# Plant weed detection using Deep Learning

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**May 2021**

# Plant weed detection using Deep Learning

**Major Project**

Submitted in partial fulfillment of the requirements

for the degree of

Master of Technology in Data Science

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**May 2021**

# Certificate

This is to certify that the major project entitled **"Plant weed detection using Deep Learning"** submitted by **Anand Ruparelia (19MCED12)**, towards the partial fulfillment of the requirements for the award of degree of Master of Technology in Data Science, Nirma University, Ahmedabad, is the record of work carried out by him under my supervision and guidance. In my opinion, the submitted work has reached a level required for being accepted for examination. The results embodied in this Major Project Part-II, to the best of my knowledge, haven't been submitted to any other university or institution for award of any degree or diploma.

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# Statement of Originality

I, **Anand Ruparelia**, **19MCED12**, give undertaking that the Major Project entitled **"Plant weed detection using Deep Learning"** submitted by me, towards the partial fulfillment of the requirements for the degree of Master of Technology in **Data Science** of Institute of Technology, Nirma University, Ahmedabad, contains no material that has been awarded for any degree or diploma in any university or school in any territory to the best of my knowledge. It is the original work carried out by me and I give assurance that no attempt of plagiarism has been made.It contains no material that is previously published or written, except where reference has been made. I understand that in the event of any similarity found subsequently with any published work or any dissertation work elsewhere; it will result in severe disciplinary action.

Signature of Student

Date: 17/05/21

Place: Ahmedabad

Endorsed by

Dr. Jigna Patel

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# Acknowledgements

It gives me immense pleasure in expressing thanks and profound gratitude to **Dr. Jigna Patel**, Assistant Professor, Computer Science and Engineering Department, Institute of Technology, Nirma University, Ahmedabad for her valuable guidance and continual encouragement throughout this work. The appreciation and continual support she has imparted has been a great motivation to me in reaching a higher goal. Her guidance has triggered and nourished my intellectual maturity that I will benefit from, for a long time to come.

It gives me an immense pleasure to thank **Dr. Madhuri Bhavsar**, Hon'ble Head of Computer Science And Engineering Department, Institute of Technology, Nirma University, Ahmedabad for her kind support and providing basic infrastructure and healthy research environment.

A special thank you is expressed wholeheartedly to **Dr. Rajesh Patel**, Hon'ble Director, Institute of Technology, Nirma University, Ahmedabad for the unmentionable motivation he has extended throughout course of this work.

I would also thank the Institution, all faculty members of Computer Science and Engineering Department, Nirma University, Ahmedabad for their special attention and suggestions towards the project work.

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# Abstract

Weeds are the plants that grow along with the primary plant in agricultural crops. These undesirable plants compete with the main crop for core elements like water, sunlight and sometimes also for the fertilizers. This causes losses to the crop quality as well as to the crop yield. The conventional solutions to this weed menace is hand weeding but this process being labour intensive, costly  time-consuming, farmers have moved towards the use of herbicides. The latter method is effective but causes environmental as well as health concerns for humans who consume these vegetable crops. Hence, Precision Agriculture suggests the variable spraying of herbicides so that the primary plants are not affected by herbicide chemicals. So, site-specific weed management has been introduced for weed control by using Artificial Intelligence. In this project, Eggplant (Brinjal) vegetable crop has been taken into consideration for weed detection through semantic segmentation of the plant and non-plant (weed) parts from images. The dataset collection for the project was done manually by taking images from a private farm in Gandhinagar, Gujarat. The images also required ground truth for the learning purposes which were generated using external software tools. Deep learning models such as UNet & LinkNet with different backbone models were utilized for the segmentation purpose.LinkNet with backbone Mobilenetv2 and Resnet34 were used and UNet with backbone Inceptionv3 and Resnet18 were used. The best results are achieved using UNet with backbone Resnet18 for a mean IoU score of 0.89. With the help of this segmentation, precise location of weeds from images can be hence achieved.

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# Chapter 1

# Introduction

According to research statistics of Food and Agriculture Organization Corporate Statistical (FAOSTAT) Database [6], India is the second largest producer of Eggplant (Brinjal) in the world after China. In 2018, India produced over 12,826,000 tonnes of eggplant across the nation [7] , which signifies the importance and popularity of the crop. It is a principal vegetable crop grown throughout India except higher altitude areas [8]. Given the importance of eggplant in the economical context, it is necessary to use techniques that maximize the productivity and yield quality of the same.

## 1.1 Effect of weeds on crops & potential solutions

To enhance the productivity of the vegetable crop, various factors such as proper maintenance in terms of water and nutrition to the crop should be considered and along with that control over weeds. These unwanted plants that grow with the primary plant are of utmost importance. Weeds hamper the yield quality as well as the quantity because they compete with the main crop for space, light, nutrients and moisture [9]. Weeds pose a threat to the harvest operations and cultivation [10] and also prove to be a breeding place for different kinds of pests. So, it becomes absolutely paramount to minimize the losses caused due to weeds.

As per the estimates, crops tend to lose 20-80% of production to pests, disease and weeds [11]. A standard solution to avoid weed menace in vegetable crops including eggplants is herbicide application [12]. Though there is a constant change in the chemical composition and growing modern techniques, the trend of herbicide application to increase crop yield and for handling weeds is on a rise [13]. There are various concerns related to environmental as well as biological impact of chemical application on crops [12]. Apart from the previously mentioned demerits, high costs of herbicides and negative effects on human health are also few concerns [14]. Viewing from the crop angle too, excessive usage of herbicides can make the weeds develop a kind of resistance against the chemicals.

Few studies have shown that a common herbicide (Glyphosate) has toxic elements which are harmful for human beings [15]. Recently in the year 2020, the Ministry of Agriculture and Farmers Welfare (Government of India) has strictly advised to prohibit the use of Glyphosate. It is amongst the 39 widely used chemicals in agriculture by the farmers to control weeds [16]. Farmers also have the option of hand weeding in farms. Hand weeding is one of the techniques to manually detect weeds by naked eye and plucking them out by hand. This is a good option but to tackle the labour shortage and elongated time and money spent in the former option, farmers resort to herbicides that protect their yield production from weeds.

## 1.2 Introduction to site-specific weed management

A continuous research is in progress to control weeds with the use of biological methods like deploying natural microbes or insects that rely and feed upon weeds [17]. So that it reduces the negative impacts of herbicide chemicals. In the conventional times, herbicide application was at uniform rate for handling weed menace but as the practice is rising globally, we have to take into account the growing technology around Precision Agriculture (PA) which follows the practice of site-specific weed management (SSWM) [18] [19]. Though, adoption of PA practices for herbicide application demands perfect weed mapping with the accurate classification of weeds and the primary host plant.

There are many existing field mapping techniques which assume that the primary host plants are seeded in perfectly aligned rows. These are popularly known as line detection techniques which tend to classify plants in a row as the primary plant and the others falling outside of those seeding lines as weeds. Though, this approach heavily relies on crops seeded in lines itself. So instead of line techniques, intra-line techniques for weed classification are employed [20]

## 1.3 Deep Learning for weed detection

As discussed previously, taking into account the developing technologies such as Machine Vision (Computer Vision) and Deep Learning (DL), which would simplify the object detection task. These technologies are extensively investigated for identification of weeds [21] [22] . Conventional techniques such as image pre-processing, feature extraction, classification and segmentation are explored for weed detection [23]. The feature extraction process sometimes includes the hand-crafted feature extraction which are further utilized for the classification. This works pretty well when images are captured under perfect conditions and also at specific growth stages of the plant. With these technique, the classification accuracy reaches at a very good performance standard of around 80-95% accuracy [19]

This task in real classification on the field becomes challenging as the image quality while testing goes for a toss in weird lighting conditions, occlusion or even by overlapping the leaves of weeds as well as crops,etc [24]. These features are usually extracted from color, texture, shape and spectrum but these are not very robust which leads to low generic and poor results. Hence, the potential of Deep Learning has been utilized in Precision Agriculture, especially for weed detection. In comparison to conventional techniques discussed above, DL can learn the hidden feature expression and hierarchical insights from the images which helps to avoid the tedious process of extracting and optimizing the features which are hand-crafted [25]

## 1.4 Weed Segmentation

Usually, there are two methods found in DL for detecting objects (from images). The first one being, drawing boxes around the images and the other one being classification of object pixels. In addition, semantic segmentation is one of the most effective approaches for alleviating the effect of occlusion and overlapping since pixel-wise segmentation can be achieved. Some deep learning algorithms have been investigated for weed detection. The initial one being easier than labelling the object pixels but not an accurate one. So, pixel wise classification is preferred which is popularly known as "Semantic Segmentation" [12].

In this research project, the core objective is to do semantic segmentation of weeds from the crop images of eggplant which can further help in estimating the weed densities for successfully achieving site-specific-weed-management for herbicide application. For that, semantic segmentation on dataset images is done. The images are collected from eggplant fields. After that, few segmentation models such as UNet, LinkNet, and FPN are trained and tested. Lastly, the one with best performance is selected based on the evaluation metric chosen.

The rest of the report is divided into sections such as Motivation, Objectives  Contribution, Literature survey  related work, Research methodology, Results, Conclusions future work. The research methodology is divided into various phases such as Data Collection, Ground Truth Generation, Data Pre-Processing, Data Augmentation, Developing Segmentation Models, Metric Evaluation on Test Data.

## 1.5 Motivation

Since the rise of human civilization, development in agriculture has been propelling along with time and constantly evolving technologies. As per the statistics provided (2018) by, The World Factbook (also known as the Central Intelligence Agency World Factbook), the Agriculture sector adds around 6.4% of the total world's economic produce where the total produce of the sector lies around \$5,0854,800 million. China turns out to be the largest contributor and followed by it is India. China and India holds a major share percentage of total global agriculture production (19.49 and 7.39 percent respectively) [26]

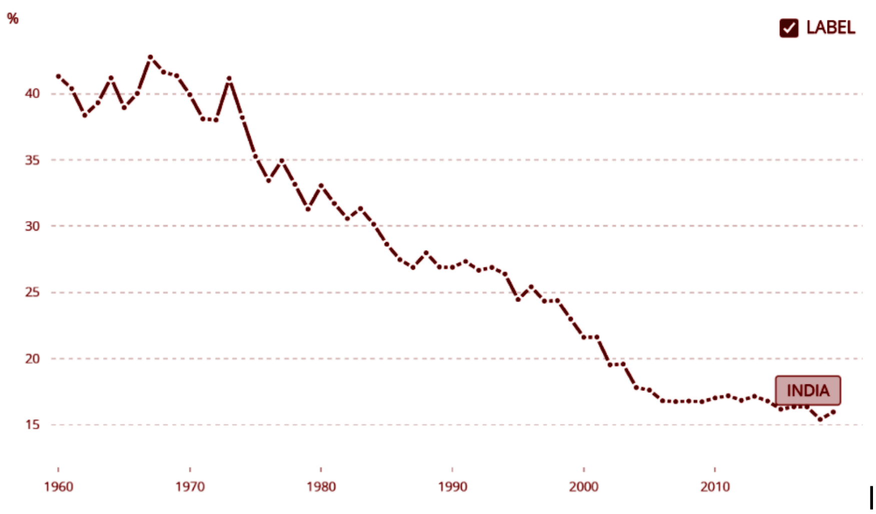


Figure 1.1: India's agriculture, forestry and fisheries contribution to GDP [1]

But, for many developing countries like India, as per World Bank, the GDP contribution of Agriculture, Forestry  Fishing combined is decreasing due to high and fast growth rates of services  industries sector as well as urban migration adds to the decline, and apart from the fact that India's agriculture sector holds a primary importance to the economy, there are few challenges such as unpredictable climate, weak supply chain and low productivity on raising agricultural productivity per unit of land that World Bank addresses for India's agriculture sector [27]

Although the challenges, As per the 2018 report of, The National Institution for Transforming India, also called NITI Aayog, agriculture and surrounding sectors hold around 49% of India's workforce, 16% of the country's Gross Domestic Product (GDP) and also ensures the food supply and security to around 1.3 billion people and in order to maintain the annual economic growth, agriculture and surrounding sectors should grow at 4% or higher rate.

Hence, economists and leaders of many countries have acknowledged and reverted impactful efforts towards the forefront significance of the Agriculture sector in their respective country's economy [28]. In many countries of the world, people have gradually developed knowledge and skills for raising better yields from lands through ancestral inherited techniques as well as with various researches  experimentations but with the advent of technology in agriculture, the sector reached new heights in terms of efficiency.

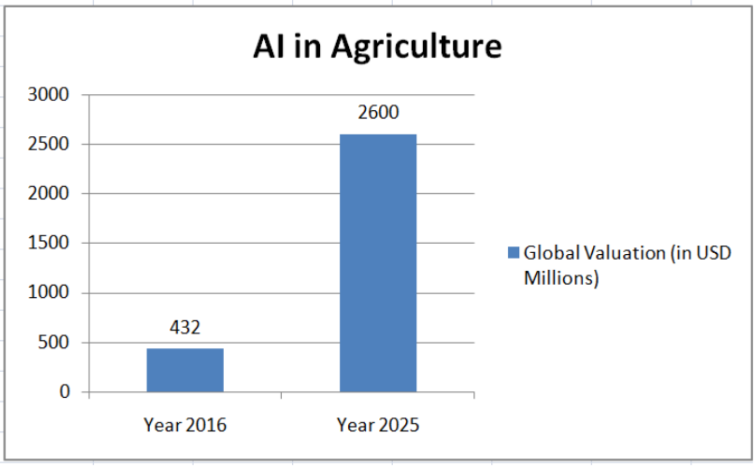


Figure 1.2: An estimate by Markets and Markets Research [2]

A research shown above in the Figure (1.2), forecasts a huge market evaluation of AI technology in agriculture and even the Agricultural tech startups have raised over 800 Million USD in the last 6 years globally. India today has almost 315 Million rural population using Smartphones & Internet.

Technology brought improvisations to irrigation systems, crop management, harvesting tools  equipments, predicting in-advance the ideal weather for sowing  harvesting, and finally Industry 4.0 which is the current state-of-the-art revolution, majorly focuses around implementing the technologies such as Internet of Things (IoT), Computer Vision, Artificial Intelligence (AI), Cloud/Cognitive Computing.

All these technologies have the potential to transform agriculture into a whole new dimension and AI is the one that's leading the race today. AI encompasses various aspects of farming and agriculture by increasing efficiency to yield healthy crops, monitor  survey crops  controlling pests  weeds. The subsets of AI such as Computer Vision  Deep Learning come into the scenario here as drones are enabled for capturing the field images/videos that identify the problem areas and predict the improvements beforehand without manual intervention  expertise.

Weed control is an important phase of farming, these unwanted plants compete with the real crop for light, water and nutrients that makes the growth of actual plants slow and more susceptible  vulnerable to destruction. Different weed management techniques are being incorporated by farmers as per the crop requirements.

Techniques such as manual weed pulling , animal grazing, flame weeding, and herbicide spraying are widely accepted for serving the purpose and the most common amongst them are manual weed pulling and herbicides [29]. Usage of herbicides is the most practiced way in developed countries whereas manual weed pulling is facing high costs due to the shortage of farm labourers in those countries [30].

Herbicides show good results over other methods but the indiscriminate and frequent usage of these chemicals is making the environment contaminated. As spraying of these herbicides is carried out to all the crops of a field regardless of crops being affected by the weeds [31].

This needs to be considered and as a part of the technological revolution, should be taken as a priority issue.

But, as the technological revolution is benefiting many sectors, agriculture is also a part of that revolution and AI can contribute to the issue by delivering solutions that cater the purpose efficiently.

## 1.6 Objectives & Contribution

### Objectives

The project objectives are mentioned below point-wise so as to stay definite on the project work as well as for betterment of the project report flow.

The objectives are listed below in a concise manner:

- Herbicide-Use Optimization
  - Saves farmers a lot of money on herbicides  aids organic farming
- Effective Site-Specific Weed Management
  - Only spraying herbicides to parts of plants that are affected with weed instead of spraying their entire fields with herbicide
- Reduce manual intervention & decrease laborious process
  - Hand weeding is a tedious process & much time consuming
- For cost-effectiveness in farm labour expenses
  - Shortages of labour has increased the cost of hand weeding
- Utilize the potential of "Precision Agriculture"
  - Technologies such as Deep Learning (DL) have been helpful in these tasks
- Improve the output metrics by proposed architecture of the model
  - Different researchers have applied various methods which would help in accomplishing the task

**Contribution:**

AI has the potential for transforming the agriculture sector and it also has been acknowledged by many researchers and scientists. Various researches have shown that, with computer vision and deep learning, weed identification can be automated due to which even, the naive farmers or farm labourers with less expertise can carry out the task of spraying herbicides on only the part of crops that are affected by the weeds and not disturbing the primary crop plant.

With the deep learning model trained on many images of plants with and without weeds, we can achieve segmentation of the weed plant from the primary crop plant picture and identify with that model's expertise by well enough accuracy that can make the process implicit and less tedious.

The research work carried out for this project deals with the weed control issue in eggplant vegetable crops. The dataset is collected manually from an eggplant field farm located near Kudasan, Gandhinagar - Gujarat. After multiple trials of dataset collection, one dataset was finalized having images under ideal as well as few rough conditions to make the model train in a better way. Ground truth related to the RGB images were generated manually using a tool and after that different segmentation models were experimented and the one with the best performance was selected for the segmentation task.

All the research project phases are discussed in upcoming sections of the report in a detailed manner. The first step before any research is carried out is to study what work has been done till now in the field of weed detection. Literature survey of the related work is therefore the initial step towards a successful research.

# Chapter 2

# Literature Survey

## 2.1 Literature Summary

The literature survey for the research work is carried out using the below shown (Figure 2.1) task flow in consideration. This flow helped us to remain concrete onto the objectives of the research project as well as helped in identifying the correct reference researches which are more aligned with the project objectives.

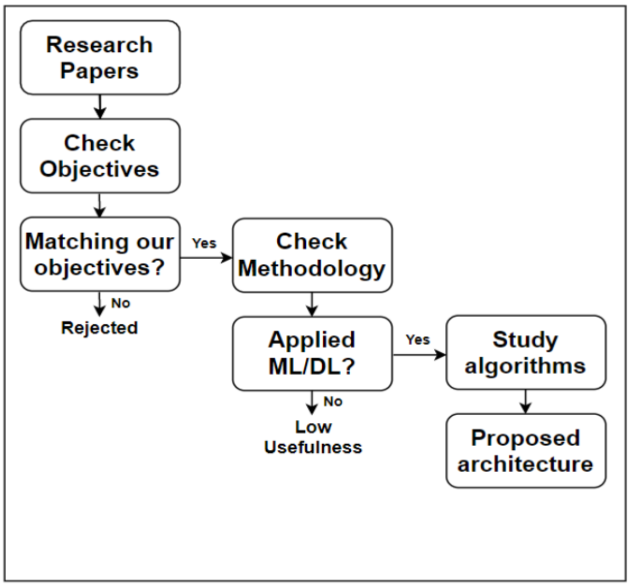


Figure 2.1: Task flow for literature survey

Identifying and classifying the research papers based on their usefulness (such as Low, Average High) aided in proposing the architecture of the project. It also helped in rejecting the researches which were either obsolete or not aligned with the project objectives of this research.

Each of the research papers are briefly explained in the following pages with their objectives, dataset description, classification methodology, results, limitations, and future scope.

This section is focused on the literature review of the research projects carried out for weed detection using various methodologies. As mentioned about the research paper usefulness technique followed for this research project, the survey would begin from the low usefulness papers and then slowly proceed towards average usefulness papers. Finally, it would conclude with the high usefulness papers and a comparison table showing the most important papers in summarized parameters with important attributes.

N.Wang et.al. [32] more than a decade before, devised a real-time embedded device for weed detection using sensors and a control module along with a global positioning system. The system was tested in two wheat fields. Though, the classification part was majorly dependent on the sensors which couldn't perform well when positions of the sensors were changed. Few years later Joaquín T.S et.at. [33] tried a 2 stage procedure on smooth ensembles of the neural networks for weed detection in orange groves. In the first stage, the main features of an image i.e Trees, Trunk, Soil and Sky are determined and in the second stage, weeds are detected from those areas which are determined as Soil in the first stage and as there can be color similarities between weed and orange leaves, applying color detection wont work here and so the above 2 stage method is developed but this research is not much useful as it uses algorithms to train that are obsolete today and event the dataset size is very small (10 training and 130 testing)

Sarmad H. et.al. [34] performed a research towards the detection of weed, wheat and barren land in a wheat crop field using background subtraction i.e image processing which is termed as a good method for the detection. The dataset is self-developed with the use of a drone (UAV) with 4000 x 3000 pixels resolution in a format of JPEG. The classification part is done using computer vision and image processing techniques. The results achieved (99%) are good enough but it is only good for detection of the weed, barren land, and wheat.

Few researchers such as M. Pérez-Ortiza et.al. [35] worked on a semi-supervised system for mapping weeds in sunflower crops but the framework is highly focusing on the row plant images taken from distant height whereas our dataset is plant level and zoomed till plant leaves and weeds. One another research by Victor Partel et.al. [36] developed a low-cost technology for precision weed management which aligns with our objective of effective herbicide application but after the classification of the plants and weeds using DL algorithms, the research lacks comparison with the traditional broadcast sprayers that are usually employed to treat the entire field to control pest.

Graph based deep learning methods for weed detection are also used by Kun Hua et.al. [37]. Graph Convolutional Network which generally targets to identify multiple types of weeds from RGB images taken in complex environments having multiple, overlapping weed and plant species in highly variable lighting conditions. Classification (here recognition) is done using ResNet-50 backbone and DenseNet-202 backbone with 5 cross fold validation and Res-Net50 backbone achieved the state of the art performance i.e Graph Weeds Nets. The limitation of this research is basically done for many different types of weeds and not specifically targeting any vegetation crop or plant. Though, the main essence from the paper achieved is the use of convolutional networks for better classification.

Along with the latest deep learning technologies used for image dataset, there are also researches that show the use of various image descriptors for feature extraction. This research by Petra B. et.al. [38] is to focus on pixel-based approaches for classification of crops versus weeds, especially for complex cases involving overlapping plants and partial occlusion. The benefits of multiscale and content-driven morphology-based descriptors called attribute profiles are examined in the study and these are compared to the state-of-the-art keypoint descriptors with a fixed neighborhood previously used in precision agriculture, namely histograms of oriented gradients and local binary patterns.

The dataset used for the study are two, the first one is the Sugar Beets 2016 dataset (280 images) and the second is Carrots 2017 dataset. Classification is done using Random Forest Classifier. The limitations include more complex variants of AP descriptors based on different hierarchies could improve pixel-based classification and further Improvements could be achieved by the combination with region-based morphological segmentation and classification, with an additional benefit of reusing the hierarchical image representation, the most computationally expensive step of both approaches, for segmentation as well as feature extraction.

The highly useful research papers are mentioned below in the form of a Table 2.1, 2.2, and 2.3 for better understanding and a clear picture of the literature referred for this project. These important papers are divided into attribute headers such as Year (of research), Title, Objectives, Methodology, Results and Limitations (with future scope)

| Year | Paper Title | Objectives | Methodology | Results | Limitations |
|---|---|---|---|---|---|
| 2017 | Weed detection in soybean crops using ConvNets | To perform weed detection in Soybean crops to classify among grass & broadleaf weed | Using CNNs for classification and comparing results with color, shape and texture features, fed to Support Vector Machines, Random Forests) | 98% with classification using CNN compared to ML algorithms i.e. 90% | As future works it aims to address the evaluation with a image dataset covering a greater range of variables, such as different locations and height of image acquisition and since all the research was performed in a controlled environment, a close accuracy rate could be achieved in practice using a more diversified image dataset that represents the most varied types of soil and weeds. |
| 2017 | Weed segmentation using texture features extracted from sub-images | To do weed detection in sugar beet crops and classifying amongst 4 weed types | RGB images are converted into Gray-Scale , then features extracted are reduced using Principal Component Analysis (PCA) & fed to Artificial Neural Networks (ANNs) | 93.3% in Sugar Beets Vs Weeds & 89.3% in discriminating 4 types of weed | The detection was entirely based on texture features itself but better performance can be achieved if combination of texture and color information is used. |

Table 2.1: Literature summary of highly useful papers - 1

| Year | Paper Title | Objectives | Methodology | Results | Limitations |
|---|---|---|---|---|---|
| 2018 | Evaluation of support vector machine and artificial neural networks in weed detection using shape features | To identify weeds from sugar beets with shape features as well as Neural Networks for effective classification | Various image processing techniques that finds out the regions of plant, shapes were used & these features were then fed to ANN, SVM | 92.2% with ANN and 95.0% with SVM | Wel, the future scope intended to achieve better results with this crop as well as to experiment with the limitation of current research i.e using deep learning models for the same as they are not experimented as of now |
| 2019 | Weed detection in canola fields using maximum likelihood classification (MLC) and CNN | To apply semantic segmentation on canola field for weed detection | Background from plant image is removed using image processing techniques such as MLC and fed to U-Net and SegNet models for segmentation | Mean Intersection over Union (IoU) is 0.8274 for U-Net and 0.8288 for SegNet | The future work is solely going to include the soil properties for getting an idea of the relationship between weed density and soil characteristics to facilitate different herbicide application amounts |

Table 2.2: Literature summary of highly useful papers - 2

| Year | Paper Title | Objectives | Methodology | Results | Limitations |
|---|---|---|---|---|---|
| 2020 | Weed density classification in rice crop using computer vision | To classify the rice crop images based on their weed density classes such as no, low and high weed | Texture based features are extracted by applying gray level co-occurrence matrix & are fed to SVM, Random Forest algorithms | 73% using SVM and 86% using Random Forest | Limitations and Future Scope of the research include,many of these techniques do not target other categories of weed such as broadleaf and sedges and dataset is also small as well as neural networks are not explored |
| 2020 | Semantic Segmentation of Crop and Weed using an Encoder Decoder Network | To do object-wise semantic segmentation of images into crop, soil, and weed | Image enhancement techniques such as Histogram Equalization & Auto Contrast were used and fed to encoder-decoder network model | Mean IoU is 9.6 | The future work is model compression through which the trained model can run on edge devices such as mobile phones without any need of high computational power. |

Table 2.3: Literature summary of highly useful papers - 3

# Chapter 3

# Research Methodology

Based on the literature review, we have proposed a architecture that is used for the project ahead. The architecture is as shown below in Figure 3.1:

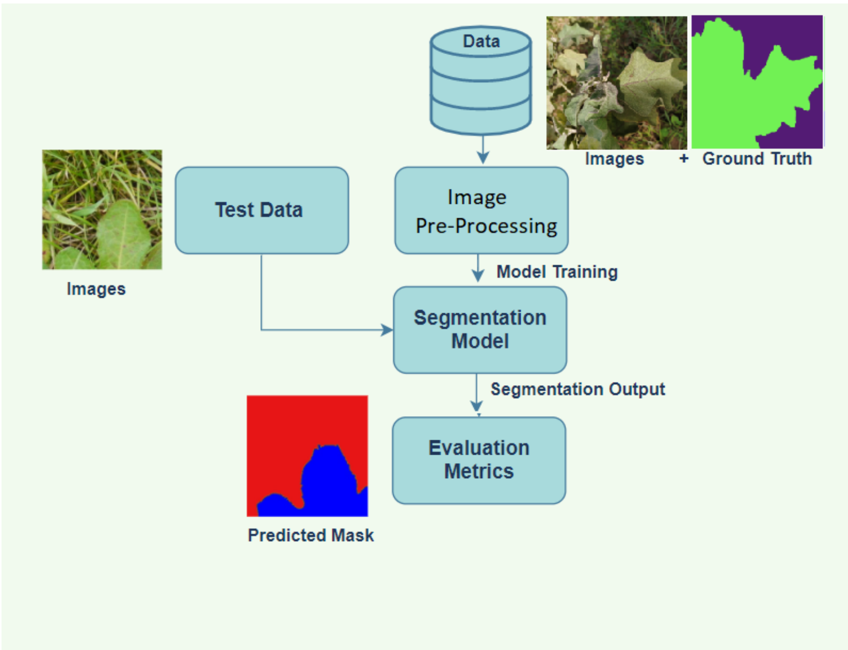


Figure 3.1: Proposed architecture

The whole research project was carried out in several phases such as, Data collection, Ground Truth Generation, Data Pre-Processing, Data Augmentation, Developing Segmentation Models, and the final step is Metric Evaluation on Test Data.

The previously mentioned phases are discussed briefly in the following subsections as shown in below Figure 3.2

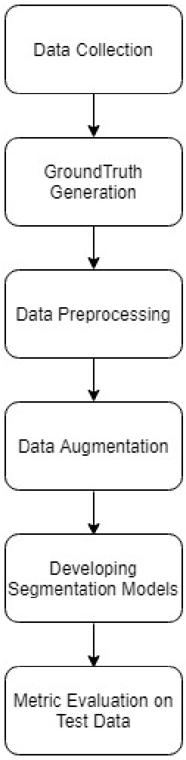


Figure 3.2: Project Flow

The project flow is devoid of the train-test split phase as it's an obvious phase for any kind of Machine Learning or Deep Learning projects. The dataset here is divided into training and testing sets. Here, the training is done on the 80% of the dataset and on the 20% of the dataset, the testing is performed. In the later part the metric evaluation is done on the test dataset.

## 3.1 Data Collection

The data used in the experiment is manually collected from a field farm of eggplant vegetable crop near Kudasan, Gandhinagar - Gujarat. There were few iterations of data capturing for ensuring the perfect quality of the images of eggplant with weeds. The process of dataset collection was followed in a manner that the images are taken from a smartphone camera. The images are in the form of RGB (Red Green Blue) format.

The ideal conditions of images were collected and few images that were not in proper lighting conditions were also added to the dataset, This is just to make the model robust and to make model train in a more better way so as when real-time images are provided to the model, the results are accurate from the previous learnings.

The data collection is done by keeping a proper level from the ground. This level is maintained properly for most of the images and few outliers are also added for more learning to the model. We have made a dataset of 55 images and after the augmentation the number rose to 218. From these 218, we have used 174 images as training and other 44 images as testing

## 3.2 Ground Truth Generation

The ground truth generation is the important step for any segmentation task because that is the label that we give along with the image to the segmentation model. As the dataset is collected manually, there is a need to generate ground truth by mapping and annotating the regions of plant and non-plant from the image (Figure 3.3). We are required to carefully divide the images into required sections.

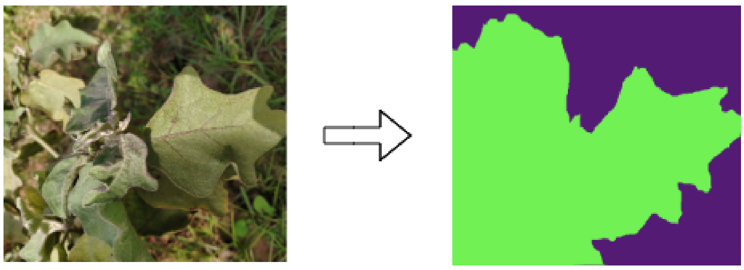

Figure 3.3: Ground Truth Generation

This would lead to a binary segmentation problem in terms of deep learning.For instance, as shown in the below collection of images, there is a standard process of a semantic segmentation process where Input, Ground Truth & Prediction are the main parts

The input part is the image that we give as an input to the segmentation model but along with that we should give the ground truth.

The Ground Truth part is the image which helps in pixel wise classification for the segmentation model. This image may contain segmented parts as per the project requirements.

Later comes the Prediction part which is the prediction output from the model. As, once the model is trained on the input images and ground truth, it would be able to generate a prediction by itself and that would be the output result of the model.

The ground truth generation is with the use of an image editor tool named GIMP. It provides various options to manipulate the images and also offers a toolkit for effective and efficient generation of the ground truth.

There are 2 different colors used for the process of generating ground truth and both of them resemble a different portion of image i.e Plant and Non-Plant. These portions are drawn with the help of GIMP cursor tool and then colored using the same.

## 3.3 Data Pre-Processing

The dataset consists of images which were collected manually, these images had varied size and shape which needed to be re-formed in a shape that is similar for all the images. This process also stays the same for the ground truth that is generated. As the dataset is developed from scratch, preprocessing is required [39].

For this research project, we have cropped and resized the dataset images from different sizes to 256 x 256, all while keeping the color channels intact [3]. After that, the images are passed from the process of normalization by subtracting the mean of each channel from the original value and later on dividing the standard deviation of the channels.

This preprocessing phase ensures that the images that are going further into the training part of the model are perfect [40] for the learning phase and will contribute in a better way for the segmentation model.

## 3.4 Data Augmentation

This phase is a usual process in a ML or DL project because to ensure that enough data is given to the model for the learning phase. As, more the data and variety in the dataset, more would be the effectiveness of the model when it comes to predicting the test inputs.

For text data augmentation, there are many methods which deal with adding more synthetic samples by getting the nearest neighbour points. Whereas while working on the image projects we can augment the data by basic methods such as flipping the image vertically, horizontally and even by adding some kind of noise to the images.

For this research project, we have augmented the data by random rotation, horizontal and vertical flip [41]. This augmentation phase helps in increasing the size of the training dataset and by adding augmented samples generated from the methods mentioned above, the learning experience of the model can be increased. This increases the accuracy or the measuring key performance indicators (KPIs) of the model when the test or actual data is given as an input to the trained model [21].

It also helps the model in learning features that were missed earlier or make stronger connections in the neural network [12]. As the deep learning frameworks usually run on the neural networks, more than one pass of the image in different forms results in robust training and prediction.

## 3.5 Developing segmentation models

Different segmentation models have been tried and tested based on the literature survey performed for this project. U-Net and LinkNet have been used with different backbone architectures as per the dataset of the project. As we had RGB images along with the binary segmentation classes with only 2 classes that are going to be differentiated. As the dataset size is average, so models have to be chosen accordingly. U-Net has been used by researchers for canola as well as paddy field image segmentation tasks and achieved good results with it [12] [42].

### 3.5.1 U-Net

U-Net is a type of CNN. As we are doing "Semantic Segmentation", the goal is to label each pixel of image with a corresponding class. U-Net Model is successful in delivering better results in pixel to pixel classification for biomedical images [43]. Hence, the very first approach is towards U-Net.

The deep learning was more focused earlier on the visual recognition tasks with convolutional networks [44]. The success of these neural networks were limited due to the fact that training set size was huge. As more dataset size was beyond the reach for biomedical images, Hence C. et al. [45] trained a network using a new approach of a sliding window to predict the class label of pixels. But, it had few drawbacks related to the slowness in training the neural network and another one being a trade-off between accuracy (localized) and the use of context. The architecture of U-Net is as shown below Figure 3.4

There are various operations which are carried out in U-NET model [44]. As, Convolutional Network is used there are several operations such as Convolution, Max-Pooling, Up-Sampling, Transposed Convolution. The convolution operation takes 2 input, one is

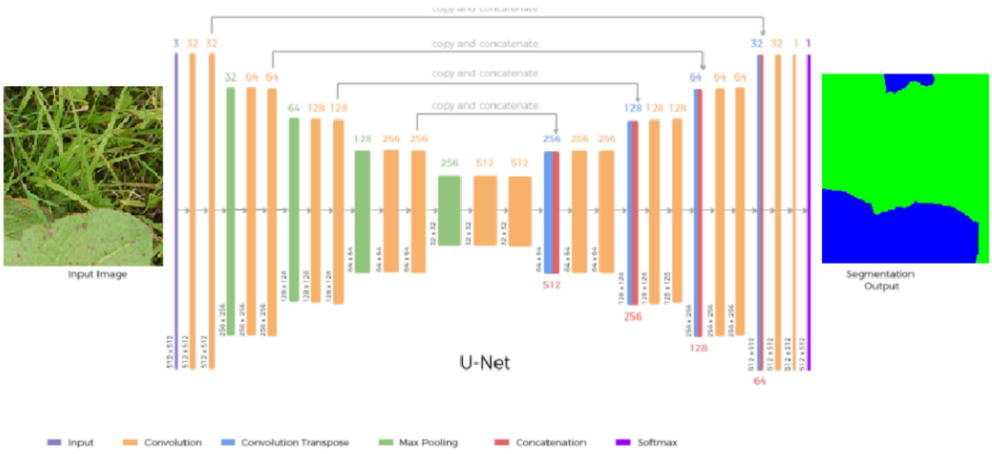


Figure 3.4: U-Net [3]

the input image and other is the set of filters or feature extractors. This gives in output, a feature map. In the Max-Pooling operation, basic task done is to decrease feature map size to ensure that there are fewer parameters in the network.The Convolution operation as well as the Max-Pooling operation effectively leads to image size reduction. This process is also known as Down Sampling. As, in semantic segmentation, we are not only expecting a box around the image, we expect a image with all the pixels classified. Hence, we need a Up-Sampling to retain the image and so by this process, we are converting an image with a low resolution to an image with a high resolution for recovering the information. In the final step, Transposed Convolution basically up-samples the image with parameters which can be learned. It is quite opposite of the usual normal convolution.

So, U-Net was developed with an architecture that consists of a path which is contracted to capture the context as well as localization. This network outperformed the priorly mentioned sliding window convolutional network.

We have used two different backbone architectures for U-Net namely, InceptionV3 and ResNet18. InceptionV3 being a large model and also it's a refinement of GoogLeNet architecture. It is selected basically because of it's good performance in previous research records and also relative low computation cost. Another one being ResNet18 which is also a backbone for one of our highly useful and referred research paper. In that research paper [12], identification of canola and weeds in RGB images is done and achieved good results. The ResNet is well-known for it's depth and also for the residual blocks. These blocks help in training a very deep architecture models.

### 3.5.2 LinkNet

LinkNet is a possibly the best framework that focuses on quick estimation through the use of an encoder-decoder structure. LinkNet is a U-shape version that varies from UNet in two major ways. To begin, it substitutes UNet's standard convolution architecture with a residual unit (res-block). Next, it changes UNet's superficial and coarse attribute composition process from "stacking" to "adding" [46]. ResNet18 is used as the Encoder in Initial LinkNet, but is one of a lightest ResNet. To solve the issue of conceptual content being discarded at encoders and has yet to be restored at decoders, LinkNet explicitly perpetuates contextual knowledge from encoder to decoder at a reciprocal stage [47].The architecture of LinkNet is shown below Figure 3.5

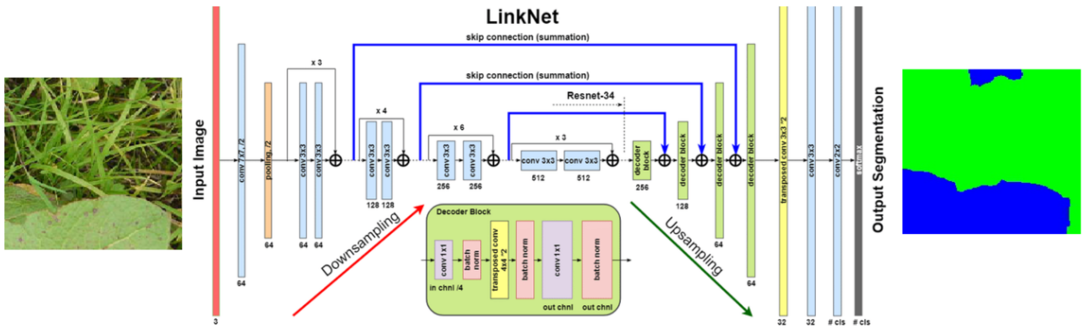


Figure 3.5: LinkNet [4]

As an effect, the resources and operations used to rediscover missing functionality are saved, resulting in a substantial reduction in running period.The whole platform is ten times quicker and very efficient than SegNet [48].

There are few operations which are carried out in the LinkNet model [46] [47], The Encoder part is a combination of Convolution and Max-Pooling layers which takes out the context from the image. Whereas, the Decoder part is consisting of Transposed Convolution and other Convolution layers that localizes the context captured in the Encoder part. There are connections between Encoder and Decoder part. These connections help to re-structure the image and tries to match the initial size of image. These parts help the framework being lightweight and hence fast and reduce the parameters in the network.

The LinkNet Framework is composed of encoder and decoder components that function together to deteriorate images and rebuild them before moving them across a certain additional convolutional level.The addition of the encoder outcome to the decoder improves LinkNet efficiency since it allows the decoder to further retrieve the relevant knowledge of encoder-block structures [48].

We have used LinkNet with 2 backbones MobileNetV2 and ResNet34. MobileNetV2 is very perfect model for feature extraction and is also based on its previous version MobileNetV1. It introduces two features such as linear bottlenecks between layers and also a shortcut connections in between the bottlenecks. ResNet34 is pre-trained on ImageNet and is generally used to extract semantic features. It reduces the model size and is better in improving the training speed. When compared to UNet, LinkNet is much faster when employed for training due to it's efficiency.

## 3.6 Metric Evaluation on test data

The metric evaluation is done on various parameters but those can be selected based on the problem statement that we are trying to solve. Here, we are doing semantic segmentation of weeds and plants. Accuracy won't fit here because that is more suitable to classification problems where images are being classified into several categories.

Also, in semantic segmentation the model's simple accuracy, precision and also the recall score does not provide the exact scene of results due to high imbalance in classes [12] [49]

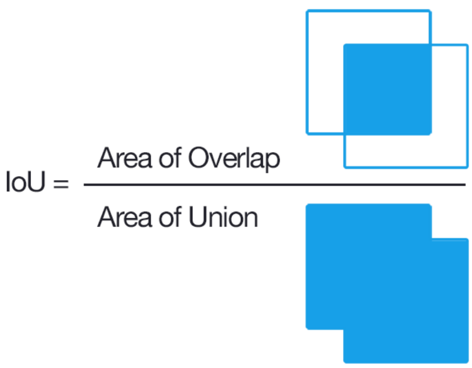


Figure 3.6: IoU (Intersection over Union) [5]

Here, we are trying to achieve a binary segmentation that creates a prediction mask which differentiates weeds and plant areas. So, accuracy won't be a correct parameter to measure the performance of the models. Hence, as per the trend of best metrics used for segmentation Intersection over Union (IoU) is used. This metric is also industry accepted and used by researchers for measuring the performance of segmentation models.

This implies,

- Close the IoU to 1, better are the results
- Close the IoU to 0, bad are the results

### 3.6.1 Results

We have evaluated the models on 44 samples and have got different IoU results for the 4 models that we used. The test Mean Intersection over Union (IoU) score is as shown in the below Table 3.1

| **Model** | **Mean IoU** |
|---|---|
| MobileNetV2 backed LinkNet | 0.83 |
| InceptionV3 backed UNet | 0.85 |
| ResNet34 backed LinkNet | 0.88 |
| ResNet18 backed UNet | 0.89 |

Table 3.1: Results

Basically, IoU is a comparison between the ground truth of the image that we gave as an input and the predicted mask that the model generated out of the input image. Hence, IoU gives the exact quantity of the overlap when compared with the union.

We have trained 4 different models with distinct backbone architectures. These segmentation models gave pretty good results when compared with each other. These models have simple architecture, faster training time and simple implementation.

The models which we have used are as listed below along with their predicted result images. As seen in the Figure 3.7, MobilNetV2 backed LinkNet showed a Mean IoU of 0.83. As, it's seen in the predicted result, it tried to capture the partition pretty well. In the figure 3.8, InceptionV3 backed UNet showed a Mean IoU of 0.85. It improved from the previous prediction as it captured the edges comparatively better.

The figure 3.9 showed a Mean IoU of 0.88 which is slightly improved and predicts the mask which is much more similar to the ground truth. This improvement is followed in Figure 3.10 where ResNet18 backed UNet showed the Mean IoU of 0.89.

- MobileNetV2 backed LinkNet

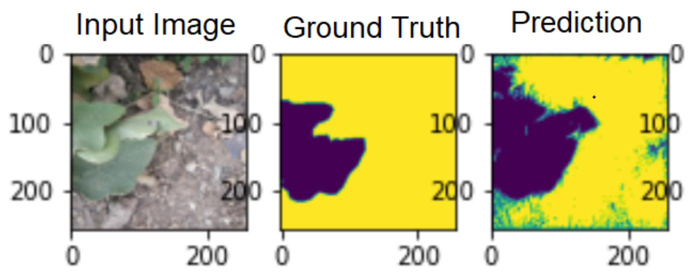


Figure 3.7: Results - 1

- InceptionV3 backed UNet

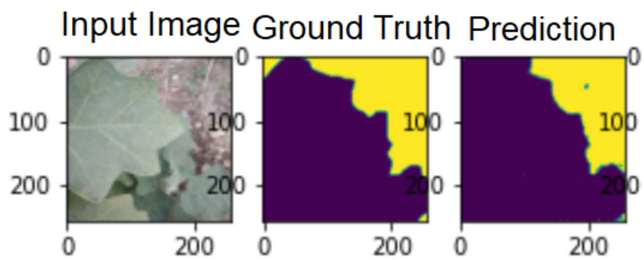


Figure 3.8: Results - 2

- ResNet34 backed LinkNet

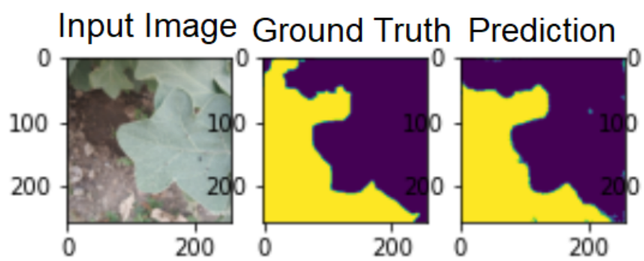


Figure 3.9: Results - 3

- ResNet18 backed UNet

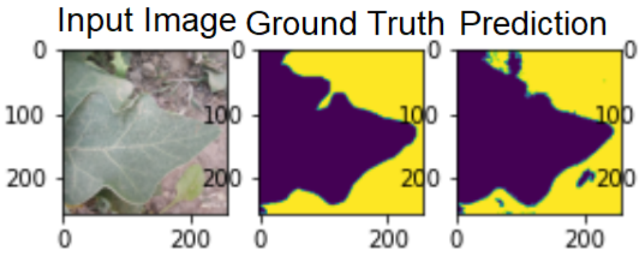


Figure 3.10: Results - 4

We have trained all the models for 30 epochs based on the dataset size for training as to avoid overfitting of the model due to excessive training. The training was done on 174 samples and the testing was done on 44 samples.

# Chapter 4

# Conclusion

Weed detection is an important aspect of farming and apart from other factors that affect the crop yield and crop quality. This one has a major share in terms of percentage. In this project, an approach is made to utilize the pros of deep learning and especially semantic segmentation. With the help of various segmentation models, we are able to segment the brinjal crop plant and weed from the image given to the model with the best score of around 90% with ResNet18 backed UNet. The results are promising and they provide a nod to achieve the objectives such as reduction in herbicide usage as well as in saving time from laborious way of hand weeding. These results also pave the way for usage of Precision Agriculture(PA) for site-specific weed management in vegetable crops.

# Chapter 5

# Future Work

In the research project done, we have achieved encouraging results with the use of weed segmentation models. This work for weed detection in eggplant vegetable crops can be extended as a part of future work by development of an end-to-end pipeline. The pipeline would include a weed classification module that takes plant images as input and with the help of a classification module, it would classify the images into plant or non-plant (weed) type. And, it would then forward only the images which are of weed type to the segmentation module to get the exact prediction mask, where the image is segmented into weed and plant. This would make a combination of classification and segmentation which would prove to be a perfect package for any application in real-time.

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