ESTIMATION OF WEED DENSITIES FOR VARIABLE RATE HERBICIDE APPLICATION

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Muhammad Hamza Asad

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Muhammad Hamza Asad, candidate for the degree of Master of Applied Science in Electronic Systems Engineering, has presented a thesis titled, *Estimation of Weed Densities for Variable Rate Herbicide Application*, in an oral examination held on August 29, 2019. The following committee members have found the thesis acceptable in form and content, and that the candidate demonstrated satisfactory knowledge of the subject material.

External Examiner: Dr. Mohamed El-Darieby, Software Systems Engineering  
Supervisor: Dr. Abdul Bais, Electronic Systems Engineering  
Committee Member: Dr. Zhanle Wang, Electronic Systems Engineering  
Chair of Defense: Dr. Eman Almehdawe, Faculty of Business Administration
Abstract

Use of herbicides is rising globally to maximize crop yield and profitability. Herbicides negatively impact environmental health and biosphere. To lessen its negative effects, herbicides have to be applied judiciously on crops. Precision agriculture practices suggest adoption of site specific weed management techniques by exploiting patchy nature of weed distribution in the fields which requires accurate weed mapping. Despite recent technical advancement and growing awareness about environment protection, site specific weed management has not got traction in farmer community. In this thesis, endeavours are made to develop relatively simple site specific weed control method using weed density based variable rate herbicide application.

Soil, Water and Topography (SWAT) maps are being used by farmers for variable rate seeding and fertilizer in prairie lands of Canada. In this work, we investigate relationship between weeds and SWAT zones and present a new method for variable rate herbicide application which combines deep learning and SWAT maps. Average weed densities are estimated in each SWAT zone through deep learning based
semantic segmentation in order to help agronomist develop variable rate herbicide prescription. The study simplifies the weed detection system with the objective to enhance savings of herbicide quantities less costs involved in site specific weed control. Manual labeling bottleneck in semantic segmentation is addressed by labelling only weed pixels. Consequently, trained semantic models zeros out crop pixel along with background pixels. The developed model has the advantage to detect new types of weeds. Binary classification of images based on weeds is also studied in this thesis to compare deep learning models.

By investigating SWAT zones and weed density relationship, it is found that the zones with higher salinity, organic matter and water content contain higher density of weeds while the driest zones like eroded hill tops have few or no weeds at all. The crop specific semantic segmentation models have shown MIOU values greater than 80% and FWIOU values more than 97%. The trained models also show robustness in detecting unseen weeds. For binary classification problem of detecting weeds in Canola field, VGG19 has shown 100% accuracy compared to other deep learning architectures.
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<tbody>
<tr>
<td>ECPA</td>
<td>European Crop Protection Association</td>
</tr>
<tr>
<td>UAV</td>
<td>Unmanned Aerial Vehicle</td>
</tr>
<tr>
<td>SWAT</td>
<td>Soil Water &amp; Topography</td>
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<td>MLC</td>
<td>Maximum Likelihood Classification</td>
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<tr>
<td>CNN</td>
<td>Convolutional Neural Network</td>
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<tr>
<td>ReLU</td>
<td>Rectified Linear Unit</td>
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<td>DL</td>
<td>Deep Learning</td>
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<tr>
<td>IOU</td>
<td>Intersection Over Union</td>
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<tr>
<td>TP</td>
<td>True Positive</td>
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<td>TN</td>
<td>True Negative</td>
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<td>FN</td>
<td>False Negative</td>
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<td>FP</td>
<td>False Positive</td>
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<tr>
<td>HSI</td>
<td>Hue Saturation Index</td>
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<td>SVM</td>
<td>Support Vector Machine</td>
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</table>
FCN  Fully Convolutional Networks
HSI  Hue Saturation Index
MIOU Mean Intersection Over Union
FWIOU Frequency Weighted Intersection Over Union
Chapter 1

Introduction

1.1 Motivation

According to European Crop Protection Association (ECPA), 40% of crop yield is lost to pests, disease and weeds [3]. Unwanted weeds contribute to one third of these losses by sharing nutrients, moisture and sunlight with host plants [4, 5]. Herbicides application is the common way to control weeds. In USA, herbicides makes up to two third of all chemical applications to crops and its use has quadrupled since 1964 [6]. This ever increasing trend of herbicide application has rung alarm bells in environmental health circles. Recent research works have shown the toxic effects of herbicide chemicals like glyphosate (chemical being used since 1974) to human health [7]. Despite all concerns and recent technological advancements, use of glyphosate is still rising globally [8].

This necessitates that a balanced approach should be followed in using herbicides.
According to precision agriculture practices, herbicides application should be site specific. Site specific weed management has the potential to mitigate negative impact of herbicides on environment while ensuring profitability of the farmers [9, 10]. It requires accurate mapping of weeds on large scale in the field which is a challenging task due to spectral similarities between weeds and host plants. Numerous techniques are implemented to detect and locate weeds in field. However site specific weed management is not getting traction in farmer community because these techniques are complex, they lack robustness for application on mass level and spraying equipment suffers from limitations in applying variable rate herbicides in real time [11].

Taking aforementioned into account, it is needed to develop a simple site specific weed control approach which is robust, accurate and scalable. From costs and benefits point of view, potential savings achieved through reduction in herbicide use should exceed the costs incurring from weed detection system and precision herbicide implements.

1.2 Related Work

In literature, we find several works that study relationship between spatial distribution of weeds and soil types, water, organic content and PH levels. However, these relationships are not sufficient to universally predict weeds in field. Weeds are field specific therefore require weed scouting for each field separately. Weed detection
can be summarized into two main categories namely interline approach and intraline
approach. Interline approach makes assumption that crop is planted in rows and
everything between rows is weeds whereas intraline approach distinguishes between
weed and crop based on shape features. Deep learning has simplified the classifica-
tion as it automatically extract features out of images. To do pixel level classification
in images, semantic segmentation is widely employed. Semantic segmentation mod-
els are employed for weed detection and mapping. However, semantic segmentation
models in agriculture are either not trained on a real dataset due to unavailability of
pixel labelled data or they are trained on a very small labelled dataset. Consequently,
they do not generalize well on real datasets.

1.3 Problem Statement

Site specific weed control using variable rate herbicide requires two things. First is
accurate weed density estimation which entails detection and localization of weeds in
the field using field imagery. Second is quantization of variable rate herbicide based
on weed density, crop density, historical field records and landscape information like
topography, shape, soil type, organic and water content. Based on this information,
variable rate herbicide prescription is made by agronomist. Highlighted steps in
Fig. 1.1 encapsulates the problems addressed in this thesis.
There are three main components of site specific weed control [11]:

1. Weed Detection System
2. Weed Management System
3. Precision Control Implements

In this thesis, scope of site specific weed control is restricted to weed detection and weed management systems. We are employing semantic segmentation for weed detection and localization. While applying semantic segmentation to agriculture images, we are faced with manual labelling bottleneck. To deal with it, we are proposing two step manual labelling procedure. To quantize variable rates, we are using Soil, Water and Topography (SWAT) maps as these maps combine electrical conductivity, water and topography maps into a single layer and divides the land into 10 zones. Fig. 1.2
summarizes the methodology used in the thesis. The subsequent subsections discuss major steps briefly.

![Diagram of methodology steps]

**Figure 1.2: Major steps of methodology**

### 1.4.1 Image Acquisition

There are four main sources of image acquisition in precision agriculture namely satellites, plane, Unmanned Aerial Vehicles (UAVs) and ground moving equipments. Each has its own advantages and disadvantages. Satellite imagery has an advantage of providing imagery of crop field at higher geographical extent in a single pass. Though resolution of satellite imagery has improved recently yet operational flexibility of UAVs and ground moving equipment out weights satellite imagery. Similarly aerial imagery through customized planes is not preferred option due to high costs involved [12]. We propose image acquisition of crop fields based on SWAT map zoning either through UAV or ground moving equipment in a grid pattern.
1.4.2 Two Steps Manual Labelling

In first step, background soil and dead plants are segmented from foreground vegetation. We are performing background segmentation for two reasons. First is to label background pixels and second is to increase the accuracy of manual labelling process as with soil and dead plants in background, there is greater probability of missing weeds in larger images. The background segmentation techniques usually employ rule based colour segmentation which does not perform under varying light and weather conditions. To address this problem, we propose use of Maximum Likelihood Classification (MLC). Signature files in MLC are updated to account for change in sunlight and weather conditions. In second step, minority class pixels which is weeds in this case are labelled. Minority class labelling accelerates the whole labelling process.

1.4.3 Feature Extraction and Classification

In deep learning, feature extraction is an automatic step embedded in the algorithm and does not need to be done separately. There are many state of art classification techniques like VGG16, VGG19, RasNet, Xception and Inception which extract higher level features out of images and perform classification tasks. At pixel level classification, UNET and SegNET are widely employed. Here we apply all these techniques and compare them for image classification and semantic segmentation. The challenge with these techniques is unavailability of labelled data. In this thesis,
endeavours are made that as much images are labelled as possible.

1.4.4 Density Estimation

Once semantic segmentation models are trained on labelled dataset, weed and crop densities are estimated in each SWAT zone. These densities provide basis to agronomist for variable rate herbicide prescriptions in each SWAT zone.

1.5 Objectives and Contributions

The objectives of this thesis are listed below:

1. To compare deep learning models to classify high resolution agriculture imagery.
2. To investigate weed density relationship with SWAT zones.
3. To map weed densities in SWAT zones for variable rate herbicide application.

The contribution of this thesis can be summarized as:

- To best of our knowledge, SWAT zones are employed first time in variable rate herbicide application.
- Two step manual labelling process is adopted: First step is background labelling and second step is labelling of minority class pixels.
- Weed densities are estimated using semantic segmentation for wheat and canola crops.
• The proposed methodology uses a real manually labelled dataset for semantic segmentation.

1.6 Thesis Outline

The rest of thesis is organized as follows:

• Chapter 2: It gives overview of related research in the field of site specific weed control and discusses the challenges faced in weed classification, detection and mapping. It also presents the problems faced in adopting site specific weed control on mass level.

• Chapter 3: All three steps of weed mapping are presented in this chapter. Both image classification and pixel classification techniques are discussed in detail.

• Chapter 4: It presents results and discusses them.

• Chapter 5: It summarizes the thesis and its contribution. It also gives future recommendations.
1.7 List of Publications


Chapter 2

Related Works

In this chapter, we discuss spatial distribution of plants with respect to soil properties. We also review image acquisition and background segmentation techniques with respect to agriculture imaging. Thereafter, interline and intraline weed detection schemes are surveyed from literature. In the end of chapter, machine learning and deep learning techniques are reviewed.

2.1 Weed Distribution and Environmental Conditions

In this section, we are discussing weed distribution and relate it with soil properties. We also review the prospects for site specific weed control and discuss hindrances in its adoption at mass level.
2.1.1 Weed Distribution and Soil Properties

Distribution and diversity of weed patches are field specific. Soil properties, cropping year, type of weeds and adaptability character of weed with changing conditions are some of the many factors that explain patchy distribution of weeds [13]. Soil properties like pH, chemical composition, texture and organic matter are correlated with weed density. Positive and negative correlation depends upon weed type. Some weeds grow faster in one environment and other in different environment [14, 15]. Metcalfe at el. employ variogram for studying spatial relationship between soil and weed count [16]. Metcalfe at el. also study variation of organic matter and moisture content in the field. Weed patches are present in the areas of high organic matter and moisture content because herbicides have been less effective in zones of high water and organic content [17]. Similarly soil texture and soil pH variations are also related with weed density. Alkaline clay soils have more weed density as compared to sandy acidic soils [18, 19]. Korres at el. study relationship of soil properties and weed types with focus on weeds along highways [20]. In a recent study, Metcalfe demonstrates correlation between weed and soil properties to make prediction of weed patches in wheat field with the objective to do site specific weed control [21]. Most of the above cited studies are focusing on soil properties and weed distribution and some relate soil moisture content with weed distribution. SWAT zones based weed distribution is a potential area for investigation because SWAT maps combine soil, water and
topography in to a single layer of map [22].

2.1.2 Prospects for Site Specific Weed Control

Weeds’ patchiness character prompts site specific management [23]. The economic benefit of variable rate herbicide is estimated by accounting different costs. If only herbicide quantity is accounted then savings are more than 50% [24]. If modern technology adoption costs and herbicide costs both are included then return on investments is not always attractive for farmers. The cost of weed control technology decreases for bigger farm holding [25]. Garibay et al. study thresholding of weed densities with the objective to make herbicides economical [26]. Castaldi at el. employs UAV imagery to explore the economic potential of patch spraying and its effects on crop yield. He does not observe economic benefit of variable rate herbicide on uniform application beneficial for first year but in subsequent years fields with variable rate become more profitable [27]. Despite the economic and environments benefits, site specific weed control is not readily adopted by farmers due to lack of accuracy and robustness in weed recognition system and limitation in spraying machinery [11].

2.2 Computer Vision and Weed Detection

Spatial distribution of weeds depends upon many factors making its prediction difficult. Therefore, weed detection using computer vision techniques is widely studied.
Traditionally, weed detection involves following four steps [28]:

1. RGB or multispectral image acquisition through UAV or ground moving equipment.
2. Background and foreground (vegetation) segmentation.
3. Feature extraction from images like shape and colour.
4. Classification based on extracted features.

### 2.2.1 Image Acquisition and Preprocessing

Saari et al. study UAV mounted sensors which acquire multispectral images for forest and agriculture applications [29]. Once images are acquired, background segmentation techniques are employed as second step. Colour based separation of background and foreground techniques are employed like HSI (Hue Saturation Index) models and Otsu-Adaptive Thresholding [9,30]. However, these colour based segmentation techniques do not perform well under shadow and varying sunlight and weather conditions. Statistical techniques like Principle Component Analysis (PCA) and clustering algorithms are also used to separate background and foreground [31–34].

### 2.2.2 Feature Extraction and Classification

Feature extraction and classification techniques can be further categorized in two main classes, interline approach and intraline approaches. Interline approach makes
assumption that host plants are planted in lines and weeds are interline [35]. Bah et al. implement normalized Hough transform for crop row detection [9]. Guerrero et al. use geometric constraints for mapping region of interest [36]. This approach has two inherent disadvantage. First is misclassification of interline crop plants as weed and second is labelling intraline weeds as host plants.

Contrary to this, intraline approach assumes that weeds can be both interline and intraline [37]. Intraline approach requires texture and shape features to be extracted from weed and host plants to distinguish between weeds and crop plants [38]. Okamoto et al. employ wavelet transform to extract features for weed classification [39]. Lastly, different machine learning tools like Support Vector Machines (SVM) and Artificial Neural Networks (ANNs) are used to classify weeds and host plants based on extracted features [40,41].

### 2.3 Deep Learning

Deep learning has emerged as a powerful machine learning tool in the field of computer vision and imaging because of its ability to extract features automatically [41]. Dyrmann at el. detect the location of mono cot and dicot weeds in cereal field images using Convolutional Neural Networks (CNN) [42]. Yu at el. apply object detection techniques like VGGNet, GoogLeNet and DetectNet for detecting weeds in turf-grass.
Semantic segmentation techniques are also being implemented [43]. Bottleneck in semantic segmentation is pixel wise labelling of images. Dyrmann overcomes this problem by synthesizing training images and labels. Weeds and host plants are placed in randomly overlapping and non overlapping configurations [44]. Potena uses a small representative dataset to label large dataset for semantic segmentation [45]. To compensate the unavailability of large labeled data for semantic segmentation, Milioto at el. input vegetation indexes as additional variables to segmentation model [46]. Above mentioned studies train models based on either a small labelled real dataset or use synthetic datasets for semantic segmentation which means that model do not generalize well to real test data.

2.4 Summary

In this chapter we have discussed relationship of weed density and soil properties like texture, pH, chemical composition and organic content. We also explored the potentials and economic viability of site specific weed control. Chapter discusses the reason for slow uptake of site specific weed control in farmer community. All four steps of computer vision in weed detection system are surveyed. In last section, we presented related works involving deep learning techniques. Basing our literature done in this chapter, we explain a methodology in the next chapter which is simple and scalable.
Chapter 3

Methodology

This chapter provides details about methodology used in the thesis. We propose weed detection and weed management mechanism which involves SWAT maps, image acquisition, image preprocessing, image augmentation, image classification and semantic segmentation techniques. SWAT map zoning simplifies the whole process by limiting weed control mechanism to 10 or fewer rates of herbicides application. While background segmentation and minority class labelling speed up labelling process which has been a bottleneck in use of semantic segmentation for precision agriculture. Results of semantic segmentation are at least same and better in case of detecting new weeds which are not seen by the model before. The framework used in this thesis can be divided into two part. First part is model training where background segmentation, image preprocessing and manual labelling processes are learned.
by model. In second part, trained model is deployed to automate weed detection process. Deployed model is improved by ground truth verification process and model is updated by re-training on new information or points of confusion. Fig. 3.1 summarizes this framework:

![Weed detection framework](image)

**Figure 3.1: Weed detection framework**

### 3.1 SWAT Maps and Image Acquisition

SWAT map is a single layer map constructed from soil electrical conductivity map, water flow map and topographical layers. SWAT mapping is not based on satellite mapping rather it is done through a patented process using land survey [47] [22]. SWAT maps divides land into maximum of 10 zones. Brief characteristics of SWAT
zones are described below:

- **Zone 1 & 2**: These are the most driest parts zones, low in organic content. These zones mostly consists of hills, sand and eroded knolls. These are less fertile slopes and are low growth areas.

- **Zone 3 & 4**: Two zones consists of shoulder slopes around Zone 1 & 2 where water runs off. These are low in organic content.

- **Zone 5 & 6**: These are mostly flat areas with mid slopes and average organic content levels.

- **Zone 7 & 8**: These zones are toe slopes and lower flat areas with more water content.

- **Zone 9 & 10**: These are low lying wet depressions with saline characteristics. Organic content level of these areas is also high.

Variable rate fertilizer and seeding are being prescribed based on SWAT zones to achieve uniform maturity and yield in all zones. Zone 1 & 2 are not fertile, so seeding rate and fertilizer rate is set higher than average for these zones. Similarly, seeding rates are also set higher for saline zones like Zone 9 & 10 but fertilizers rate is reduced for saline zones [48]. Fig 3.2 refers to SWAT map of wheat field being investigated for variable rate herbicide application.
RGB images are collected from fields in early growth stage of crop using quad mounted camera in a way that each SWAT zone present in the field is adequately represented. For the purpose, images sample are taken every 60ft on 80 ft apart pass in a grid pattern.

### 3.2 Image Preprocessing

In image preprocessing, we will discuss two step manual labelling involving MLC for background segmentation and weed pixel labelling and data augmentation techniques.
3.2.1 Background Segmentation using Maximum Likelihood Classification

As a first step of manual labelling, MLC is used in this research for segmenting vegetation from background soil and dead plants. Training samples are selected from both background and green vegetation. Mean and covariance matrix are calculated from training samples called as spectral signatures. MLC is based on two main principles. First is Bayes’ Theorem and second is the assumption that training samples are normally distributed [49]. If class $i$ is represented by $C_i$ and the feature vector is represented by $v$ then Bayes’ theorem states that:

$$ P(c_i|v) = \frac{P(v|c_i) \times P(c_i)}{P(v)} $$  \hspace{1cm} (1)$$

The $v$ belongs to $C_i$ if the probability at Equation (1) is greatest among all classes which is binary classification in this case:

$$ P(c_i|v) > P(c_j|v) $$  \hspace{1cm} (2)$$

Whereas:

$$ P(v) = \sum_{i=1}^{N} P(v|c_i) \times P(c_i) $$  \hspace{1cm} (3)$$
Substituting Equation (1) in Equation (2), we obtain:

\[ P(v|c_i) \times P(c_i) > P(v|c_j) \times P(c_j) \]  

where \(P(v|c_i)\) is likelihood probability and the probability of class being existent in the image is \(P(c_i)\). In this case, the class probability is taken as same for vegetation and background. As \(v\) is normally distributed in all multispectral bands, \(P(v|c_i)\) can be given by following relationship:

\[ P(v|c_i) = (2\pi)^{-0.5} \times |Y_i|^{0.5} \times \exp\left(-\frac{1}{2}(v - z_i)^T \right) \times Y_i^{-1}(v - z_i) \]

where \(Y_i\) (covariance matrix) and \(z_i\) (mean) are spectral signatures calculated from training samples. To make MLC segmentation work in varying light conditions and shadowed images, spectral signatures are updated with changing light conditions, colour of vegetation and texture of background soil. In some images shadows of imaging equipment is also present which requires special attention. A single set of signature files like rule based colour segmentation does not work well for all datasets. It may compromise the quality of labelling. Fig. 3.3 shows the variations in dataset.

To address this issue, dataset is divided into batches of similar images after inspecting each of the image. Then similar group of images are fed at once to ARCGIS software package for selecting a representative training set to calculate spectral signatures for MLC segmentation [50]. After background is segmented, noise is removed from segmented images using median filter. Fig. 3.4b and Fig. 3.4d are background segmented images of Fig. 3.4a and Fig. 3.4b.
Figure 3.3: Examples of images with shadows, varying sunlight and colours
Figure 3.4: Background segmented images through MLC
3.2.2 Manual Labelling

Labelling of images at pixel level is a major bottleneck in employing semantic segmentation for precision agriculture. In agriculture, big labelled image data is not available [51]. In this thesis, we propose labelling only weed plants as weeds are the minority class. It is done for two main reasons: First the objective is to find weed density and second is to speed up manual labelling process. Manual labelling at pixel level is very tedious and time consuming. Minority labelling has significantly accelerated the labelling process. For manual labelling Labelme tool is used [52, 53].

Fig. 3.5 shows a sample image and its manual label for reference.

(a) Original RGB image with weeds
(b) Manually Labelled image

Figure 3.5: Manual labelling of weeds in RGB images using LabelMe
3.2.3 Data Augmentation

Data augmentation is a technique in which image data set is enhanced without actually capturing new data. In this thesis, it is applied to avoid overfitting and improve the performance of model in varied scenarios. Different type of augmentation methods are applied to data in a random fashion namely, horizontal flip, vertical flip, cropping, zero padding, scaling, shearing, rotation, noise addition and contrast variations. These augmenters are applied in random combination varying from 1 to 3 at a time. To speed up model training, image size needs to be decreased. Instead of compromising resolution, each image is split into four tiles with dimension 800 x 544. At the inference stage, images are stitched back to original size.

3.2.4 Feature Extraction

CNN has revolutionize image classification and segmentation due to its ability to automatically extract features. A typical CNN architecture consists of alternating convolutional and max pooling layers. Convolutional layer extracts features out of images while max pooling layers reduce the dimension of feature space. After these layers, there are fully connected layers and top most layer has usually softmax as an activation function for multi class classification. Addition of more layers, increases the ability to learn detailed features in the image but it also increases the complexity of the model and requires more computational power. Numerous deep learning CNN
architectures have been developed like VGG16 [54], RasNet50 [55], Inception V3 [56] and Xception [57]. We will further explore VGG16 and RasNet50 in detail as we are using these networks for feature extraction in semantic segmentation.

VGG16 uses simple 3 x 3 size kernel in convolution layers and 2 x 2 size in max pooling layer. There are two fully connected layers of size 4096. Rectified Linear Unit (ReLU) is the activation function in these layers whereas softmax is the activation function in top layer. Suffix 16 in VGG16 shows the number of weight layers. Fig. 3.6 refers to VGG16 architecture.

In RasNet, instead of using sequential layers in VGG16, micro-architectures are used where residues forward in the layers [58]. RasNet models are more deeper than VGG models but require less space for its weights due to global pooling layer instead of fully connected layers. Fig. 3.7 shows residue based micro-architecture in RasNet.
3.2.5 Semantic Segmentation

Semantic segmentation is classification of image at pixel level. Deep learning based semantic segmentation consists of two main blocks. One is encoding block and other is decoding block as shown in Fig. 3.8.

Encoding block extracts features by downsampling input image while decoding block upsamples the feature space to target labels. In this thesis we are using VGG16 and Rasnet50 as feature extractors. Architecture of decoding block depends upon meta-architecture scheme used for semantic segmentation. In some techniques, up-sampling is single stage and while others do it through multi stages. For semantic segmentation, we are using UNET and SegNet as meta-architecture schemes for weed mapping and density estimation [1, 2]
SegNet

SegNet is based on the concept of Fully Convolutional Network (FCN). In FCN, fully connected top layers are also replaced with convolutional layers [59,60]. Contrary to FCN, SegNet has staged upsampling decoder. Deconvolutional layers are transpose of convolutional layers. To help decoding blocks rightly upsample, indexes of max pooling layer are transferred from encoding blocks to decoding blocks. Contrary to other DL based techniques, SegNet performs well on small datasets [61]. Fig. 3.9 shows network architecture of SegNet.

UNET

UNET is also a Fully Convolutional Network (FCN). Unlike SegNet, in UNET, whole feature map is transferred from encoder block to decoder block which requires
Figure 3.9: SegNet meta-architecture [1]
more memory compared to SegNet. The skip connections between encoder and decoder blocks perform concatenation operation. The objective of concatenating skip connections is to combine local information extracted from encoding block with global spatial information. UNET also performs well on small datasets [62]. Fig. 3.10 refers to typical UNET architecture.

![Figure 3.10: UNET meta architecture [2]](image)

**3.2.6 Weed Density Estimation**

After weed mapping through semantic segmentation, weed density is estimated. Two types of weed densities are calculated. One parameter is average weed density
in each zone given by following equation:

\[
\text{Average Weed density} = \frac{\text{Weed pixels in zone}}{\text{Total pixels in zone}}
\]  

(6)

Other density parameter is weed patch density in each SWAT zone. The rationale of calculating this density is to estimate the density of weed patches. Weed patch density is estimated by following equation:

\[
\text{Average Patch density} = \frac{\text{Weed pixels in zone}}{\text{Total pixels of only weedy images of a zone}}
\]  

(7)

3.3 Summary

In this chapter, we have introduced the techniques and algorithms used in our site specific herbicide control. We discussed about SWAT maps, image acquisition method, MLC, manual labelling, augmentation techniques, CNN architectures and semantic segmentation architectures. Next chapter is result and analysis chapter which presents results and makes discussion on them.
Chapter 4

Results and Analysis

In this chapter, metrics are discussed for comparing and evaluating models. We present results for two case studies. Case Study-I deals with binary classification problem of weedy and non-weeds images of Canola field. Semantic segmentation models are also trained for canola field. In Case Study II, three wheat fields are investigated for SWAT zone - weed density relationship. Also, semantic segmentation models are tested on these fields for estimating density. The chapter also makes discussion about results.

4.1 Evaluating Metrics

Below is the brief discussion about metrics used for evaluation of image classification and segmentation models.

1. Majority Class Classifier (MCC) is selected as base model for comparison. In
case of class imbalance data, MCC accuracy serves as bottomline accuracy above which trained models should perform [63]. MCC is given by following equation:

\[
MCC\text{Accuracy} = \frac{\text{Majority Class Instances}}{\text{Total Instances}}
\]  

(1)

2. Precision score is the percentage of rightly classified positives. It measures the exactness of model. Precision is given by following equation:

\[
\text{Precision} = \frac{\text{True Positives (TF)}}{\text{True Positives(TF) + False Positives(FP)}}
\]  

(2)

3. Recall score is percentage of relevant instances rightly classified out of all relevant instances

\[
\text{Recall} = \frac{\text{True Positives(TP)}}{\text{True Positives(TP) + False Negatives(FN)}}
\]  

(3)

4. F1 score combines precision and recall into one metric which is harmonic mean of precision and recall.

\[
F1 = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}
\]  

(4)

5. Intersection Over Union (IOU) is a common metric used in semantic segmentation and object detection to measure positional correctness of predicted class labels. Intersection signifies the area of overlap between predicted and ground truth while union is total area of predicted class and ground truth after adjustment of overlap.
area. Ideally, area of overlap and area of union should be equal resulting in IOU value
of 1. IOU is given by below equation:

\[
IOU = \frac{\text{Area of overlap}}{\text{Area of union}}
\]  \hspace{1cm} (5)

6. Mean Intersection Over Union (MIOU) is average of IOUs of each class given
by following equation:

\[
MIOU = \frac{IOU_i + IOU_j}{k}
\]  \hspace{1cm} (6)

where \( i \) and \( j \) are pixel classes and \( k \) is number of classes which is 2 in our case.

7. Frequency Weighted Intersection Over Union (FWIOU) is superior than raw
MIOU because it gives importance to each class based on its representation in data.

\[
FWIOU = w_i \times IOU_i + w_j \times IOU_j
\]  \hspace{1cm} (7)

where \( w_i \) and \( w_j \) are the weights of each class.

### 4.2 Case Study I

The data for case study-I is provided by SAIRS Ltd. It consists of 906 images
with 442 non-weedy images and 464 weedy images belonging to two different growth
stages. For semantic segmentation, only single growth stage is considered.
4.2.1 Binary Classification

In the first case study, high resolution imagery from Canola field is used to train binary classification models. It classifies images into weed or no weed images. For the evaluation purpose, dataset is randomly divided into training and test data of sizes 85% and 15% respectively. In preprocessing steps, the RGB image data is normalized between 0 and 1. Tools used in the study are ARCGIS for MLC and Keras running on Tensorflow (Python 3.6) for CNN based classification. To speed up the model training, NVIDIA GPU support is employed. To compare results, different CNN architectures like VGG19, Xception and Inception V3 are trained by unfreezing their top layers for fine-tuning to new data set. All models are trained for 50 epochs. Fig. 4.1 shows loss and accuracy curves.

Table 4.1 compares the CNN models on loss, accuracy, recall, precision and F1 score metrics. The performance of VGG19 is better than other two models with better model fit having the lowest loss on training and test data sets while the test and training accuracies are 100%. Other models have also accuracies more than 95% but these models are readily over fitting the data. Inception V3 shows the poorest performance among all three models owing to the depth of the network and relatively smaller data set resulting in an over fit model (see Fig. 4.1a ). The recall score is relatively lower than precision score for Xception and Inception V3 models which means models can not detect some of the images with weeds. For visualization how
Figure 4.1: Loss and accuracy curves of VGG19, Inception V3 and Xception Networks
well the proposed methodology is successful in classifying canola and weeds, result images are shown in Fig. 4.2. Fig. 4.2a and its background subtracted image Fig. 4.2b contain majority of host plant and just one weed plant and it is rightly classified by the proposed methodology as a weedy image. However, the proposed methodology has its limitation that it does not distinguish between images with one weed plant or numerous weed plants. Next section endeavours to address this problem by mapping weeds on each image for calculating weed densities. Using weed densities multiple (more than two) herbicide application rates are made possible on field.

Table 4.1: Model comparison

<table>
<thead>
<tr>
<th></th>
<th>Xception</th>
<th>VGG19</th>
<th>Inception V3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training Loss</td>
<td>0.0193</td>
<td>0.0014</td>
<td>0.0000</td>
</tr>
<tr>
<td>Test Loss</td>
<td>0.095</td>
<td>0.0087</td>
<td>0.11</td>
</tr>
<tr>
<td>Training Accuracy</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Test Accuracy</td>
<td>98.52%</td>
<td>100%</td>
<td>96.32%</td>
</tr>
<tr>
<td>Precision Score</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Recall Score</td>
<td>0.97</td>
<td>1.00</td>
<td>0.9264</td>
</tr>
<tr>
<td>F1 Score</td>
<td>0.9848</td>
<td>1.00</td>
<td>0.9618</td>
</tr>
</tbody>
</table>

4.2.2 Semantic Segmentation

Four semantic segmentation models of UNET and SegNet each with VGG16 and Rasnet50 as base models are trained on case study-I canola field dataset. Data set is split into training set and test set of 85% and 15% respectively. Prior to training, training data is further split into training and validation sets of 85% and 15%.
Figure 4.2: Sample classified Image using VGG19 through proposed methodology. Images courtesy of SAIRs Ltd.
respectively. All models are trained for 100 epochs with Adadelta [64] as optimizer. Fig. 4.3 shows the convergence curves for trained models. It is observed that SegNet meta-architecture converges faster than UNET on given dataset. In SegNet, both validation and training loss curves do not vary much beyond 50th epoch.

Table 4.2 compares models on accuracy, IOU, MIOU and FWIOU metrics for test dataset. SegNet and UNET with Rasnet50 as base model are out performing VGG16 based models. If we compare SegNet and UNET meta architectures, SegNet performs slightly better than UNET. Accuracy is of the trained models is very high which can be misleading as background and crop pixels are majority class. In scenarios where class imbalance exists, majority class classifier accuracy is minimum criterion above which trained models should have accuracies. Our trained model exceeds majority class classifier accuracy of 98.23%. This problem is addressed by IOU metric which provides criterion for each of class separately. Ideally, IOU value should be one. In our case, IOU of weed class is critical in accurate weed mapping and density estimation. Rasnet50 based SegNet model has highest IOU for weeds. Similarly, MIOU and FWIOU are also highest for Rasnet50 based models.

Table 4.2: Model Comparison

<table>
<thead>
<tr>
<th>Models</th>
<th>Accuracy</th>
<th>F1-Score</th>
<th>IOU Non-Weed</th>
<th>IOU Weed</th>
<th>MIOU</th>
<th>FWIOU</th>
</tr>
</thead>
<tbody>
<tr>
<td>UNET_VGG16</td>
<td>0.9906</td>
<td>0.9952</td>
<td>0.9905</td>
<td>0.57</td>
<td>0.7805</td>
<td>0.9830</td>
</tr>
<tr>
<td>UNET_Rasnet50</td>
<td>0.9928</td>
<td>0.9964</td>
<td>0.9927</td>
<td><strong>0.6622</strong></td>
<td>0.8274</td>
<td>0.9868</td>
</tr>
<tr>
<td>SegNet_VGG16</td>
<td>0.9911</td>
<td>0.9955</td>
<td>0.9910</td>
<td>0.5930</td>
<td>0.7920</td>
<td>0.9839</td>
</tr>
<tr>
<td>SegNet_Rasnet50</td>
<td>0.9948</td>
<td>0.9929</td>
<td><strong>0.9928</strong></td>
<td><strong>0.6648</strong></td>
<td><strong>0.8288</strong></td>
<td><strong>0.9869</strong></td>
</tr>
</tbody>
</table>
(a) UNET with VGG16 as base model
(b) UNET with RasNet50 as base model
(c) SegNet with VGG16 as base model
(d) SegNet with RasNet50 as base model

Figure 4.3: Convergence curves of trained models for 100 epochs
Comparing these results with other similar works like Xu Ma et al.’s recent work on weed detection in rice field, it is found that SegNet is performing better than UNET architecture [65]. Similarly, proposed methodology has shown an improvement of 24% and 16% in MIOU and FWIOU respectively. In the methodology used in this paper regarding manually labelling only weed pixels results in better performance because the number of labelled images are significantly increased. The trained semantic models zero out crop pixels along with background pixels. Crop pixels are not separately classified because the objective of the study is to estimate weed density \( w_d \) for variable rate herbicide application. However, crop density \( c_d \) can be estimated by subtracting weed density from background segmented vegetation density \( v_d \) given by following equation:

\[
c_d = v_d - w_d
\]  

(8)

Fig. 4.4 shows original images and heatmaps of weeds as predicted by Segnet Rasnset50.

In this test image, there are canola plants and two types of weeds. The models combines two types of weeds into one class and crop and background into other class. It is a binary classification of pixels. Though it is difficult to ascertain that what is being learned by model during training yet it is intended that model learns shape of crop plants and clubs it with background and everything other vegetation in the image is labelled as weeds. Advantage of this scheme is developing a simplified fast method
Figure 4.4: Original RGB test images and predicted heatmaps

(a) Original RGB Image-I from test dataset
(b) Predicted weeds heatmap of Image-I

(c) Original RGB Image-II from test dataset
(d) Predicted weeds heatmap of Image-II
for labelling of weeds which is extremely difficult and tedious if we manually label each and every pixel. Higher IOUs, MIOU and FWIOU are attributed to a relatively bigger dataset for model training. UNET and SegNet work good on small dataset but higher training instances increase model’s ability to generalize well. However, there is one disadvantage of this methodology it requires crop specific model training which is manageable in Canadian Prairies because of small crop mix. Fig. 4.5 and Fig. 4.6 shows original test images and their predicted weed heatmaps for the points where model fails to distinguish between weeds and canola plants.

One of the most common point where model confuses is stem part of canola plants as highlighted in Fig. 4.5a. Model classifies canola stem pixels as weeds confusing it with grass weed or wheat plants. Though model is good at mapping weeds in canola lines but it confuses sometimes in images where weeds leaves overlap canola leaves. In Fig. 4.6a wheat leaf is overlapping canola leaf. Model fails to map wheat leaf as shown in Fig. 4.6b.

4.3 Case Study II

The study is being conducted in collaboration with CropPro consulting, Canada. RGB images are collected from three wheat fields at early growth stage using quad mounted Sony DSC-RX100M2 camera. Field-1 has moderate level of weeds. Field-2 is highly weedy while Field-3 has very low or no weeds at all. Total 2109 images are
Figure 4.5: Original RGB test images and predicted heatmaps are highlighting the points where model confuses canola stems as weeds.
Figure 4.6: Original RGB test images and predicted heatmaps are highlighting the points where model fails on overlap points.
collected from these wheat fields taking samples from all available SWAT zones in those fields in a grid pattern of 60 ft by 80 ft. The data set is augmented to 4702 images using different combinations of techniques like flipping, rotation, shearing, scaling, noise addition, colour variations and blurry effects. The original images are resized and divided into four tiles of 800x544 to deal with memory constraints without compromising image resolution. Weed scouting is also performed by CropPro in these fields and they found 15 different types of weed in these wheat farms. Table 4.1 summarizes the type of weeds found:

<table>
<thead>
<tr>
<th>Table 4.3: Types of weeds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fox Tail</td>
</tr>
<tr>
<td>Lambs Quarter</td>
</tr>
<tr>
<td>Kochia</td>
</tr>
<tr>
<td>NF Catchfly</td>
</tr>
<tr>
<td>Dandelion</td>
</tr>
<tr>
<td>Volunteer Canola</td>
</tr>
<tr>
<td>Plaintain</td>
</tr>
<tr>
<td>Wormwood</td>
</tr>
<tr>
<td>Smart Weed</td>
</tr>
<tr>
<td>Hemp Nettle</td>
</tr>
<tr>
<td>Canada Thistle</td>
</tr>
<tr>
<td>Sow Thistle</td>
</tr>
<tr>
<td>Cattails</td>
</tr>
<tr>
<td>Field Horse Tails</td>
</tr>
<tr>
<td>Willow Herb</td>
</tr>
</tbody>
</table>

4.3.1 Weed Density and SWAT Zones

Two average density parameters namely average weed density and average weed patch density are calculated for each SWAT zone. Fig. 4.7a plots average weed density and average weed patch density against zone numbers for Field-1. Field-1 does not contain zone 1 & 2. Fig.4.7b lists number of images sample taken per zone. In Field-1, weeds are also sparse except in saline zones as evident from low average weed density parameter. In Zone 6 and onward, overall weed density increases modestly.
but average weed density in weed patches increases significantly especially in Zone 10. As using SWAT zones, variable seeding and fertilizer are being practised on these fields to maximize yield of the fields. Higher weed density at Zone 10 is attributed to its characteristic low lying topography and higher organic matter and moisture content. There are four different types of weeds present in Field-1.

In Field-2, there are more weed patches and patch density is also higher. 11 various types of weeds are found in Field 2. Fig. 4.8a refers to % density - zone graph. There is an increasing trend as we move from Zone 1 to Zone 10. In dry Zones 1, 2, 3 & 4, density rise is modest but as we go beyond that density rises sharply. Images are taken for these fields after rain which has resulted in higher average weed density and average weed patch density. Histogram of images samples per zone are shown in Fig.4.8b which indicates the extent of each SWAT zone presence in field.

In Field-3, average weed density and average patch density of SWAT zones indicate that there are few sparse weeds in the field. The trend observed in Field 1 & 2 is also not visible in this field as shown in Fig.4.9a. The field mostly consists of dry lands and there are few images of Zones 7,8,9 and 10. Fig.4.9b refers to distribution of images in each zone. Most of images are concentrated in Zones 1 - 6.

It can be observed that weed densities vary from field to field depending on other factors in addition to Zone type like rain and previous herbicides applications which means a universal zone specific herbicide rate can not be selected for every field.
(a) Field-1: Average weed density and average weed patch density

(b) Image Count per Zone

Figure 4.7: Weed density vs SWAT zones and image count per zone for field-1
(a) Field-2: Average weed density and average weed patch density

(b) Image count per zone

Figure 4.8: Weed density vs SWAT zones and image count per zone for field-2
(a) Field-3: Average weed density and average weed patch density

(b) Image count per zone

Figure 4.9: Weed density vs SWAT zones and image count per zone for Field-3
However, with in the field, weed densities are higher in wet and saline zones and these decrease in dry and high zones which necessitates that weed scouting should be done prior to selecting appropriate herbicide rate for each zone of a field. This is the point where Artificial Intelligence (AI) and DL play their role by automating weed scouting activity and finding weed density in each zone. Table 4.4, Table 4.5 and Table 4.6 summarize weed density details of Field-1, Field-2 and Field-3 respectively.

Table 4.4: Field-1 zone-wise weed densities

<table>
<thead>
<tr>
<th>Zone ID</th>
<th>Total Images</th>
<th>Weedy Images</th>
<th>Average Weed Density</th>
<th>Average Patch Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>41</td>
<td>1</td>
<td>0.0004878</td>
<td>0.02</td>
</tr>
<tr>
<td>5</td>
<td>33</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>90</td>
<td>04</td>
<td>0.00798</td>
<td>0.1795</td>
</tr>
<tr>
<td>7</td>
<td>64</td>
<td>02</td>
<td>0.0014</td>
<td>0.0365</td>
</tr>
<tr>
<td>8</td>
<td>56</td>
<td>6</td>
<td>0.03198</td>
<td>0.2985</td>
</tr>
<tr>
<td>9</td>
<td>46</td>
<td>6</td>
<td>0.0128</td>
<td>0.0981</td>
</tr>
<tr>
<td>10</td>
<td>43</td>
<td>16</td>
<td>1.3056</td>
<td>3.509</td>
</tr>
</tbody>
</table>

Table 4.5: Field-2 zone-wise weed densities

<table>
<thead>
<tr>
<th>Zone ID</th>
<th>Total Images</th>
<th>Weedy Images</th>
<th>Average Weed Density</th>
<th>Average Patch Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>78</td>
<td>43</td>
<td>0.56</td>
<td>0.65</td>
</tr>
<tr>
<td>2</td>
<td>131</td>
<td>105</td>
<td>0.57</td>
<td>0.6966</td>
</tr>
<tr>
<td>3</td>
<td>144</td>
<td>77</td>
<td>0.55</td>
<td>0.63</td>
</tr>
<tr>
<td>4</td>
<td>152</td>
<td>110</td>
<td>0.5595</td>
<td>0.74</td>
</tr>
<tr>
<td>5</td>
<td>124</td>
<td>92</td>
<td>0.8648</td>
<td>1.132</td>
</tr>
<tr>
<td>6</td>
<td>92</td>
<td>68</td>
<td>1.319</td>
<td>1.752</td>
</tr>
<tr>
<td>7</td>
<td>112</td>
<td>90</td>
<td>1.7106</td>
<td>2.11</td>
</tr>
<tr>
<td>8</td>
<td>81</td>
<td>72</td>
<td>3.5257</td>
<td>3.95</td>
</tr>
<tr>
<td>9</td>
<td>110</td>
<td>106</td>
<td>4.71</td>
<td>4.54</td>
</tr>
<tr>
<td>10</td>
<td>67</td>
<td>67</td>
<td>6.44</td>
<td>6.44</td>
</tr>
</tbody>
</table>
As explained in Section 3.1, 10 SWAT zones can be merged into 5 zones based on similarity in characteristics of consecutive zones. We also investigate relationship of merged zones with weed densities. It is observed that monotonically increasing trend is observed as we move from merged Zone 1 to 5 in Field 1 & 2. It means that there exists a strong relationship between weed density and merged adjacent SWAT zones except in Field-3 as shown in Fig. 4.10, Fig.4.11, Fig.4.12.

To quantify the strength of relationship between weed density and SWAT zones, correlation coefficients are calculated between weed densities and SWAT zones. It is found from correlation coefficients Field 1 & 2 that a positive relationship exists between weed densities (taking individual weed density of each image) and SWAT zones but it is a weak relationship. However, average weed density and average patch density have strong relationship with SWAT zones for these zones and it becomes more stronger with merged zones. In case of Field-3, negative correlation of -0.0032

<table>
<thead>
<tr>
<th>Zone ID</th>
<th>Total Images</th>
<th>Weedy Images</th>
<th>Average Weed Density</th>
<th>Average Patch Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>52</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>153</td>
<td>1</td>
<td>0.000257277</td>
<td>0.039361</td>
</tr>
<tr>
<td>3</td>
<td>131</td>
<td>4</td>
<td>0.0100474</td>
<td>0.2632</td>
</tr>
<tr>
<td>4</td>
<td>119</td>
<td>1</td>
<td>0.0000934</td>
<td>0.011</td>
</tr>
<tr>
<td>5</td>
<td>63</td>
<td>1</td>
<td>0.0008931</td>
<td>0.05626</td>
</tr>
<tr>
<td>6</td>
<td>40</td>
<td>4</td>
<td>0.003098</td>
<td>0.03098</td>
</tr>
<tr>
<td>7</td>
<td>19</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
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<td>13</td>
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<td>0.00348</td>
<td>0.04526</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Figure 4.10: Field-1 weed densities vs merged SWAT zones relationship

Figure 4.11: Field-2 weed densities vs merged SWAT zones relationship
Figure 4.12: Field-3 weed densities vs merged SWAT zones relationship shows that SWAT zones and weed density have no relationship as weeds are very sparse in this field. Average weed density and average patch density has negative weak relationship with SWAT zones due to two main reasons: Firstly, size of Zones 7-10 is very small than Zones 1-6 and secondly, weeds are sparsely distributed in the field with low densities per image. Table 4.7 summaries correlation coefficients between different density parameters and SWAT based zoning.

Table 4.7: Correlation coefficients between weed density and SWAT zones

<table>
<thead>
<tr>
<th>Density Parameters</th>
<th>Field-I</th>
<th>Field-II</th>
<th>Field-III</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weed Density</td>
<td>0.24</td>
<td>0.44</td>
<td>-0.0032</td>
</tr>
<tr>
<td>Average Weed Density</td>
<td>0.5902</td>
<td>0.8817</td>
<td>-0.1881</td>
</tr>
<tr>
<td>Average Patch Density</td>
<td>0.6102</td>
<td>0.9081</td>
<td>-0.3276</td>
</tr>
<tr>
<td>Average Weed Density (Merged Zones)</td>
<td>0.7217</td>
<td>0.7656</td>
<td>-0.3176</td>
</tr>
<tr>
<td>Average Patch Density (Merged Zones)</td>
<td>89.63</td>
<td>92.33</td>
<td>-0.4615</td>
</tr>
</tbody>
</table>
4.3.2 Semantic Segmentation

For semantic segmentation UNET and SegNet meta architectures are used with VGG16 and RasNet50 as base model respectively. Models are trained to classify image pixels into two classes namely weed class and background & crop plants class. Table 4.8 summarizes the hyper parameter settings for the two segmentation models.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iterations per epoch</td>
<td>512</td>
</tr>
<tr>
<td>Optimizer</td>
<td>Adadelta</td>
</tr>
<tr>
<td>Batch Size</td>
<td>2</td>
</tr>
<tr>
<td>No. of epochs</td>
<td>100</td>
</tr>
<tr>
<td>Input image height</td>
<td>544</td>
</tr>
<tr>
<td>Input image width</td>
<td>800</td>
</tr>
</tbody>
</table>

To evaluate and fine tune model on given image data set, it is divided into train, validation and test dataset with the split ratio of 70%, 15% and 15% respectively. Thereafter dataset is augmented to avoid overfitting and achieve better generalization. The trained model is evaluated on accuracy, precision, recall, F1 and IOU metrics.

Fig. 4.13 and Fig. 4.14 shows the training and validation curves for loss and accuracy of UNET and SegNet models. Higher accuracies and lower losses are partly due to imbalance dataset.

Table 4.9 summarizes the metrics for evaluation on test dataset. For comparison purpose, accuracy for majority class classifier (base model) is calculated which is 98.27%. Accuracy of the trained model using UNET exceeds MCC accuracy by 55.
Figure 4.13: Convergence curves for UNET models

(a) Training and validation loss curves for UNET

(b) Training and validation accuracy curves for UNET
Figure 4.14: Convergence curves for SegNet models

(a) Training and validation loss curves for SegNet

(b) Training and validation accuracy curves for SegNet
1.30% and using SegNet accuracy exceeds MCC accuracy by 1.37%. Similarly, F1 score for UNET and SegNet are 99.77% and 99.81% whereas IOU score of weeds for UNET and SegNet is 79.15% and 81.28% respectively. Similarly, MIOU and FWIOU values are higher for SegNet as compared to UNET. The proposed methodology for semantic segmentation has shown relatively better performance over wheat field as compared to canola field.

Table 4.9: Evaluation metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>UNET with VGG16</th>
<th>SegNet with RasNet50</th>
</tr>
</thead>
<tbody>
<tr>
<td>MCC Accuracy</td>
<td>98.27%</td>
<td>98.27%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>99.55%</td>
<td>99.62%</td>
</tr>
<tr>
<td>Precision</td>
<td>99.60%</td>
<td>99.71%</td>
</tr>
<tr>
<td>Recall</td>
<td>99.90%</td>
<td>99.91%</td>
</tr>
<tr>
<td>F1-score</td>
<td>99.77%</td>
<td>99.81%</td>
</tr>
<tr>
<td>IOU-Background and crop</td>
<td>99.55%</td>
<td>99.61%</td>
</tr>
<tr>
<td>IOU-Weeds</td>
<td>79.15%</td>
<td>81.28%</td>
</tr>
<tr>
<td>MIOU</td>
<td>89.35%</td>
<td>90.445%</td>
</tr>
<tr>
<td>FWIOU</td>
<td>99.19%</td>
<td>99.29%</td>
</tr>
</tbody>
</table>

From model comparison, it is evident that RasNet50 based SegNet model is performing better than VGG based UNET model on all metrics. Fig. 4.15 and Fig. 4.16 show how SegNet and UNET zero out crop pixels along with background pixels. It is observed from these images that SegNet predicted heatmaps have relatively sharp contours for weeds compared to UNET ones which might effect weed densities. The places of moderate crop-weed overlap are also mapped by these models.

As per developed methodology for Case Study-II, models are trained in a way that crop pixels and background pixels are classified in to one class and weed pixels
Figure 4.15: Weeds mapped on test images through SegNet and UNET.
Figure 4.16: Weeds mapped on test images through SegNet and UNET
to other class. This means semantic models should ideally learn shape features of crop and spectral properties of background and club them together into one class while labelling remaining pixels as weeds. It is pertinent to mention that there are no means available to ascertain that what model is actually learning except having clues from testing it on various images. If model is learning something close to ideal scenario then it should be able to map new types of weeds which were not included in data at learning stage. To test model performance on new types of weeds, images of wheat crop containing new weeds types are feed for inference. Fig.4.17a contains a new weed type called Horsetail (highlighted). The trained SegNet model successfully detects and maps the weed as shown in Fig.4.17b.

There are some points where models confuse weed and crop-background classes. In blurry images wheat plants are mapped as weed. Models fail to identify crop plants because of indistinct shapes. So, model labels every vegetation in the image as weed. At image preprocessing stage, training images were made blurry to improve models performance on blurry images. However, when model is confronted with blurry images like Fig.4.18, it fails to crop and weed pixels.

Model also confuses at edges of the images and the places where there exists a high level of overlap between weed and crop plants. Fig.4.19a refers to an image where a weed is overlapped with crop plants. In Fig.4.19b, model fails to map weed in image heatmap.
(a) Test image with new type of weed namely Horsetail.

(b) Horsetail detected and mapped by model

Figure 4.17: SegNet model performance on detecting new types of weeds
Figure 4.18: Examples of model confusion on blurry images
Figure 4.19: Heatmap of image without highlighted weed.
4.4 Summary

In this chapter, we compared performance of VGG19, Inception V3 and Xception for classification of Canola images. We also investigated weed density relationship with SWAT zones and observed increasing trend of weed density in wet, saline and low lying zones. There exists strong correlation between merged SWAT zones and weed density. Exception to this trend is observed in Field-3 because there are very few individual weeds found across field. SegNet and UNET model results are compared and analysed. This chapter also includes details on under and over performing points of SegNet and UNET semantic models.
Chapter 5

Conclusions and Future work

5.1 Conclusions

In this thesis, we have compared various deep learning techniques for classification of high resolution RGB imagery with the objective to make a binary decision for herbicide application. Secondly we have investigated weed density relationship with SWAT zones and made observations that low lying, wet and saline zones have more weed concentration than dry, less fertile high elevations. For merged SWAT, weed density exhibits a strong relationship with zones. Weed density monotonically increases as we move from dry to wet zones. However, SWAT zones and weed density may not show any relationship at all for sparsely placed weeds. At the end, we trained semantic segmentation models to estimate average weed density and weed patch density in each zone for a zone specific herbicide prescription map. Semantic segmentation has shown relatively better performance for wheat fields as compared to
canola one. When comparing UNET and SegNet, SegNet performed well over UNET. Similarly, Rasnet50 has shown better results than VGG16 as feature extractor.

By combining SWAT zones with semantic segmentation, three benefits can be realized. First benefit is to replace weed scouting activity with UAV / Quad mounting camera in SWAT zones. Second benefit is getting synergy by using already proven SWAT based variable rate fertilizer and seeding equipment and controllers for variable rate herbicides. Third benefit is the potential of using up to 10 different herbicides rates depending upon weed density in each zone which is better than uniform rate application field but less than a total instance based herbicide application. Using this simple technique, quantity of herbicides application can be reduced while not compromising its efficacy as studies involving real time weed detection applications and instance herbicide application demand speed and computation power and have risk of missing individual weeds which may develop as bigger weed patch in succeeding crop seasons. From semantic segmentation point of view, in this study manual labelling of images are accelerated by just labelling weeds and zeroing out crop pixels along with background pixels. This technique has one disadvantage that it requires training of crop specific semantic segmentation models. This work can be extended by training new models for other crops. As some weeds are SWAT zone specific like saline tolerant Kochia weed, relationship between SWAT zones and types of weeds can be a potential area of study for varying chemical composition of herbicides in
different SWAT zones.

5.2 Future Work

Following are the list of recommendations for furthering this research work.

- Model training on other crops to increase the practicality of this methodology.
- An improved model can be trained by increasing number and variety of weeds.
- Identification of critical weeds specific to SWAT zones which might need special herbicide composition.
- Studying the effects of SWAT based variable rate herbicide application on weed distribution in field for next sowing season.
- Investigating the prospects of extrapolating weed densities of SWAT zones for transition boundaries and filling the gap between sample points.
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