset created by Aarhus University Signal Processing group in collaboration with the University of Southern Denmark [38] was used for this study. The authors report an accuracy over 96% and have a view that VGG+SVM achieves a good generalized recognition accuracy.

In [40], weed detection in perennial ryegrass was done using deep learning techniques. There were two datasets constructed, one dataset with images containing single weed species and another dataset with images consisting of multiple weed species. These two datasets were used to train deep learning models such as AlexNet, GoogLeNet, and VGGNet. The first dataset was a balanced dataset while the other was an unbalanced dataset. For the single species, dataset AlexNet and VGGNet performed better when compared to GoogLeNet, these models also formed well with other datasets consisting multiple weed species.

Some research also used deep learning for weed classification by applying semantic segmentation or object detection. In [41], the discrimination of rice seedlings was done using the deep fully convolutional network (FCN), SegNet [42]. SegNet is based on an encoder and decoder (codec) structure which has a lower computational cost and higher precision. The number of classes was three: soil, rice, and weeds. The structure of the SegNet is shown in figure 2. The SegNet achieved a pixel-wise classification accuracy of 91% for soil, 94% for rice, and 94% for weeds. The classical semantic models such as U-Net achieved an accuracy of 97% for soil background, 46% for rice, and 69% for weeds. A fully convolutional network (FCN) model [43] had an accuracy of 83% for soil background, 92.1% for rice, and 92.9% for weeds

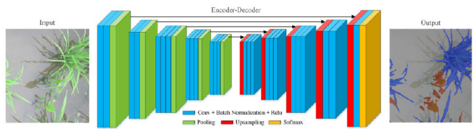


Fig.2: *Architecture of SegNet [41].*

In [44], the classification of sugar beets and weeds was done using semantic segmentation. The images collected were converted to SegNet format and annotated. For the model training, maximum iterations were 640 epochs, the learning rate was set to 0.001, the batch size was 6, and the weight delay rate was

0.005. With the test data, an average accuracy of 80% was obtained by model.

In [45], the classification of sugar beet crops and weeds was done using CNN. The input was represented in 14 different formats based on indices like EGI, ERI, etc. The input was resized and channel-wise contrast normalization was done.

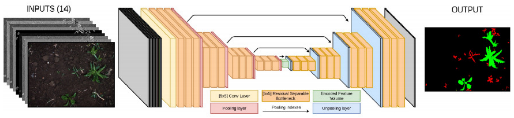


Fig.3: *Encode and Decode architecture for pixel-wise segmentation of crop and weed [45].*

The CNN model with a rectified linear unit (ReLu) was used with three different image datasets captured at different places. The experiment was also carried out by inputting only RGB representations. The CNN model with input with the extra representations performed well with an accuracy of 95%. The authors report that inputting the additional information speeds up the training process, and generalization capability of the model. Thus, it increases the overall performance of the model.

In [46], weed detection in a canola field was done using maximum likelihood classification and deep learning techniques. As the first step, the soil background and vegetation are segmented using maximum likelihood classification. Then, the pixels are segmented as either belonging to crop class or weed class. The deep learning techniques such as SegNet, UNET, and encoder architectures like VGG16 and ResNet-50 were used and their performance is compared. It was found that the SegNet based on ResNet-50 performed well when compared to other architectures.

In [47], the discrimination of crop and weeds was done using deep learning techniques using context-independent pixel-wise segmentation. Authors claim that this method is particularly useful for datasets where object-annotated data is not available or it is very small. The model used was UNET and based on a modified VGG-16 encoder followed by a binary pixel-wise classification layer.

In [48] the implementation of crop and weed discrimination is done using a deep learning model. Its deployment used a low-cost mobile SBC Raspberry Pi 3 Model B+. The ground truth labels used were generated semi-automatically with the UNET model. The developed deep learning model involves the concepts of DenseNet, ResNet, and MobileNets. The model's deployment on the Raspberry Pi 3 Model B+ gave satisfactory results with detecting weed area up to 67% and misclassification of crop area up to 0.9%. The crop and weed area segmentation was done from videos at more than 10 frames per second.

In [49], weed detection in romaine lettuce crops was done using a deep learning model. Around 3000 images of lettuce crops and weeds were collected from an organic farm. The green vegetation was retained using Otsu's thresholding. The vegetation was labeled as crop and weeds semi-automatically using MATLAB. First, 500 images were manually labeled. A Convolutional neural network (CNN) model with YOLO-v2 [50] was trained with these images to label the rest of the images. All the images labeled by the model were again manually inspected and corrected through adjustment. Then the labeled images were used as training data for CNN models such as ResNet-50, ResNet-101, MobileNet, InceptionResnet V2, SqueezeNet, VGG16, and VGG19 which were used as the feature extraction layers for the YOLO-v2 model to identify lettuces. The authors report that the CNN model with VGG16 outperformed all other models with a mean average precision of 93% with new data the data the model had never seen 20% of the test data.

3. METHODOLOGY

3.1 Dataset Preparation

Two digital cameras (Canon PowerShot SD3500 IS) and Sony Cybershot (DSC-W220) were used to acquire images from paddy fields around Manipal region of Karnataka State in India. Images were acquired under natural variable lighting conditions with the camera set at different heights of 0.61m, 0.91m, and 1.22m from the ground. The cameras were fixed on a tripod and were facing down towards ground. Images were also acquired from a Raspberry Pi (RP_ov5647) camera installed in the paddy field. The weeds and crops of varying canopy sizes were selected to increase the difficulty of identification. The dataset contains paddy plants and weeds from early growth stage (1-leaf seedling stage) to flowering stage. These growth stages are very critical because the effect of weeds will be maximized [51]. Detection and removal of weeds in this period is crucial because weeds compete with crops vigorously during this period. Therefore, weed control methods applied during this period will be very effective [52]. Both transplanted and direct-seeded rice fields were selected for acquisition. A detailed explanation of dataset creation can be obtained from [53], [54], [55]. In addition to our own dataset, we have also used the dataset created by [41]. Images of these two datasets were combined. Images were preprocessed to remove the soil background.

3.1.1 Extraction of Green Plants

The images had to be pre-processed to remove soil background and retain only green vegetation before the annotation process was carried out. The images acquired from the field presented a variety of challenges due to complex backgrounds and complex plant objects. Since the paddy fields require standing water, several challenges such as reflections, shadows of plants, and other objects near the fields arise. In addition, illumination changes rapidly during the rainy season. This is yet another unavoidable factor of variation, resulting in highly dynamic scene capturing. Therefore, in these circumstances, extracting only green plants becomes a challenge. Foreground objects (plants) were segmented from the background (soil and water) using the YCbCr model. The segmentation of green plants from the complex background consists of the following steps. Firstly, extraction of only the plant pixels in the image based on the YCbCr color model is done to eliminate the background and the shadows. Figure 4 shows the steps involved.

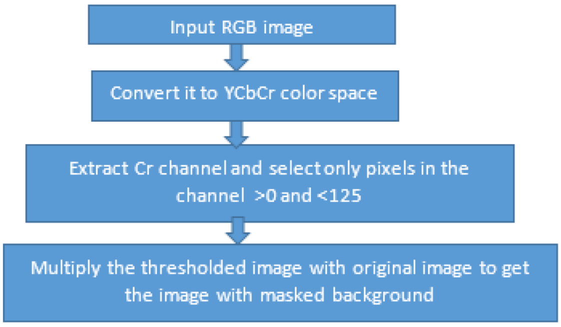


Fig.4: *Steps involved in Green plant segmentation using the YCbCr color model.*

Each plant type, that is, paddy, grass, broadleaved weed, and sedges was annotated with different colors and images containing a single type of plant. That is, isolated images were obtained as explained in [55] . After this step, the dataset was grouped into two sets. The first dataset consisted of only isolated images, and the second dataset consisted of images of more than one plant type. Images with too heavy overlapping and images that were not clear were not included in the dataset. Figure 5 and 6 show images from the first dataset and Figure 7 and 8 show images from the second dataset.

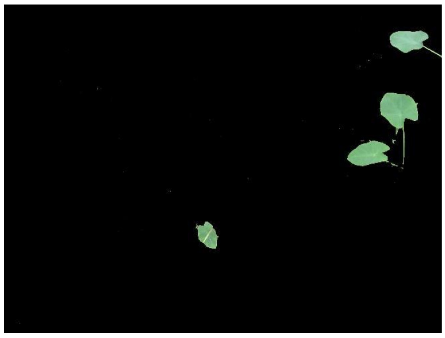
3.2 Dataset Description

In the South India region where these images were taken in the paddy field, three types of weeds are prevalent. These weeds are Grass (Echinochloa crus-galli), sedges -Cyperus difformis) and broadleaved weed (Monochoria vaginalis). Since in the paddy fields there is no clear demarcation between paddy and weed growth, the images captured for this research also have both weeds and paddy visible in the same image. Hence in this research, the objective was not only to differentiate different kinds of weeds, but also to identify the weed type amongst paddy. To clearly achieve both goals the research and the dataset were divided into two subparts:

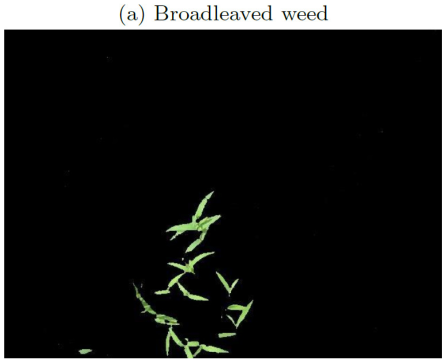
(a) Grass weed

(b) Sedges weed

Fig.5: *Images with one plant type (from the first dataset).*

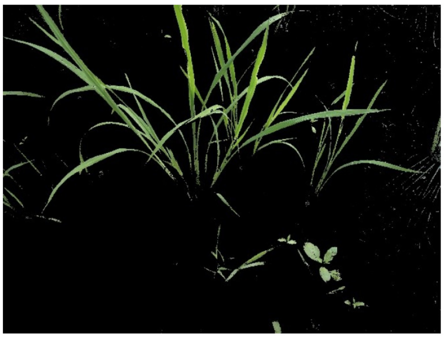


(a) Broadleaved weed



(b) Grass weed

Fig.6: *Images with only one plant type (from the first dataset).*



(a) Paddy field image after removing soil background

(b) Paddy field image after removing soil background

Fig.7: *Images with more than one plant species (from the second dataset).*

The first part of the research uses Dataset-1, which has images that consist of only one type of plant (isolated images). The possible plant types are grass, broadleaves weed, sedges, and paddy. The focus during this subpart is to show that the model can differentiate between all four classes distinctly. Dataset-1 contains a total of 2063 images. 18% of each class is split into the testing set and the rest of the images are used for training the model.

The second part of the research uses Dataset-2 which consists of images with more than one plant type along with the isolated images of Dataset-1. This dataset has three classes : broadleaves weed, sedges, and grasses. The images in this dataset have weeds along with paddy, which is the natural scenario of any paddy field. Using this dataset, the model can classify the type of weed even in the presence of paddy in the image. Dataset-2 contains a total of 2878 images. 18% of each class is split into the testing set and the rest of the images are used for training the model.

The distribution of images in the training and test sets is given in Table 1 for Dataset-1 and Table 2 for Dataset-2.

(a) Paddy field image after removing soil background

(b) Paddy field image after removing soil background

Fig.8: *Images with more than one plant species (from the second dataset).*

Table 1: *Dataset-1 Description*

Class	**Train**	**Test**	**Total**
Broad-Leaved	365	80	445
Grass	652	143	795
Paddy	356	78	434
Sedges	319	70	389

Table 2: *Dataset-2 Description*

Class	**Train**	**Test**	**Total**
Broad-Leaved	752	165	917
Grass	1134	249	1383
Sedges	474	104	578

3.3 Method

Convolutional Neural Networks are often used for computer vision tasks such as image classification, object detection, and image recognition. When an image is an input in a CNN model, each layer generates several activation maps. Each layer is responsible for extracting features. As layers increase, the features to be extracted move from basic to complex.

In the first model of this research, a Simple Convolutional Neural Network has been implemented. It has 3 Convolutional and MaxPool layers followed by 2 fully connected layers. A Dropout layer was added between the two fully connected layers to reduce overfitting. In the last layer, a softmax activation function was used.

The second model implemented in this research was AlexNet. In 2012, AlexNet achieved state-of-the-art accuracy against other computer vision techniques at that time [56]. It has 5 convolutional and

Table 3: *Hyperparameters for the models*

Models	Optimizer	Batch Size	Dropout Rate	Learning Rate
VGG-16	SGD (momentum 0.9)	64	0.3	0.001
Resnet-50	SGD (momentum 0.9)	32	0.3	0.001
AlexNet	Adam	32	0.3	0.0001
Simple CNN	Adam	32	0.5	0.001

Table 4: *Evaluation parameters for the multi-class classification problem*

Evaluation Parameter	Formula	Describes
Accuracy	$\left(\sum_{i=1}^{l}\left(\left(TP_{\mathrm{i}}+TN_{\mathrm{i}}\right)/\left(TP_{\mathrm{i}}+TN_{\mathrm{i}}+FP_{\mathrm{i}}+FN_{\mathrm{i}}\right)\right)\right)/l$	Average per class effectiveness of the classifier
Recall	$\left(\sum_{i=1}^{l}TP_{\mathrm{i}}/\left(TP_{\mathrm{i}}+FN_{\mathrm{i}}\right)\right)/l$	An average per-class effectiveness to of a classifier identify class labels
Precision	$\left(\sum_{i=1}^{l}TP_{\mathrm{i}}/\left(TP_{\mathrm{i}}+FP_{\mathrm{i}}\right)\right)/l$	An average per-class of the agreement data class labels with those of a classifiers
F1-Score	$\left(\sum_{i=1}^{l}\left(\left(2\times TP_{\mathrm{i}}\right)/\left(\left(2\times TP_{\mathrm{i}}\right)+TN_{\mathrm{i}}+FP_{\mathrm{i}}+FN_{\mathrm{i}}\right)\right)\right)/l$	Relates the real positives with those given by the classifier based on per-class average

max-pooling layers followed by 3 fully connected layers. A Relu activation function is used after every convolutional and fully connected layer. It has over 62 million trainable parameters.

The VGG-16 model was implemented next in this research. The Visual Geometry Group proposed the VGG architecture which is very appealing because of its uniform architecture [57]. Three VGG-E models VGG-11, VGG-16, and VGG-19, were created that contained 11,16, and 19 layers respectively. In this research, the VGG-16 model was used. It contains 13 convolutional layers (along with few max-pooling layers) followed by 3 fully connected layers. VGG-16 has a total of 138 million parameters.

Residual Neural Network was proposed by [58]. It was the fourth model implemented in the research. ResNet-50 has 48 convolution layers, 1 max-pooling layer, and 1 fully connected layer. ResNet is able to train ultra-deep neural networks with the help of residual learning frameworks. It has over 25 million trainable parameters.

In this research, the paddy-weed dataset was trained and tested on four different models. The Google Colab was used for the implementation of this research work along with the Keras and Tensorflow APIs. The various models mentioned above were implemented and modified based on our project needs. Transfer learning was used in the VGG-16, Resnet-50, and Alexnet models to get better results. Pre-trained weights from Imagenet were used in the initial layers of the models. To minimize the overfitting of models, a dropout layer was added. Extensive hyperparameter tuning was performed on all four models using GridSearch with a k-fold cross-validation set (cv=5) technique to customize the model to the given dataset. Parameters that were tuned are Optimization Algorithms, Learning Rate, Dropout Rate, and Batch Size. The models were trained with different optimizers: Stochastic Gradient Descent (SGD), Adam, and RMSProp. Models were also trained using different batch sizes (16,32,64), dropout rates (0.3,0.4,0.5) and learning rates (0.01,0.001,0.0001). These parameters with above mentioned hyper-parameter values were placed in a grid and every combination of hyper-parameter values was tested using k-fold cross-validation. In k-fold cross-validation, the dataset is split into k groups, in which one of these groups is taken as the test set and k-1 groups as the training set. This process is repeated for each group being the test set and the average of the models is used as the result. This grid search CV was performed for the four models and the hyper-parameter values for which we received the best accuracy are recorded in Table 3.

4. RESULTS AND DISCUSSIONS

According to [59], to evaluate the performance of the classifier in a multi-class classification case, for each separate class C_{i}, the TP_{i}, TN_{i}, FP_{i}, FN_{i}, $\mathrm{Accuracy}_{\mathrm{i}}$, $\mathrm{Recall}_{\mathrm{i}}$, and $\mathrm{Specificity}_{\mathrm{i}}$ can be calculated from the counts, $\mathrm{count}_{\mathrm{i}}$ from each class C_{i}. The performance of the classifier is calculated in two ways, one using macro-averaging and another using micro-averaging. In the case of macro-averaging, an evaluation param

eter is the average of the same parameter. In the case of micro-averaging, the cumulative sums of counts to get the cumulative values of TP, TN, FP, and FN are

Table 5: *Result of Dataset-1*

Class	Precision				Recall				F1 Score			
	VGG16	**AlexNet**	**ResNet-50**	**Simple CNN**	**VGG16**	**AlexNet**	**ResNet-50**	**Simple CNN**	**VGG16**	**AlexNet**	**ResNet-50**	**Simple CNN**
Broad- Leaved	0.98	0.59	0.84	0.58	0.94	0.82	0.76	0.41	0.96	0.69	0.80	0.48
Grass	0.77	0.67	0.70	0.49	0.96	0.70	0.82	0.47	0.85	0.68	0.76	0.45
Paddy	0.82	0.62	0.77	0.56	0.69	0.66	0.68	0.83	0.74	0.64	0.72	0.67
Sedges	0.89	0.63	0.80	0.49	0.97	0.42	0.74	0.45	0.93	0.53	0.79	0.47
Macro-Average	0.87	0.65	0.78	0.53	0.89	0.65	0.75	0.54	0.87	0.63	0.78	0.54
Weighted Average	0.85	0.65	0.76	0.52	0.90	0.67	0.76	0.53	0.86	0.65	0.76	0.50

Table 6: *Result of Dataset-2*

Class	Precision				Recall				F1 Score			
	VGG16	**AlexNet**	**ResNet-50**	**Simple CNN**	**VGG16**	**AlexNet**	**ResNet-50**	**Simple CNN**	**VGG16**	**AlexNet**	**ResNet-50**	**Simple CNN**
Broad- Leaved	0.97	0.60	0.87	0.51	0.82	0.84	0.80	0.58	0.89	0.69	0.84	0.54
Grass	0.88	0.71	0.78	0.55	0.97	0.72	0.85	0.69	0.93	0.71	0.82	0.61
Sedges	0.88	1.00	0.82	0.52	0.88	0.38	0.72	0.32	0.88	0.55	0.77	0.41
Macro-Average	0.91	0.77	0.82	0.53	0.89	0.65	0.79	0.53	0.90	0.65	0.81	0.52
Weighted Average	0.91	0.73	0.81	0.53	0.91	0.69	0.80	0.58	0.90	0.67	0.82	0.55

Table 7: *Accuracy obtained by the models*

Dataset	VGG16	ResNet-50	AlexNet	Simple CNN
Dataset-1	0.88	0.78	0.64	0.51
Dataset-2	0.91	0.80	0.66	0.53

obtained and then evaluation parameters are calculated. In this study, macro-averaging is used since this will make all classes be treated equally, whereas micro-averaging helps bigger classes. The calculation of evaluation parameters for multi-class classification is shown in Table 4, where l is the number of Classes.

Table 5 shows the result obtained from Dataset-1 and Table 6 shows the result obtained by Dataset-2. Table 7 shows the accuracy obtained by the models.

The VGG16 model outperforms the other models. The VGG16 model's performance is good with both datasets. This means that the VGG16 model is able to identify the plants with 90% precision not only with isolated images but also with images with more than one plant species. In instances where class imbalance exists, majority class classifier accuracy is the minimum criterion. Both the trained VGG16 model and VGG16 test model obtained an accuracy of around 90%. This result is close to the result achieved by [41]. Even though [41 used semantic segmentation, their research is being used for comparison as it is also based on weed detection in paddy. Moreover, our work did not use any kind of data augmentation techniques, but only real-field images taken in actual field conditions. The ResNet-50 model achieved decent results. However, the performance of the AlexNet was very poor. The poor performance is a result of to class imbalance. This shows that the class imbalance hinders the performance of some models. Here class imbalance is improportionate distrubution of the samples among classes. The VGG16 and ResNet-50 models achieved good precision for sedges type weed and high recall for broadleaved weed.Since sedges constitute a minimum of 20% of dataset-2 it has minimum F1 score for all 4 models. Grasses constitute a maximum of 50% of dataset-2 and give the best F1 score result for all the 4 models. Dataset-1, which has isolated images and a fair balance of classes, gives a better F1 score for all 4 classes across models.

This research work demonstrated that the deep learning techniques are the best ways to achieve computer vision-based weed identification. We are of the opinion that the datasets used in this study were quite complex compared to other studies. Even though our dataset size is small, we could achieve good results with the VGG16 model.We believe that VGG16 models could achieve more than 95% accuracy with larger datasets. In [41], there were images with only one type of weed. However, our work captured all three broad categories of weeds found in paddy fields.

Computer-vision based weed detection techniques can be used to detect and identify weeds so that specific herbicides can be recommended to farmers. Through this study, we investigated the deep learning models in classifying weeds of paddy crop. Deep learning models such as VGG16, ResNet-50, and AlexNet were used in this study. The results showed that the VGG16 model achieved promising accuracy and outperformed the other two models.

The classification of weeds and paddy crop done by [53], [54], [55] using conventional machine learning techniques like SVM, Random Forest classifiers and multiple classifier systems gave a decent accuracy in a range from 80% to 90%. Conventional machine learning techniques inherently require domain expertise to construct the feature set and use it for classification. Deep learning techniques, on the other hand, use representation-learning that helps a machine to automatically discover discriminative features for classification or object detection [60]. Therefore, deep learning models are more suitable for in-field weed detection and identification problems. As a part of future work, we intend to expand the dataset with 3D images and work with the above deep learning models and analyze their performance. In addition, we are planning to carry out pixel-wise classification of paddy fields which could be used for selective herbicide spraying and also in the realization of effective weeding robots.

5. CONCLUSION

In this study, we investigated the performance of four deep learning models: AlexNet, VGG16, ResNet-50, and simple CNN. The models were used classification of three type of weeds of paddy fields: grass, sedges and broadleaved weed. The result obtained showed that the VGG16 model outperformed all other models with an accuracy of over 90%. The poor performance of other models may be the result of the imbalanced dataset. Thus, this research study showed that the class imbalance may be detrimental to the performance of the models. As a part of our future research work, we intend to develop an automatic herbicide spraying robot and herbicide recommendation system for weed patches in paddy fields.

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