WEED DETECTION USING IMAGE PROCESSING AND DEEP LEARNING TECHNIQUES

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering

By

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SCHOOL OF COMPUTING

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(DEEMED TO BE UNIVERSITY)
Accredited with Grade "A" by NAAC | 12B Status by UGC | Approved by AICTE
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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **GUNDRALA AMARNADH (Reg. No -39110359) and MUNDRU AKHIL (Reg. No - 39110653)** who carried out the Project Phase-2 entitled **"WEED DETECTION USING IMAGE PROCESSING AND DEEPLEARNING TECHNIQUES"** under my supervision from January 2023 to April 2023.

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DECLARATION

I, **Gundrala Amarnadh (Reg.No- 39110359),** hereby declare that the Project Phase-2 Report entitled **“Weed Detection Using Image Processing and Deep learning Techniques”** done by me under the guidance of **Dr.G.Kalaiarasi, M.E.,Ph.D.,** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Computer Science and Engineering**.

Amarnath

DATE: 20.04.2023

PLACE: Chennai **SIGNATURE OF THE CANDIDATE**

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ABSTRACT

Agriculture is one of the origins of human sustenance in this world. Nowadays due to massive increase of population, people need the greater productive capability of the agriculture to meet the demands. In order to increase the productivity of crop, farmers should need to detect the weed plants in the crop so that they can easily remove it from the crop. So, the modern technologies can change the situation of farmers and decision making in agricultural field in a better way. In this project image processing and deep learning approaches where used to solve weed detection problem in the agriculture industry. In this project, crop and weed detection data using bounding boxes with different samples of images from the various resources which will detect the weed plants from the crop plants. Some hundreds of images were taken in the data set. Based on these images user choose to decide which is weed plant and crop plant. This project mainly focuses on the analysis of the agriculture data and finding optimal fields to maximize the crop production usingdeep learning algorithms like CNN, SVM and some more based on the data sets. Initially we consider images of the data set that are passed into the algorithm as the input to obtain efficient accuracy. The output of this project is to detect the weed plants from the crop. This project reduces the risk management for the farmers as based on the algorithm.

Keywords: Image processing, Crop plants, Convolutional Neural Networks, YOLOV3, deep learning, multi spectral imaging.

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LIST OF ABBREVIATIONS

CNN	-	Convolutional Neural Network
KNN	-	K Nearest Neighbors
SVM	-	Support Vector Machines

CHAPTER 1

INTRODUCTION

This chapter explains about detecting the weed plants using image processing, in olden days weed detection was done by employing some men, especially for that purpose. They will detect the weed by checking each and every place of the field. Then they will pluck them out manually using their hands. Later with the advancement in the technology they started using the herbicides to remove the weeds. But to detect the weeds they are still using manual power in many parts of the world. Later there came few methods to detect the weeds automatically but due to lack of their accuracy, they are unable to reach to the people. Then they started using image processing for this purpose. In this proposed project our main aim is to detect the weed in the crop by using image processing. Agriculture is an important in India. It is in dispensible for the sustenance and growth of the Indian economy. On an average, about 70% of the households and 10% of the urban population is dependent on agriculture as their source of livelihood. India is a large producer of several agricultural products. India has a wide range of agro climates and soil types. The highly diverse agriculture and fanning systems are beset with different types of weed problems. Weeds are the plants growing in a wrong place which compete with crop for water, light, nutrients and space, causing reduction in yield and effective use of machinery and can cause a disturbance in agriculture. Weeds can also host pests and diseases that can spread to cultivated crops. Farmers spend a large amount of time and money managing weeds. Weeds cause 10-80% crop yield losses besides impairing product quality and causing health and environmental hazards. Crop-specific problematic weeds are emerging as a threat to cultivation, affecting crop production, quality of product and income of farmers. Traditionally, weed control in India has been largely dependent on manual weeding.Later with the improvement in the technology, people started using herbicides to take out the weeds.

1.1 DEEP LEARNING

Deep learning has become one of the most evolving technologies in the current period. Deep learning can be simply explained as scientific study of algorithms and models in statistics where machines can easily understand to perform and solve specific tasks. This technique has become agile and it has been a requirement in most of the fields.

1.2 OUR MOTIVE

Our motive for this project is to detect the weed plants with maximum amount of accuracy in our detection . For this dataset was collected from Weed plants and crops in agriculture sector dataset from Kaggle database of Agriculture crop and weed image records and used that dataset in our three modules to detect the weed plants using YOLO V3 Algorithm.

1.2.1 Image Samples

The number of weed plants in agriculture fields have been increasing and there are very less efficient methods to detect the weed plants. The methods used in this project would bring more efficiency the detection methods. To do so different weed and crop image samples are to be collected and make it as a dataset. Then the samples of the images we have collected are refined to increase the accuracy percentage.

1.2.2 Efficient Technique

Convolutional Neural Network (CNN) algorithm is considered as the best algorithm compared to other algorithms since it gives better accuracy after testing with few other algorithms.

1.2.3 Increased Accuracy

There are many algorithms in the past for detecting the weed plants but the algorithms that are used in our project will increase the efficiency in detecting the weed plants in crop fields. The deep learning algorithm called Convolutional Neural Network (CNN) with yolov3 gives us higher accuracy compared to others.

1.3 DATA MINING

Data extraction is the way to find designs in expansive informant indexes including AI crossing point strategies, measurements and database frames. Information Mining is an interdisciplinary field of software engineering and measuring that aims to separate data from information collection (with keen strategies) and transform data into an understandable structure to be used further**.**

CHAPTER 2

LITERATURE SURVEY

In [1] Philipp Lottes “Fully Convolutional Networks With Sequential Information for Robust Crop and Weed Detection in Precision Farming” The paper proposes a new approach to crop and weed detection in precision farming using fully convolutional neural networks(FCN) with sequential information. The proposedmethod takes into account the temporal and spatial characteristics of the crops andweeds by using a combination of FCN and recurrent neural networks (RNN). The FCN was used for spatial feature extraction, while the RNN was used to capture the temporal dependencies of the crop and weed growth. This combination of FCN and RNN allows for more accurate detection of crops and weeds, as it takes into account the growth patterns and changes over time. The paper evaluates the proposed approach on a dataset of crop and weed images captured in different weather conditions and lighting conditions. The results showed that the proposed approach outperforms traditional methods and achieves a high accuracy in crop and weed detection. The paper presents a promising approach for improving crop and weed detection in precision farming using deep learning techniques.

In [2] Nan Li “Real-Time Crop Recognition in Transplanted Fields With Prominent Weed Growth”, The paper presents a novel method for recognizing crop plants of field images with a high weed presence. This method segments crop plants from overlapped weeds based on the visual attention mechanism of the human visual system using a neural network. The network utilizes ResNet-10 as backbone, while introducing side outputs and short connections for multi-scale feature fusion. The Adaptive Affinity Fields method was adopted to improve the segmentation at object boundaries and for fine structures. To train and test the network, a field image data set has been created which consists of 788 color images with manually segmented annotations. The images are captured under challenging conditions with extremely high weed pressure.

In [3] Ajinkya Paikekari, Vrushali Ghule, “Weed detection using image processing”, The paper proposes a new approach for weed detection in agricultural fields using image processing techniques. The proposed method involves capturing images of the agricultural field using a camera mounted on a mobile robot. The images are preprocessed to remove noise and enhance the contrast of the image. Then, the images are segmented to separate the plants from the background using thres holding techniques. After segmentation, the features of the plants are extracted using shape and texture analysis. The features are then used to classify the plants into crops and weeds using a support vector machine (SVM) classifier. The paper evaluates the proposed approach on a dataset of images captured in an agricultural field. The results show that the proposed approach is effective indetecting weeds with an accuracy of 94.16%. The approach is cost-effective, and it has the potential to be used as an alternative to herbicides, reducing the environmental impact of weed control.

In [4] Frank Liebisch, "Weed Net:Dense Semantic Weed Classification Using Multi spectral Images and MAV for Smart Farming",The paper proposes a new approach for weed classification in agricultural fields using multispectral images and a micro aerial vehicle (MAV) for smart farming. The proposed approach involves capturing multispectral images of the agricultural field using a MAV equipped with a camera. The images was preprocessed to remove noise and enhance the contrast of the image. The paper evaluates the proposed approach on a dataset of images captured in an agricultural field. The results had shown that proposed approach was effective in dense semantic segmentation of weeds with an accuracy of 94.5%.

In [5] Gurpreet Khurana, "Weed Detection Approach Using Feature Extraction and KNN Classification", The paper proposes a new approach for weed detection in agricultural fields using feature extraction and K-nearest neighbor (KNN) classification. The proposed approach involves capturing images of the agricultural field using a camera, preprocessing the images to remove noise, and extracting features such as color, texture, and shape using various image processing techniques. The extracted features are then used to train a KNN classifier to distinguish between weeds and crops. The performance of the proposed approach was evaluated on a dataset of images of weeds and crops captured in agricultural fields. The proposed approach was effective in detecting the weeds with an accuracy of 91%.

In [6] S.Manoruthra, "Automated Weed Removal System Using Artificial Neural Network", The paper proposed a new approach for automated weed removal in agricultural fields using artificial neural network (ANN). The proposed approach involves capturing images of the agricultural field using a camera mounted on a mobile robot and processing the images using ANN for feature extraction and classification of weeds. The proposed approach used dataset of images of different weed species under various lighting and environmental conditions, which was used to train the ANN. The proposed approach shown results with 93% accuracy.

In [7] J. Irías Tejeda; "Castro Algorithm of Weed Detection in Crops by Computational Vision", The paper has focused on the creation of an image- processing algorithm to detect the existence of weeds in a specific site of crops. The main objective has been to obtain a formula so that a weed detection system can be developed through binary classifications. The initial step of image processing is the detection of green plants in order to eliminate all the soil in the image, reducing information that was not necessary. This algorithm establishes an accurate monitoring of weeds and can be implemented in automated systems for the eradication of weeds in crops, either through the use of automated sprayers for specific site or a weed- cutting mechanism.

In [8] Kumar G, Bhatia PK (2014) "A detailed review of feature extraction in image processing systems" in this paper feature extraction techniques are applied to get features that will be useful in classifying and recognition of images. Feature extraction techniques were helpful in various image processing applications e.g. character recognition. As features define the behavior of an image, they show its place in terms of storage taken, efficiency in classification and obviously in time consumption also. Here in this paper, we are going to discuss various types of features, feature extraction techniques and explaining in what scenario, which features extraction technique, will be better.

In [9] Aichen Wang , "A review on weed detection using ground-based machine vision and image processing techniques", The paper provided a comprehensive review of various ground-based machine vision and image processing techniques used for weed detection in agriculture. The review covered a wide range of techniques, including color-based, shape-based, texture-based, deep learning-based, and multispectral-based methods. The paper discusses the advantages and limitations of each technique and compares their performance based on different evaluation criteria, such as accuracy, processing time, and suitability for different types of weeds and crops. It also provides an overview of the datasets used for training and testing the different techniques and highlights the need for more comprehensive and standardized datasets for bench marking. The paper concluded that ground-based machine vision and image processing techniques had the potential to revolutionize weed management in agriculture, by reducing the use of herbicides and improving crop yield.

In [10] Faisal Ahmed , “Classification of crops and weeds from digital images: A support vector machine approach” , The paper proposes a novel method for classification of crops and weeds from digital images using support vector machines (SVMs). The proposed method consists of several stages, including image acquisition, preprocessing, feature extraction, and classification. The proposed method worked on dataset of images of both crops and weeds.The results had shown that the SVM apporoach outperforms the other techniques in terms of accuracy. The proposed method achieved an accuracy of 96.5%.

In [11] Maurilio Di Cicco , “Automatic model based data set generation for fast and accurate crop and weeds detection”, The authors proposed a novel method for automatic dataset generation for crop and weed detection using a model-based approach. The proposed method consists of several stages, including data acquisition, image processing, and annotation. For data acquisition, the authors use a mobile robot equipped with cameras to capture images of crops and weedsin a field. The captured images were processed and then annotated with ground truth labels using semi-automatic annotation tool. The proposed method achieves an accuracy of 96.2% and had a processing time of 8.1 seconds per images

[12] R Aravind “Design and development of automatic weed detection and smart herbicide sprayer robot”, In this paper, an image processing algorithm is used to take images of the plantation rows at regular intervals and upon identifying the weeds in the image, the herbicide is sprayed directly and only on the weeds. The algorithm predominantly uses an Erosion and Dilation approach to detect weeds. The colour image is converted to binary by extracting the green parts of the image. The amount of white pixels present in the region of interest is determined and regions with higher white pixel count than the predefined threshold are considered

as weed.

2.1 INFERENCES FROM LITREATURE SURVEY

There are some logically strong inferences that can be made from the literature review. The Thesis is to composite the ideology of using deep learning algorithms for the prognosis, detection of weeds and crops. It is important to deal majorly with the kind of machine learning algorithms that would suit the purpose and be centric on the major objectives - being able to detect the presence of a weed plants in the most accurate possible way. The literature surveys conclude the use of Naive Bayes and Support Vector Machine algorithms for the prediction of weed plants. There are two major parameters that are involved in understanding the suitability of the respective methodologies and they are - the time taken to execute the prediction process and the accuracy of the detective result. It is clear through various studies and experimentation's that SVM classifier is the best of all the algorithms owing to the extremely high accuracy rates. But when it comes to the time taken to execute the predictive process, the Naive Bayes classifier reflects higher suitability since it takes the least possible time to execute the process.
From the above-mentioned literature works, it is clear that there has been effective research on this topic has been done and many models have been proposed.

1. It is evident that the above-mentioned systems have their own pros and cons.
2. While some of the recent works involve hybrid technologies and provide better accuracies, they are still far from what is needed.
3. With higher accuracy, comes the need for low computational costs, high processing speed, and most of all, the convenience of use.

It is evident that the above-mentioned systems have their own pros and cons.While some of the recent works involve hybrid technologies and provide better accuracies,they are still far from what is needed.

2.2 OPEN PROBLEMS IN EXISTING SYSTEM

The existing systems are simple and effective but are extremely vulnerable to impact. Moreover, state-of-the-art methods leverage only one algorithm which causes inaccurate results. This could lead practitioners to false assumptions and improper diagnosis and treatments provided to patients. Although detection results achieved are promising, these traditional approaches are still far from being highly accurate and efficient.

CHAPTER 3

AIM AND SCOPE OF THE PRESENT INVESTIGATION

3.1 AIM OF THE PROJECT

- To identify and detect weed and crop plants with their bounding boxes.
- To find best accuracy for weed detection using YOLOV3 .

3.2 SCOPE OF THE PROJECT

The diagnosis of weed detection is a crucial task in Agriculture, as weed plants are becoming increasingly prevalent worldwide in agriculture sector.Identifying the weed plants early can help in preventing the progression of the forming other weed plants in agriculture can increase in crop yield and reducing the risk of complications. YOLOV3 techniques can be utilized to develop detect models for various weed plants in agriculture fields. These models can analyze various parameters, such as color, size, and other data to identify potential weed plants. In summary, the development of a machine learning-based diagnostic model for weed plants has enormous potential to improve the accuracy and efficiency of crop yield. With proper integration of different factors, such models can provide personalized detection, improve outcomes of crop and reduce pesticides costs which in turn benefit the farmer with better crop yield.

3.3 PROBLEM DEFINITION

To Working on the identification of weeds among plant crops using specific weed photos is our current project.Additionally,have to calculate the correctness of various plants by analyzing with deep learning algorithms and employing CNN. The entire procedure is broken down into numerous necessary stages in the subsections below, beginning with obtaining photos for the deep neural network classification process develop and implement Machine Learning and deep learningapproaches that learns the general patterns of the weed plants, and a weed plants model is trained to detect weed plants and their bounding boxes to detect wherethe weed plant in image with their efficient accuracy. To bring better efficiency tothe algorithms which will be used in finding the accuracy of the weed plants.The subsets for necessary stages are given below They are:

1. Datasets.
2. Image pre-processing and labeling
3. Prepare training and Test image data set
4. Pre-processing images For CNN
5. Detecting and expunging weeds in the initial stages of crop growth with machine learning technique can minimize the usage of herbicides and maximize the crop yield for the farmers.
6. The objective is to use convolution neural network to perform weed detection in crop images.The proposed model deals with a weed detection system based on YOLO neural network.

3.4 TITLE JUSTIFICATION

This project replaces the traditional approach by using different deep learning algorithms in order to detect the weed from.The use of technology in agriculture has increased in recent year and deep learning is one such trend that has penetrated into the agriculture field.The main challenge in using big data in agriculture is identification of effectiveness of big data analytic. Efforts are going onto understand how big data analytic can agriculture productivity.The present project gives insights on various techniques applied to detect weeds and also signifies the important lacunae points in the proposed area of research.

3.5 OBJECTIVE

The Objective of this project is to detect weed plants by using Datasets with the help of techniques such as CNN, KNN etc.To identify a weed plant in various cropswith the image processing.The weeds detection method can be based on position and edge features which are under target can easily, rapidly and accurately separated from the background.We use the previous pictures to return weed coordinates.We work on different techniques to achieve higher accuracy. The output of this project is to distinguish the crop and weed plant.

3.6 ANALYSIS AND EXPLANIATION OF PROBLEM

The need of detection and removal of weed in the field is important in agriculture industry.In olden days weed detection was done by inspecting each and every place in the field by employing some men participating for that intention.Later with the improvement in technology people started using herbicides to take weeds. But to identify the weed still require physical power in many parts of the world.After thatfew methods of weed detection without using human intervention were discovered.So we came up with an idea of doing the project to detect the weed plants in order to obtain higher accuracy. Image processing and deep learning approaches could be applied to solve weed detection problem.

3.7 ADVANTAGES OF THIS MODEL

3.7.1 High Accuracy

The system predicts the results with 100 % accuracy for the dataset that we have used while creating this application. While the accuracy might be different in some cases, it will still be high enough to be trustworthy at a large scale.

3.7.2 Immediate Results

The results here are predicted within seconds of entering the details. You don’t need to wait for a doctor to come, unlike in traditional method.

3.8 Feasibility Study

A feasibility study for a weed detection using machine learning techniques project would evaluate the viability of the project from various perspectives. Some of the key factors to consider in a feasibility study for this type of project include:

3.8.1 Economic Feasibility

The project team would need to assess whether the costs associated with developing and implementing the system are feasible and within budget. This includes the cost of acquiring the necessary hardware and software, hiring skilled personnel, and ongoing maintenance and support costs. Technical Feasibility The project team would need to evaluate whether the necessary technology and resources are available to develop and implement a deep learning-based weed detection in agriculture fields. This includes the availability of suitable datasets for training and testing the machine learning algorithms and the necessary computational resources to build and deploy the system.

3.8.2 Social Feasibility

Social feasibility of a weed detection using deep learning techniques project refers to whether the project is acceptable and suitable for the society in which it will be implemented. It is an important aspect of the feasibility study, as it can affect the adoption of the system by the target audience, including farmers and agricultre. Some considerations related to social feasibility that should be considered:

1.Ethical considerations

2.User acceptability

3.Cultural considerations

4.Accessibility

CHAPTER 4

REQUIREMENT ANALYSIS

As aforementioned, as a part of the project need to make use of machine learning to pre-process, train and test the data. For that to happen we need few requirements like software consisting of suitable OS, Python, and a platform to develop the code. Additionally we need some special modules should be imported to make the model development go with ease.

4.1 SOFTWARE REQUIREMENTS

4.1.1 Python

Latest version of python software should be installed and kept ready. Python is widely considered as the preferred language for teaching and learning ML (Machine Learning).As compared to c, c++ and Java the syntax is simpler and Python also consists of a lot of code libraries for ease of use. Though it is slower than some of the other languages, the data handling capacity is great.

4.1.2 OPEN CV

Open CV (Open Source Computer Vision Library) is an open source computer vision and machine learning software library. Open CV was built to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in the commercial products. Being a BSD-licensed product, Open CV makes it easy for businesses to utilize and modify the code.

4.1.3 SPYDER

Spyder is an open-source cross-platform integrated development environment for scientific programming in the Python language.

4.1.4 JUPYTER NOTEBOOK

The Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and narrative text. Uses include: data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and much more.

4.1.5 RAM

It is good to have as much RAM as possible, because as the size of the dataset increases it is difficult to load and work with RAM less than 4GB.

4.2 PROCEDURAL REQUIREMENTS

4.2.1 NUMPY

Numpy is python package which stands for ‘Numerical Python’.It is the core library for scientific computing,which contains a powerful n-dimensional array object, provide tools for integrating C,C++.It is also useful in linear algebra, random number capability etc.

4.2.2 SPICY

Spicy is an open source python library which is used to solve scientific and mathematical problems. It is built on the Numpy extension and allows user to manipulate and visualize data with a wide range of high-level commands. As mentioned earlier, Spicy builds on Numpy and therefore if you import Spicy, there is no need to import Numpy.

4.2.3 OPENCV-PYTHON

It is a library of Python bindings designed to solve computer vision problems. cv2. imread() method loads an image from the specified file. If the image cannot be read (because of missing file, improper permissions, unsupported or invalid format)then this method returns an empty matrix.

4.2.4 Time

The time() function returns the number of seconds passed since epoch.

4.2.5 SYSTEM TYPE

Intel® Core 2 i3-5500U CPU @ 2.4.

CHAPTER 5
DESCRIPTION OF THE PROPOSED SYSTEM

This Methodology proposes that weeds detection method can be based on position and edge features. The weeds which are under target can easily, rapidly and accurately in separated from the background. In this way we can solve many technical problems related precise pesticide and in farmland vehicle navigation's system. Usually the weeds a image contains three elements soil, crops and weeds. Therefore, the weed detection is method which the literature proposed is divided three steps, that is soil because of background segmentation, crop elimination and weeds extraction.

5.1 PROCESS MODEL

Project Flow:

- User interacts with the UI to enter the input.
- Entered input is analyzed by the model which is integrated.
- Once the model analyses the input the prediction is showcased on the UI.

To accomplish this, we have to complete all the activities and tasks listed below:

- Data Collection
    1. Collect the dataset or create the dataset
- Data Pre-processing
    1. Drop unwanted features
    2. Checking for null values
    3. Handling categorical data
    4. Splitting data into train and test
- Model Building
    1. Import the model-building Libraries.
    2. Initializing the model
    3. Training and testing the model.
    4. Evaluation of Model
    5. Save the Model
- Application Building
    1. Create an HTML file.

2. Create a CSS file.
3. Build a Python Code.

5.2 ARCHITECTURE OF THE PROPOSED SYSTEM

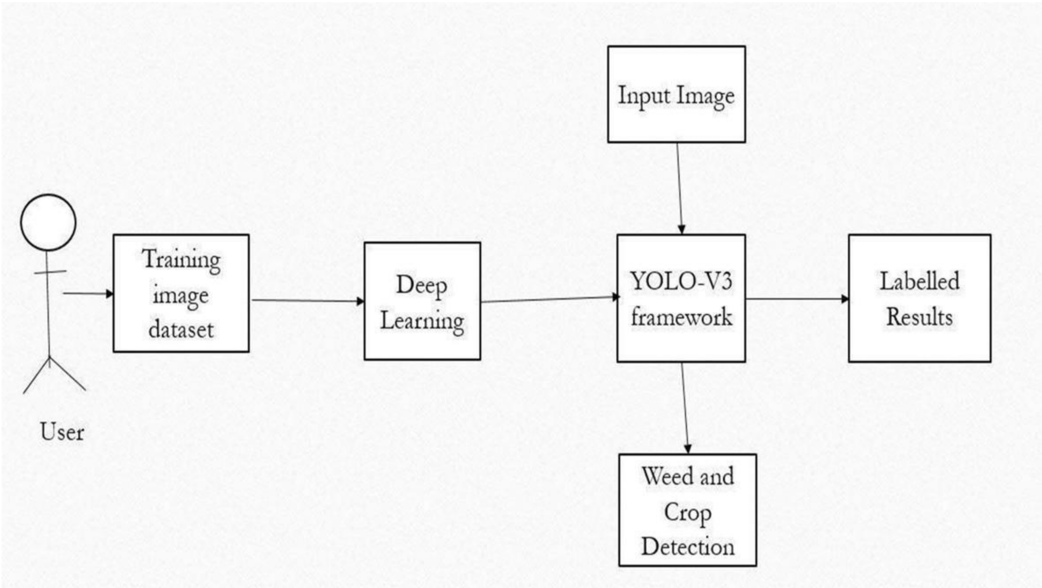

Fig 5.1: System Architecture

Deep learning is a subset of machine learning that uses artificial neural networks to learn and make predictions from data. It involves training a neural network to recognize patterns and relationships in large datasets by processing multiple layers of information. Deep learning has gained popularity in recent years due to its ability to improve accuracy in tasks such as image recognition, speech recognition, natural language processing, and autonomous driving. It has also been used in various fields such as healthcare, finance, and cyber security, among others. Some popular deep learning frameworks include TensorFlow, PyTorch, and Keras. YOLOv3 (You Only Look Once version 3) is a popular object detection algorithm developed by Joseph Redmon, Ali Farhadi, and others at the University of Washington. YOLOv3 is an improvement over its predecessor, YOLOv2, and is capable of detecting and localizing objects in real-time video with high accuracy.

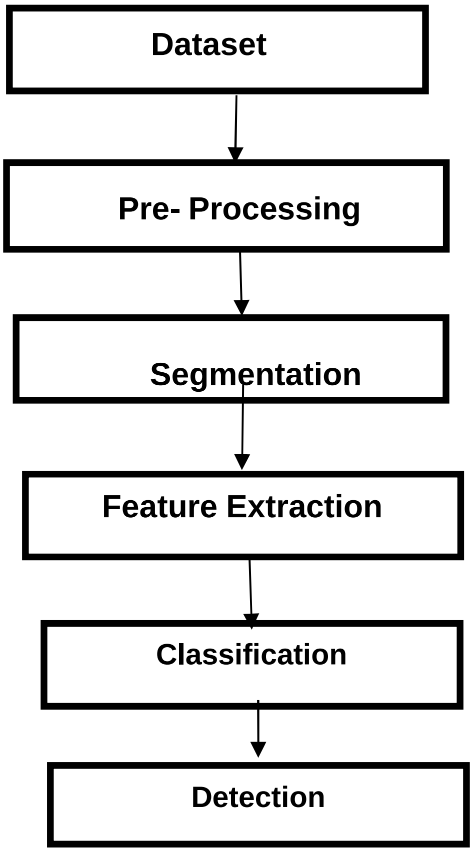

FIG 5.2: FLOW CHART OF PROPOSED MODEL

5.3 DATASET

Dataset is collected from kaggle website which consists of 1300 images, we will train the dataset using YOLO algorithm. When designing models or algorithms for learning features, our goal is to separate the factors of variation that explain the observed data. The depth of a deep learning model conceptually refers to said model's layer count and parameter complexity. Typically, the more confounding factors of variability in the dataset, the deeper and more complex the model required to achieve acceptable performance. Despite our efforts to mitigate inter- scene variance of photographed images in the design of the optical system; scene and target variability will persist in our target application. Thus, a major design consideration in the construction of this dataset is to capture images that reflect the full range of scene and target variability in our target application. Hence we have chosen to abide several factors of variation, namely: illumination, rotation, scale, focus, occlusion, dynamic backgrounds; as well as geographical and seasonal variation in plant life. Two primary goals were established to achieve the required variability and generality of the dataset. First, collect at least 1,000 images of each target species. Second, attain a 50:50 split of positive to negative class images from each location. The first goal is a necessity when training high-complexity CNN's which require large labeled datasets. The second goal helps to prevent over-fitting of developed models to scene level image features by ensuring targets are identified.

5.4 PRE-PROCESSING

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating amachine learning model. When creating a machine learning project, it is not alwaysa case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So for this, we use data pre-processing task. A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly usedfor machine learning models. Data pre-processing is required tasks for cleaningthe data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning.

5.5 FEATURE SELECTION

After pre-processing features are extracted for detecting the weed plant. Feature extraction is a part of the conditionality reduction process, in which, an initial set of the raw data is divided and reduced to more manageable groups. The technique of extracting the features is useful when you have a large data set and need to reduce the number of resources without losing any important or relevant information. Feature extraction helps to reduce the amount of redundant data from the data set.

5.5.1 COLOR FEATURES

Color and shape analysis techniques for discriminating crop, weeds and soil. In real time applying of herbicides uniformly across a whole field, seems undesirable in both economic and environmental terms. Color-based methods are more robust to partial occlusion and generally require less computation than shape-based methods. The weeds are extracted from the images using image processing and described by shape features. A classification based on the features reveals the type and number of weeds per image. Features are used, which enable an optimal distinction of the weed classes. The selection can be done using data mining algorithms, which rate the discriminant s of the features of prototypes.

5.5.2 SHAPE FEATURES

Shape-based imaging techniques are able to classify plants with almost 90 percent accuracy in laboratory environments as well as field tests under ideal conditions. The first step describes unconnected objects as a function of some geometrical features:

- Major axis length
- Area
- The ratio of the major
- Length squared to the area
- Roundness

Thus, each object was represented as a vector in the feature space. In order to determine which features were the most useful to discriminate between weeds and crop, a primary selection process was carried out.

5.5.3 TEXT FEATURES

The co-occurrence matrix is used to obtain textual features. The co-occurrence matrix method of texture description based on the repeated occurrence of gray level configuration is described by a matrix of relative frequencies.Text featurescan be broadly categorized into three types:

1. ***Syntactic features***: These features refer to the structure and grammar of the text, such as the parts of speech, sentence length, and word order. Examples of syntactic features include the frequency of nouns, verbs, adjectives, and adverbs.

2. ***Semantic features***: These features refer to the meaning of the text, such as the presence of specific keywords or topics. Examples of semantic features include sentiment analysis, named entity recognition, and topic modeling.

3. ***Structural features***: These features refer to the layout and formatting of the text, such as font size, boldness, and headings. Examples of structural features include the length of the document, the number of paragraphs, and the presence of bullet points or numbered lists.

Detection systems use shape, texture, or color parameters to classify various types of plants and frequently employ machine intelligence with learning capabilities in order to deal with the dynamic complexity of unstructured environments . The selection of the image processing techniques and the classifier algorithm are both important in detection systems. The image processing techniques process the raw image to find features, such as shape outlines and color.

5.6 CLASSIFICATION

Classification techniques are used to classify the weed. Feature vectors are passed as input to the classifiers. In classification classifiers are trained, validated and tested using images of different weed. Some classifiers are artificial neural network, probabilistic neural network genetic algorithm and edge based classifier etc.The goal of classification is to develop a model that can accurately predict the class of new, unseen data based on the patterns learned from the training data.

In classification, the input data is typically represented as a feature vector, which contains a set of features or variables that describe the data. For example, in a dataset of customer transactions, the features could include customer age, purchase amount, and product category. The output of the classification model is a class label, which indicates the predicted category for a given input.Evaluation metrics such as accuracy, precision, recall, and F1 score can be used to assess the performance of a classification model. These metrics provide an indication of how well the model is able to correctly classify new data based on the patterns learned from the training data.Classification is widely used in various fields, such as image recognition, natural language processing, fraud detection, and customer segmentation.

This Project proposes that weeds detection method can be based on position and edge features. The weeds which are under target can easily, rapidly and accurately in separated from the background. In this way we can solve many technical problems related precise pesticide and in farmland vehicle navigation's system. Usually the weeds a image contains three elements soil, crops and weeds.Therefore, the weed detection is method which the literature proposed is divided three steps, that is soil because of background segmentation, crop elimination and weeds extraction.

5.7 CONVOLUTION NEURAL NETWORK

Convolutional Neural Networks (CNN's) are a type of deep learning algorithm that are commonly used for image recognition and computer vision tasks.CNN's are designed to automatically detect and extract features from images, making them well-suited for tasks such as object detection, image classification, and image segmentation.

A CNN consists of multiple layers, each of which performs a specific operation on the input data. The first layer is typically a convolutional layer, which applies a set of filters to the input image to extract features such as edges, corners, and textures.The output of the convolutional layer is then passed through a pooling layer, which down samples the data and reduces the dimensionality of the feature maps.

After several layers of convolution and pooling, the output is flattened and passed through one or more fully connected layers, which perform the final classification or regression task. During training, the CNN learns to adjust the weights of the filters and fully connected layers in order to minimize the error between the predicted output and the true output.

One advantage of CNNs is that they can learn features automatically from the raw input data, without the need for hand-engineered features. This makes them particularly useful for tasks such as image recognition, where the features that are relevant for classification may not be immediately obvious.

CNN's have been used in a wide range of applications, such as facial recognition, self-driving cars, medical imaging, and natural language processing. Some popular CNN architectures include AlexNet, VGG, ResNet, and Inception.

In this project the model has been proposed working on the weed plants by using CNN Framework called YOLO(You look only Once).

5.7.1 BACKGROUND OF CNN

CNN’s were first developed and used around the 1980s. The most that a CNN could do at that time was to recognize handwritten digits. It was mostly used in the postal sectors to read zip codes, pin codes, etc. The important thing to remember about any deep learning model is that it requires a amount of data to train and also requires a lot of computing resources. This was a major drawback for CNN's atthat period and hence CNN's were only limited to the postal sectors and it failed to enter the world of machine learning.

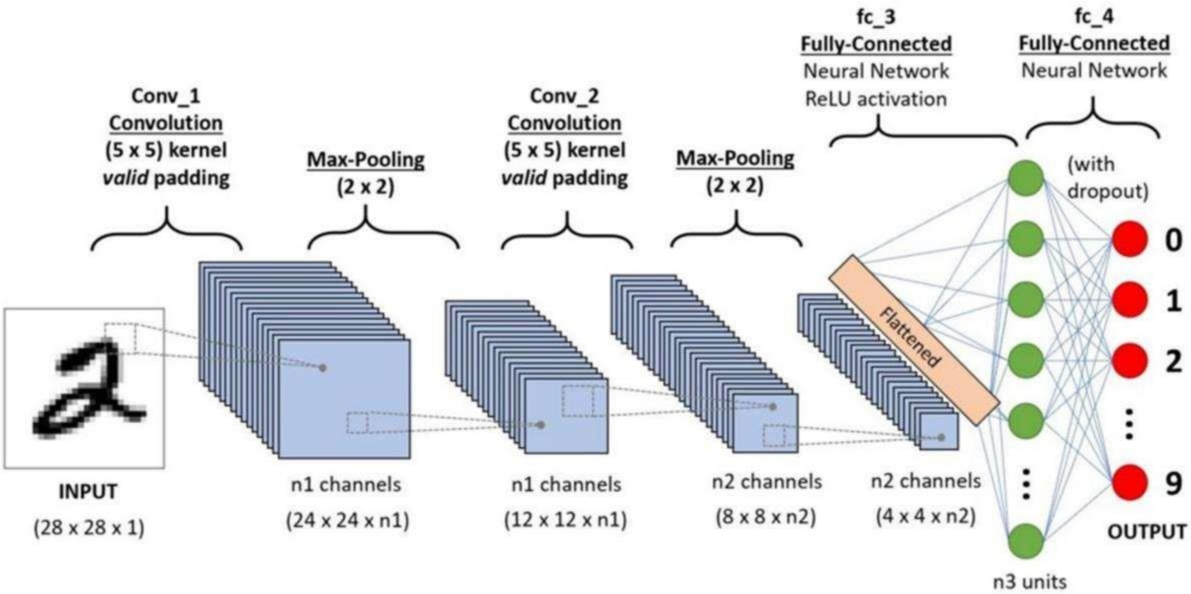

Fig 5.3:Working of CNN

In deep learning, a convolutional neural network (CNN/ConvNet) is a class deep neural networks, most commonly applied to analyze visual imagery. It uses a special technique called Convolution.Convolutional neural networks are composed of multiple layers of artificial neurons. Artificial neurons, a rough imitation of their biological counterparts, are mathematical functions that calculate the weighted sum of multiple inputs and outputs an activation value. When you input an image ina ConvNet, each layer generates several activation functions that are passed on to the next layer.CNN is one of the important training algorithm in deep learning.It is fully connected neural network.

5.7.2 LAYERS OF CNN

1. Convolution layer
2. Non-Linearity (ReLU)
3. Pooling layer
4. Fully Connected layer

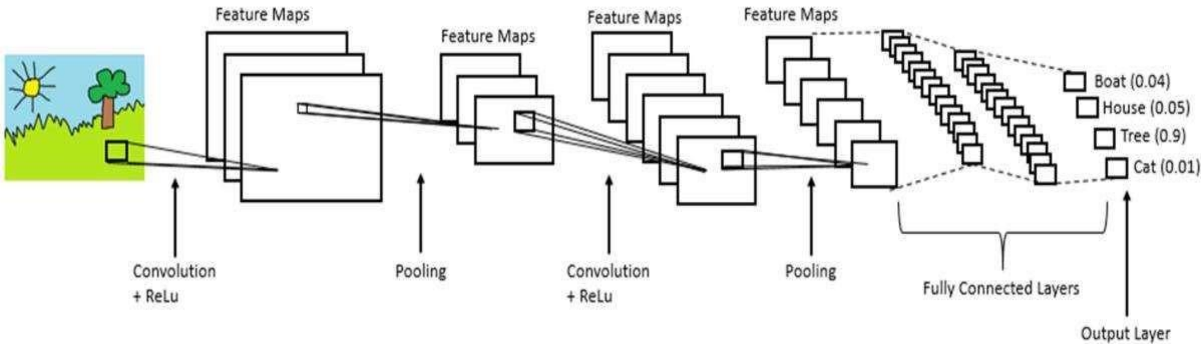

Fig 5.4: Layers of Convolution Neural Networks

This first layer usually extracts basic features such as horizontal or diagnol edges.This output is passed on to the next layer which detects more complex features such as corners or computational edges. As we move deeper into the network it can identify even more complex features such as objects, faces, etc.

5.7.3 CONVOLUTIONAL LAYER

This layer is the first layer that is used to extract the various features from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size MxM. By sliding the filter over the input image, the dot product is taken between the filter and the parts ofthe input image with respect to the size of the filter (MxM).

The output is termed as the Feature map which gives us information about the image such as the corners and edges. Later, this feature map is fed to other layers to learn several other features of the input image.

Based on the activation map of the final convolution layer, the classification layer outputs a set of confidence scores (values between 0 and 1) that specify how likely the image is to belong to a “class.” For instance, if you have a ConvNet that detects cats, dogs, and horses, the output of the final layer is the possibility that the input image contains any of those animals.

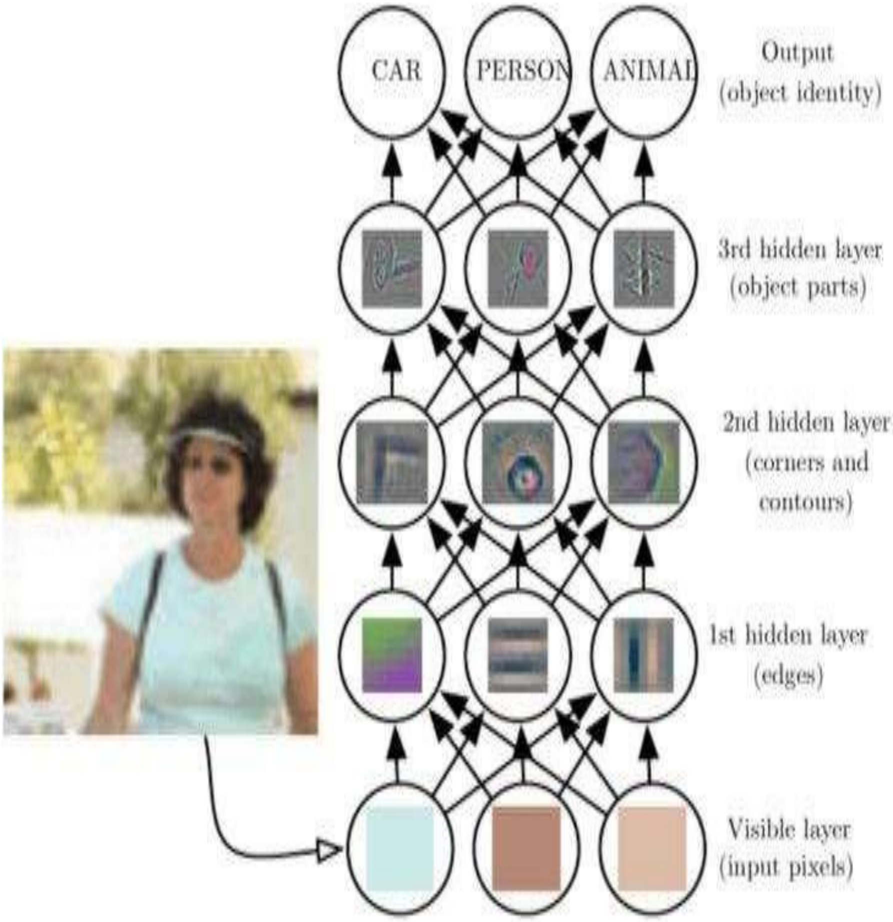

Fig 5.5:Convolution layer

5.7.4 Non-Linearity

The Rectified Linear Unit, or ReLU, is not a separate component of the convolutional neural networks' process. The purpose of applying the rectifier function is to increase the non-linearity in our images. The reason we want to do that is that images are naturally non-linear. When you look at any image, you'll find it contains a lot of non-linear features (e.g. the transition between pixels, theborders, the colors, etc.). The rectifier serves to break up the linearity even further in order to make up for the linearity that we might impose an image when we put it through the convolution operation.

Non-linearity refers to the property of a system or function where the output is not directly proportional to the input. In other words, a non-linear system or function does not follow a straight line when plotted on a graph. Non-linearity is an important concept in various fields, including mathematics, physics, engineering, and computer science. In machine learning, non-linearity is particularly important because many real-world problems involve complex, non-linear relationships between input features and output variables. Non-linear functions are used invarious types of neural networks, including deep neural networks, convolutional neural networks, and recurrent neural networks. These non-linear functions allow neural networks to model complex relationships between input features and output variables, making them more powerful than linear models.One common non-linear function used in machine learning is the Rectified Linear Unit (ReLU), which is widely used as an activation function in neural networks. The ReLU function returns the input if it is positive, and returns zero if the input is negative. This simple non-linear function has been shown to work well in practice, and is used in many state-of-the-art neural network architectures.Other non-linear functions used in machine learning include sigmoid functions, hyperbolic tangent functions, and soft max functions. These non-linear functions allow neural networks to model complex relationships between input features and output variables, and are an essential component of many machine learning algorithms.

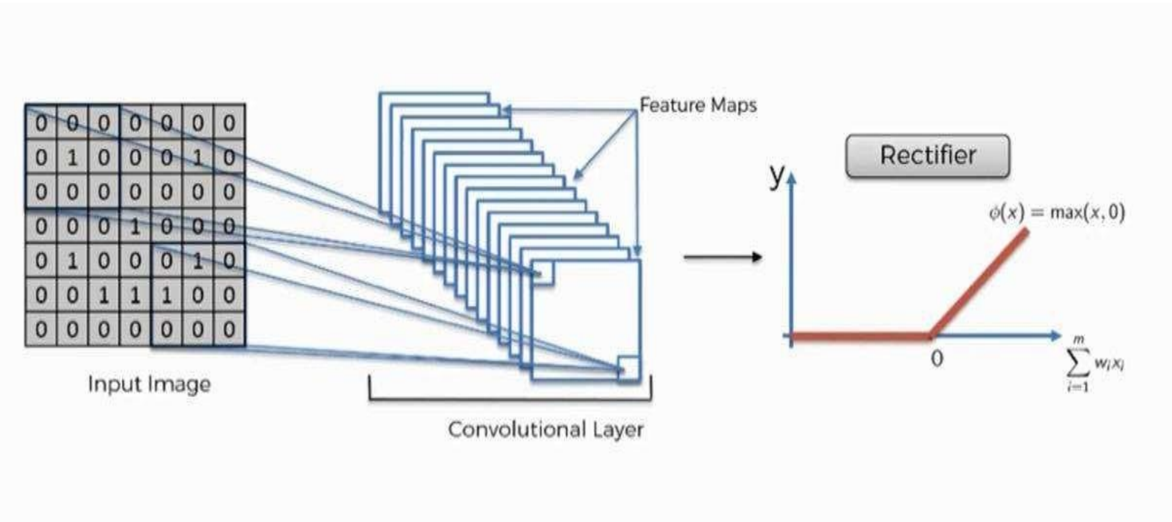

Fig 5.6:Non Linearity

5.7.5 POOLING LAYER

In most cases, a Convolutional Layer is followed by a Pooling Layer. The primary aim of this layer is to decrease the size of the convoluted feature map to reduce the computational costs. This is performed by decreasing the connections between layers and independently operates on each feature map. Depending upon method used, there are several types of Pooling operations.

In Max Pooling, the largest element is taken from feature map. Average Pooling calculates the average of the elements in a predefined sized Image section. The total sum of the elements in the predefined section is computed in Sum Pooling. The Pooling Layer usually serves as a bridge between the Convolution Layer and the FC Layer.

There are several types of pooling operations that can be used in a pooling layer, including max pooling, average pooling, and L2 pooling. In max pooling, the maximum value in each pooling window is selected as the output, while in average pooling, the average value in each window is used. L2 pooling calculates the root mean square of the values in each window.

The pooling layer works by dividing the feature maps into non-overlapping windows and applying the pooling operation to each window. The size of the window and the stride of the pooling operation are hyper parameters that can be tuned to control the amount of down sampling and the level of feature preservation.

The main benefit of using a pooling layer is that it reduces the dimensionality of the feature maps, which can help to reduce over fitting and improve the efficiency of the model. Additionally, the pooling operation can help to capture the most important features in the input data, making the model more robust to small changes in the input.

However, one potential drawback of using a pooling layer is that it can result in a loss of information, especially if the pooling window size is too large. This can lead to a decrease in the overall performance of the model, especially for tasks that require high spatial resolution, such as object detection or image segmentation.

5.7.6 Fully Connected Layer

A fully connected layer, also known as a dense layer, is a type of layer commonly used in neural networks for tasks such as image classification, natural language processing, and speech recognition. In a fully connected layer, each neuron is connected to every neuron in the previous layer, giving it access to all of the information in the input.

The fully connected layer is typically the last layer in a neural network and is used to perform the final classification or regression task. During training, the weights of the neurons in the fully connected layer are adjusted so that the output of the network matches the desired output.

The output of a fully connected layer can be computed as a dot product between the input and a weight matrix, followed by the addition of a bias term and the application of an activation function. The activation function is used to introduce non-linearity into the network and is typically a function such as the sigmoid function, the ReLU function, or the soft max function.

One advantage of using a fully connected layer is that it allows the network to learn complex relationships between input features and output variables, making it well-suited for a wide range of machine learning tasks. However, fully connected layers can be computationally expensive, especially for large input sizes or deep networks.

To address this issue, some neural network architectures use a combination of convolutional layers and fully connected layers. In these architectures, the convolutional layers are used to extract features from the input, which are then passed to one or more fully connected layers for final classification or regression. This approach can be more computationally efficient than using fully connected layers alone, while still allowing the network to learn complex relationships between input features and output variables.

5.7.7 CONVOLUTIONAL KERNALS

In convolutional neural networks (CNNs), a kernel (also known as a filter or a convolutional filter) is a small matrix of weights that is used to scan over the input data and perform a convolution operation. The kernel slides over the input data, one small region at a time, and applies a dot product between its weights and the values in the current region. The result of this dot product is used to compute a single value in the output feature map.

The size of the kernel and the stride of the convolution operation are hyper parameters that can be tuned to control the size and complexity of the feature maps generated by the network. The weights of the kernel are learned during training using back propagation and stochastic gradient descent, and are optimizedto minimize the loss function of the network.

Convolutional kernels are typically small matrices, such as 3x3 or 5x5, and are designed to capture local patterns in the input data, such as edges, corners, or other distinctive features. By stacking multiple convolutional layers together, a CNN can learn to recognize increasingly complex patterns and objects in the input data.

One advantage of using convolutional kernels in a neural network is that they can be shared across different regions of the input data. This sharing of weights allows the network to learn translation-invariant features, which are important for tasks such as object recognition, where the same object may appear in different parts of an image.

Another advantage of using convolutional kernels is that they can be used to reduce the dimensionality of the input data. By applying a convolution operation with a stride larger than 1, the output feature map can be down sampled, reducing the number of parameters in the network and improving its computational efficiency.

Overall, convolutional kernels are a key component of convolutional neural networks, allowing them to learn complex patterns and objects in the input data while minimizing the number of parameters required by the network.

Each convolutional layer contains a series of filters known as convolutional kernels. The filter is a matrix of integers that are used on a subset of the input pixel values, the same size as the kernel. Each pixel is multiplied by the corresponding value in the kernel, then the result is summed up for a single value for simplicity representing a grid cell, like a pixel, in the output channel/feature map. These are linear transformations, each convolution is a type of affine function.In computer vision the input is often a 3 channel RGB image. For simplicity, if we take a greyscale image that has one channel (a two dimensional matrix) and a 3x3 convolutional kernel (a two dimensional matrix). The kernel strides over the input matrix of numbers moving horizontally column by column, sliding/scanning over the first rows in the matrix containing the images pixel values. Then the kernel strides down vertically to subsequent rows. Note, the filter may stride over one or several pixels at a time, this is detailed further below.

Creating a feature map from a convolutional kernel

Below is a diagram showing the operation of the convolutional kernel.

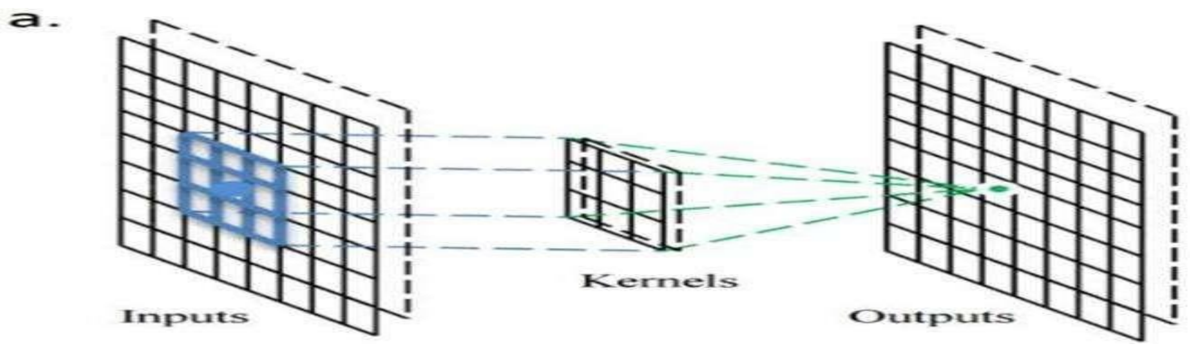

Fig 5.7: A stride one 3x3 CNN kernel acting on 8x8 input

5.7.8 PADDING

In a convolutional neural network (CNN), padding refers to the addition of extra pixels or values around the edges of an input feature map before applying a convolutional operation. The purpose of padding is to control the spatial dimensions of the output feature map, especially at the edges and corners of the input.

When a convolutional kernel is applied to the input feature map, it slides over the input and computes a dot product between its weights and the values in the current region. For example, a 3x3 kernel applied to a 5x5 input feature map would result in a 3x3 output feature map.

However, as the kernel slides over the input, it does not cover the edges and corners of the input feature map, resulting in a smaller output feature map. Thiscan be problematic, as information at the edges and corners of the input feature map may be important for the task at hand.

To address this issue, padding can be used to add extra pixels or values around the edges of the input feature map, effectively increasing its size. By adding padding, the convolutional operation can be applied to the entire input feature map, resulting in an output feature map with the same spatial dimensions as the input.

Padding can take two main forms: "valid" padding and "same" padding. Valid padding means that no padding is added, and the output feature map has smaller spatial dimensions than the input. Same padding means that padding is added so that the output feature map has the same spatial dimensions as the input.

Overall, padding is a useful technique for controlling the spatial dimensions of the output feature map in a CNN and ensuring that important information at the edges and corners of the input feature map is not lost during convolution.

Reflection padding is by far the best approach, where the number of pixels needed for the convolutional kernel to process the edge pixels are added onto the outside copying the pixels from the edge of the image. For a 3x3 kernel, one pixel needs to be added around the outside, for a 7x7 kernel then three pixels would be reflected around the outside. The pixels added around each side is the dimension, halved and rounded down.

With padding, the output from a input of width w and height h would be width w and height h (the same as the input with a single input channel), assuming the kernel takes a stride of one pixel at a time.

5.7.9 RGB 3 CHANNEL INPUT

Most image processing needs to operate on RGB images with three channels. A RGB image is a three dimensional array of numbers otherwise known as a rank three tensor. When processing a three channel RGB image, a convolutional kernel that is a three dimensional array/rank 3 tensor of numbers would normally be used. It is very common for the convolutional kernel to be of size 3x3x3 —the convolutional kernel being like a cube.

Usually there is at least three convolutional kernels in order that each can act as a different filter to gain insight from each colour channel. The convolution kernels as a group make a four dimensional array, otherwise known as a rank four tensor. It is difficult, if not impossible, to visualize dimensions when they are higher than three. In this case imagine it as a list of three dimensional cubes.The filter moves across the input data in the same way, sliding or taking strides across the rows then moving down the columns and striding across the rows until it reaches the bottom right corner:

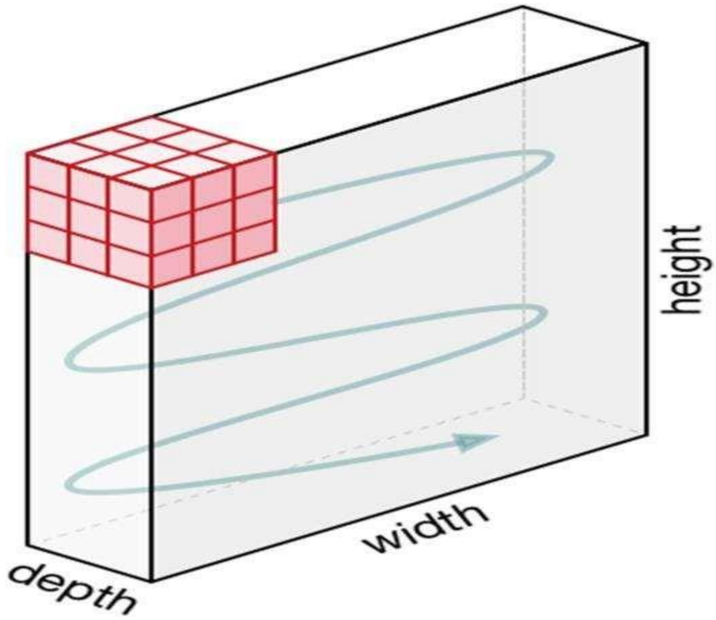

Fig 5.8: 3x3x3 convolutional kernel acting on a 3 channel

With padding and a stride of one, the output from an input of width x, height y and depth 3 would be width x, height y and depth 1, as the cube produces a single summed output value from each stride. For example, with an input of 3x64x64 (say a 64x64 RGB three channel image) then one kernel taking strides of one with padding the edge pixels would output a channel/feature map of 64x64 (one channel).

STRIDES:

It is common to use a stride two convolution rather than a stride one convolution, where the convolutional kernel strides over 2 pixels at a time, for example our 3x3 kernel would start at position (1,1), then stride to (1,3), then to 1, 5) and so on, halving the size of the output channel/feature map, compared to the convolutional kernel taking strides of one. With padding, the output from an input of width w, height h and depth 3 would be the ceiling of width w/2, height h/2 and depth 1, as the kernel outputs a single summed output from each stride.

For example, with an input of 3x64x64 (say a 64x64 RGB three channel image), one kernel taking strides of two with padding the edge pixels, would produce a channel/feature map of 32x32.

5.8 YOLO Network

The tiny YOLO (You Only Look Once) framework, a lighter and faster version of YOLO.YOLO (you look only once), as its name implies, is a neural network capable of detecting the bounding boxes of objects in an image and the probability that they belong to a class in a single step. YOLO uses convolutional networks and it was selected for its good performance in object and pattern recognition, which has given it a recent good reputation in fields such as the recognition of means of transportation and animals, and the tracking of moving objects. The first version of YOLO came out in 2016; Its architecture consisted of 24 convolutional layers working as feature extractors and two dense or fully connected layers that performed predictions. YOLO was used for its significant enhancements and feature extraction layers which were replaced by the Darknet-53 architecture. YOLO uses a few tricks to improve training and increase performance, including: multi-scale predictions, a better backbone classifier, and more.We collected1300 images, before combining these images with some field images to train the developed model.It is a neural network capable of detecting the bounding boxes of objects.

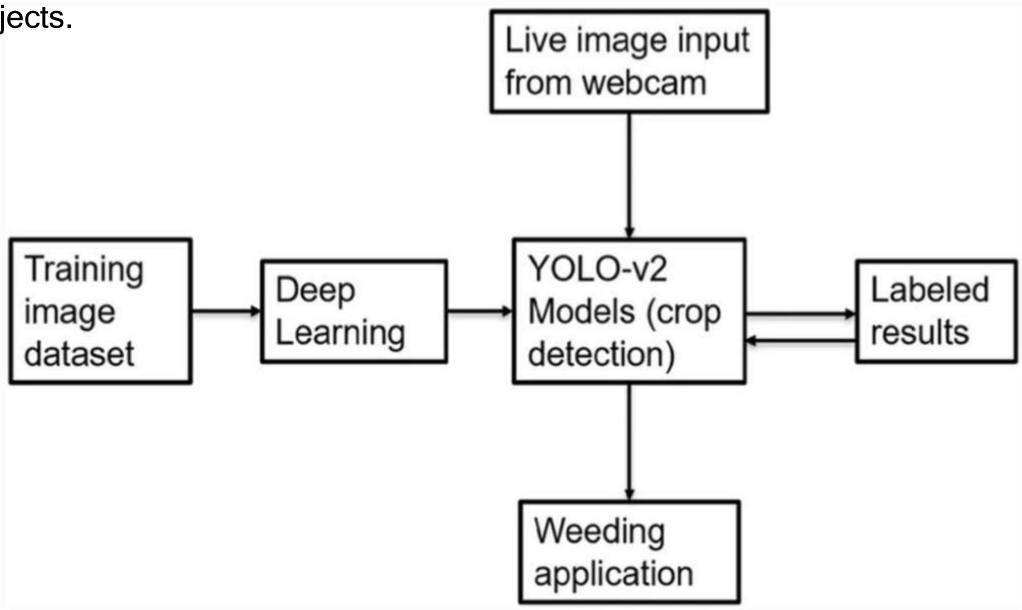

Fig 5.9: A diagram based on convolutional neural network YOLO

As seen in above Figure , once the model is trained to identify the crop an algorithm uses bounding box coordinates from the model to remove crop samples from the image. Later, a green filter binarizes the image, so pixels without vegetation become black, while the pixels accepted by the green filter become white. Finally, vegetation that does not correspond to the crop is highlighted, thereby simplifying the percentage calculation of weeds per image. In order to get the most out of YOLO in terms of effective detection of objects and speed, it was decided not to use edge detection and to consider the entire bounding box generated by the model as crops, although this might affect weed calculation since the closest weed to the crop could be lost during estimation. YOLO is a Deep Learning architecture proposed by Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi in the paper 'You Only Look Once: Unified, Real-Time Object Detection' [1] uses a totally different approach. It is a clever convolutional neural network (CNN) for object detection used in real-time. Further, It is popular because it has a very high accuracy while also being able to run in real-time or used for real-time applications. The YOLO algorithm "only looks once" at the input image that is it needs only one forward propagation pass through.

5.8.1 Yolo Working

It is capable of detecting the bounding boxes of an objects in an image.

CNN(convolutional neural networks) which is selected for pattern recognition. In terms of CNN

vector like Pc, Bx, By, Bw, Bh,C1, C2

CNN understands only numbers.

were Pc=probability of class

Bx, By = co-ordinates of the center of the image

Bw = width of the box

Bh = height of the box

C1 = dog class

C2 = images class

Prior detection systems use localizers or classifiers to carry out the detection process. The regions of the image with High scoring are considered for detections. YOLO algorithm uses a completely different approach. The algorithm applies a single neural network to the entire full image. Then this network divides that image into regions which provides the bounding boxes and also predicts probabilities for each region. These generated bounding boxes are weighted by the predicted probabilities.

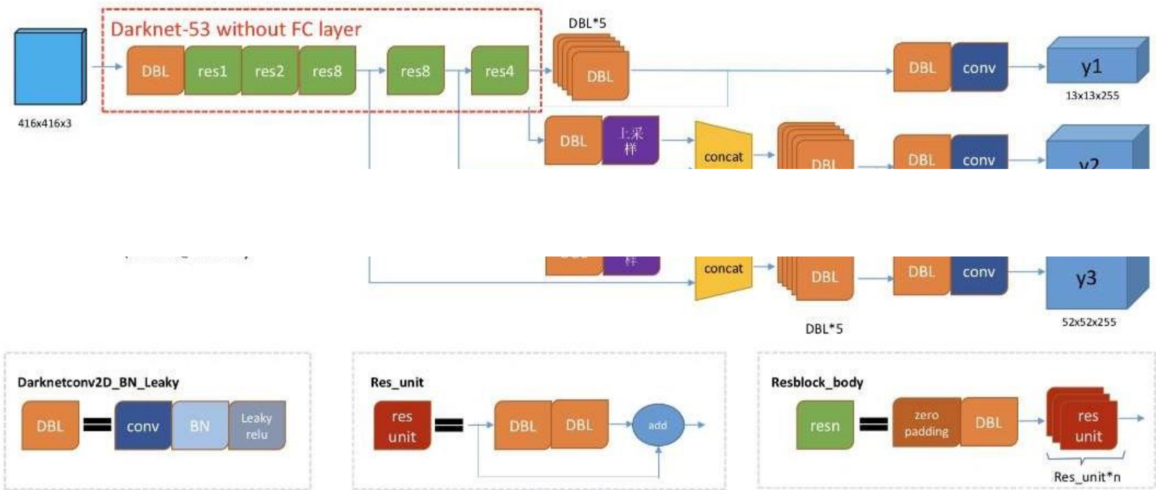

Fig 5.10: Yolo Algorithm Structure

If we have more objects in single picture then YOLO divides the image into some kind of grid cells like 4 *4 or 9*9 or 16*16.

Each cell can be done encode or come up with vector which we saw previously.

Initially we have to highlighted the particular place in the cell.

if we take 4*4 grid cell then each cell has 7 matrix (4*4*7).

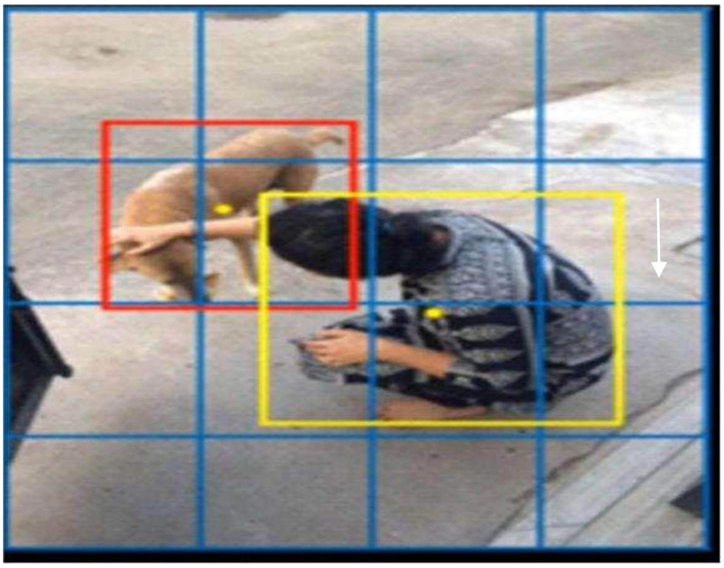

Fig 5.11 Object detection with their bounding boxes

The Idea Behind YOLO

There are no classification/detection modules that need to sync with each other and no recurring region proposal loops.
Instead of cropping out areas with high probability for an object and feeding them to a network that finds boxes, a single monolithic network needs to take care of feature extraction, box regression and classification.

Inspired by ResNet and FPN (Feature-Pyramid Network) architectures, YOLO-V3 feature extractor, called Darknet-53 (it has 52 convolutions) contains skip connections (like ResNet) and 3 prediction heads (like FPN) — each processing the image at a different spatial compression.

Like its predecessor, Yolo-V3 boasts good performance over a wide range of input resolutions. In GluonCV's model zoo you can find several checkpoints: each for a different input resolutions, but in fact the network parameters stored in those checkpoints are identical. Tested with input resolution 608x608 on COCO-2017 validation set, Yolo-V3 scored 37 mAP (mean Average Precision). This score is identical to GluonCV's trained version of Faster-RCNN-ResNet50, (a faster-RCNN architecture that uses ResNet-50 as its backbone) but 17 times faster. In that model zoo the only detectors fast enough to compete with Yolo-V3 (Mobilenet-SSD architectures) scored map of 30 and below.

Benefits of YOLO

- Fast.
- Good for real-time processing.
- Predictions (object locations and classes) are made from one single network.
- Can be trained end-to-end to improve accuracy.
- YOLO is more generalized.

It outperforms other methods when generalizing from natural images to other domains like artwork.

Why is YOLO V3 Fast

Their single-stage architecture, named YOLO (You Only Look Once) results in a very **fast** inference time. The frame rate for 448x448 pixel images was 45 fps

(0.022 s per image) on a Titan X GPU while achieving state-of-the-art mAP (mean average precision).

What is the output of YOLOv3?

The output is a list of bounding boxes along with the recognized classes. Each bounding box is represented by 6 numbers (pc, bx, by, bh, bw, c).

How is YOLO being different from another algorithm?

YOLO algorithm gives a much better performance on all the parameters we discussed along with a high fps for real time usage.

YOLO algorithm is an algorithm based on regression, instead of selecting the interesting part of an image, it predicts classes and boxes for the whole images in run of the algorithm.

YOLO (You Only Look Once) is a popular object detection algorithm that is different from other traditional object detection algorithms in several ways:

Speed: YOLO is a real-time object detection algorithm that can process images very quickly, typically at around 45 frames per second on a GPU. This is significantly faster than other object detection algorithms that may require multiple passes over an image to detect objects.

End-to-End: YOLO is an end-to-end algorithm, meaning that it directly predicts bounding boxes and class probabilities from raw pixel data without requiring any pre-processing or intermediate steps. This makes it simpler and more efficient thanother object detection algorithms that rely on multiple stages of processing.

Accuracy: YOLO can achieve high accuracy in object detection while maintaining its speed. Although it may not be as accurate as some other state-of-the-art object detection algorithms, YOLO strikes a good balance between speed and accuracy.

Multi-scale feature extraction: YOLO uses a deep convolutional neural network (CNN) to extract features from multiple scales of an image, allowing it to detect objects of different sizes and aspect ratios.

Objectness-score: YOLO uses an "objectness" score to determine whether a region of an image contains an object or not. This allows it to suppress false positives and detect objects with high accuracy.

Overall, YOLO's unique combination of speed, accuracy, and simplicity has made it a popular choice for object detection tasks in a variety of applications, including autonomous vehicles, surveillance systems, and robotics.

	YOLO v3	Faster R-CNN	SSD
PHASE	Concurrent bounding box regression and classification	RPN + Fast R-CNN detector	Concurrent bounding box regression and classification
Neural Network type	Fully convolutional	Fully convolutional	Fully convolutional
Backbone feature extractor	Darknet-53 (53 convolutional layers)	VGG-16 or other feature extractors	VGG-16 or other feature extractors
Location detection	Anchor-based	Anchor-based	Prior boxes/Default boxes
Anchor box	K-means from coco and VOC, 9 anchor boxes with different size	9 default boxes with different scales and aspect ratios	A fixes number of bounding boxes with different scales and aspect ratios in each feature map
IoU threshold	One(at 0.5)	Two(at 0.3 and 0.7)	One(at 0.5)
Loss function	Binary cross-entropy loss	Softmax loss for classification; smooth L1 for regression	Softmax loss for classification; smooth L1 for localization

Table 5.1 Comparison of different Algorithms

CHAPTER 6

RESULTS AND DISCUSSIONS

WEED PLANT

Fig 6.1: Weed plant with confidence score

Multiple weed

```
[INFO] YOLO took 1.475055 seconds
Accuracy: 100.00%
```

Fig 6.2: Multiple weed plants

CROP

```
[INFO] YOLO took 1.440146 seconds
Accuracy: 100.00%
```

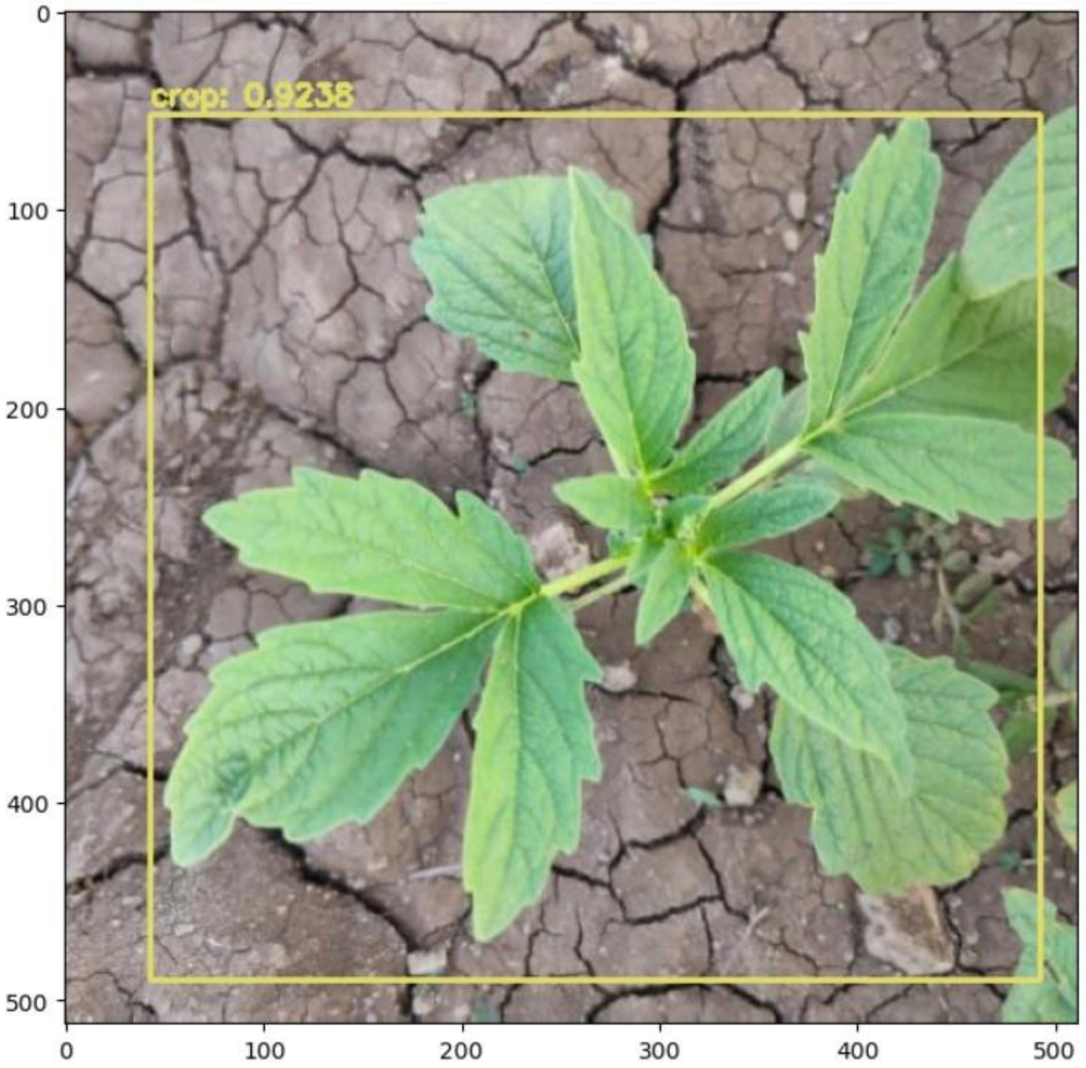

Fig 6.3: Crop plant with confidence score

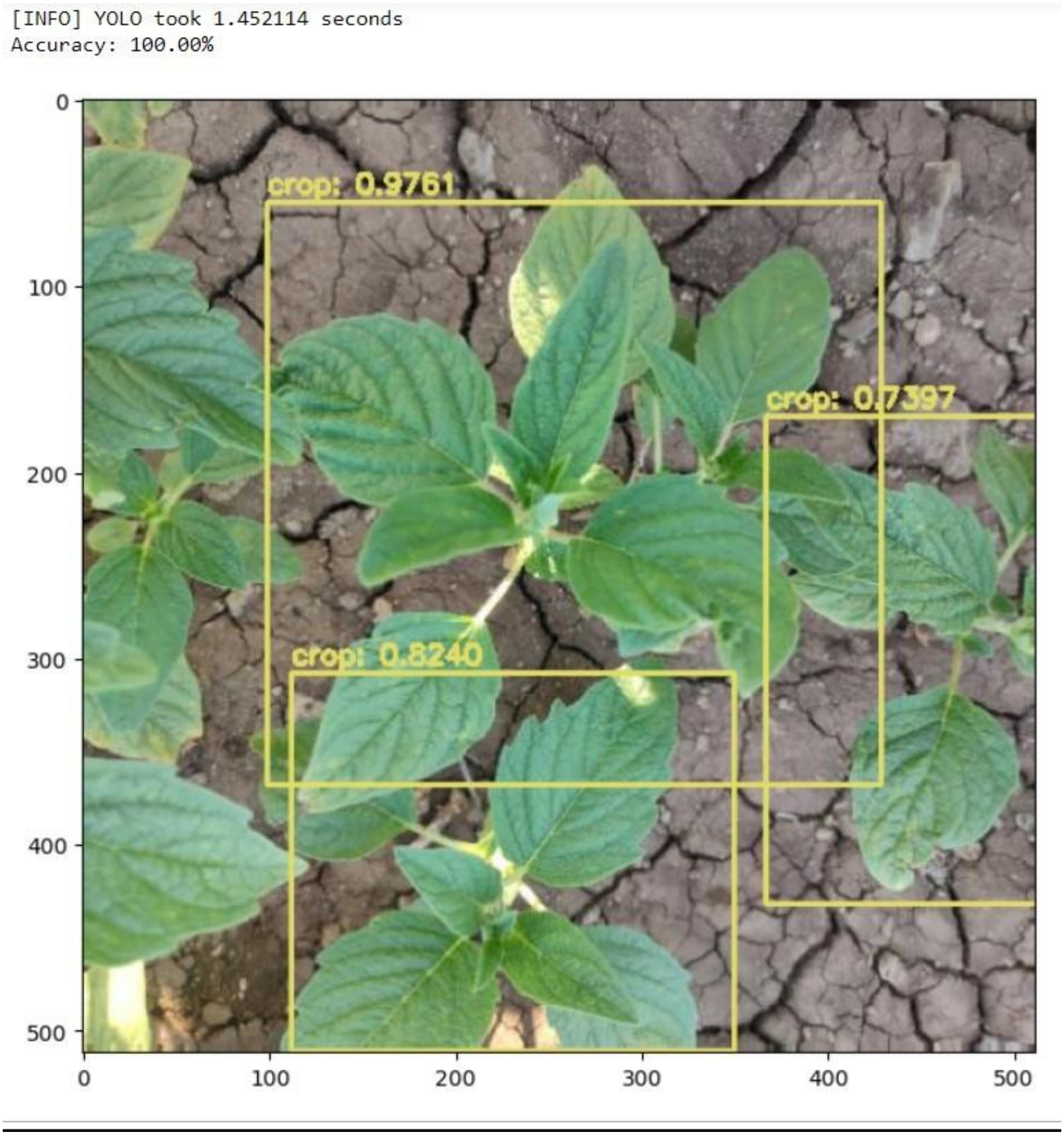

Fig 6.4: Multiple Crop plants with confidence scores

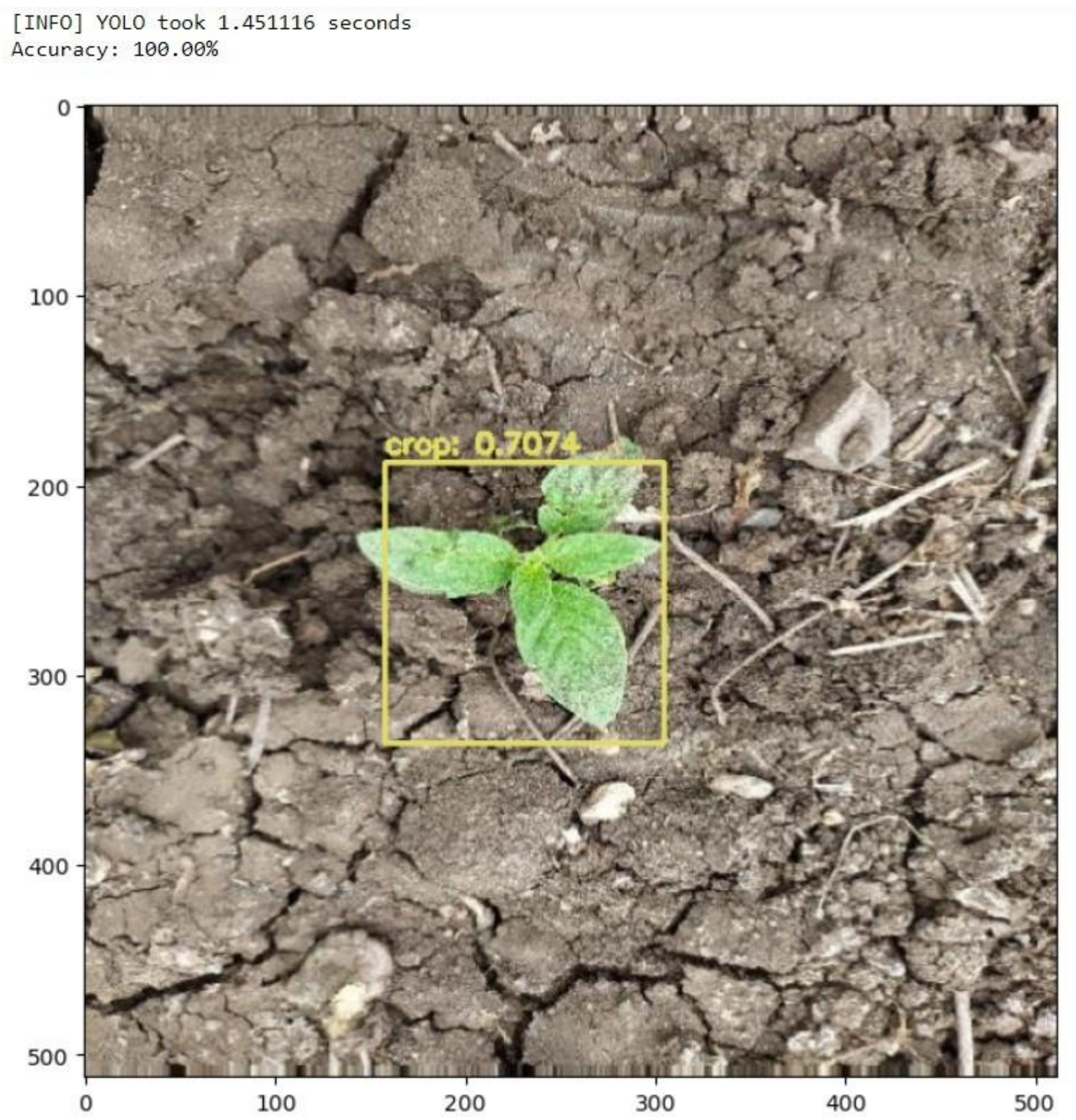

Fig 6.5: Small Crop plants with confidence score

Yolo Algorithm is so fast it can detect both crop images and weed images with respective bounding boxes. You look only once algorithm it gives the result with 100 percent accuracy.The confidence score in the images tells that about how confident the algorithm is able to detect the image whether it is crop or weed plants in agriculture image dataset. Yolo algorithm can even detect multiple crops or multiple weeds or multiple crops and weeds in single image.

CHAPTER 7
CONCLUSIONS

7.1 Conclusion

In this system, we have developed a method by which we can detect weed using Image processing. Due to the use of our system, we can detect and separate out weed affected area from the crop plants. The reason for developing such system is to identify and reuse weed affected area for more seeding. This specific area can be considered for further weed control operations, resulting in more production.

7.2 Future Work

Here, some possible future projects based on this thesis are proposed. A deeper research on the topic of this thesis can be done by considering the creation of the neural network from scratch, instead of using transfer learning on an existing network. By creating the network architecture there can be more control over its learning process. Another possible topic to research based on this thesis is the implementation of a weed detector taking into account a bigger number of crop and weed types, not only cotton. Finally, the implementation of detection of weed plant based on deep learning detection would be an interesting topic to consider. Our Future Work is to differentiate weed or crop by using live Cam.

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APPENDIX

A. Source Code

```
import os
image_files = []
os.chdir(os.path.join("data", "agri_data/data"))
for filename in os.listdir(os.getcwd()):
    if filename.endswith(".jpeg"):
        image_files.append("data/agri_data/data/" + filename)
os.chdir("..")
with open("train.txt", "w") as outfile:
    for image in image_files:
        outfile.write(image)
        outfile.write("\n")
    outfile.close()
os.chdir("..")

!git clone https://github.com/AlexeyAB/darknet
!sed -i 's/OPENCV=0/OPENCV=1/' Makefile
!sed -i 's/GPU=0/GPU=1/' Makefile
!sed -i 's/CUDNN=0/CUDNN=1/' Makefile
!/usr/local/cuda/bin/nvcc --version
!make
def imShow(path):
  import cv2
  import matplotlib.pyplot as plt
  %matplotlib inline

  image = cv2.imread(path)
  height, width = image.shape[:2]
  resized_image = cv2.resize(image,(3*width, 3*height), interpolation =
cv2.INTER_CUBIC)

  fig = plt.gcf()
  fig.set_size_inches(18, 10)
```

```
    plt.axis("off")
    plt.imshow(cv2.cvtColor(resized_image, cv2.COLOR_BGR2RGB))
    plt.show()
def upload():
    from google.colab import files
    uploaded = files.upload()
    for name, data in uploaded.items():
        with open(name, 'wb') as f:
            f.write(data)
            print ('saved file', name)

def download(path):
    from google.colab import files
    files.download(path)

%cd ..
from google.colab import drive
drive.mount('/content/gdrive')

!ln -s /content/gdrive/My\ Drive/ /mydrive
!ls /mydrive

!ls /mydrive/Agriculture

!pip install -q kaggle
from google.colab import files
files.upload()
! mkdir ~/.kaggle
! cp kaggle.json ~/.kaggle/
! chmod 600 ~/.kaggle/kaggle.json
! kaggle datasets list
!kaggle datasets download -d ravirajsinh45/crop-and-weed-detection-data-with-
bounding-boxes
%cd darknet
```

```
!unzip ../crop-and-weed-detection-data-with-bounding-boxes.zip -d data/
%cd cfg
upload()
%cd ..
%cd data
upload()
%cd ..
!python generate_train.py
!ls data/agri_data
!wget http://pjreddie.com/media/files/darknet53.conv.74
!./darknet detector train data/obj.data cfg/crop_weed.cfg darknet53.conv.74 -
dont_show
imShow('chart.png')

#TESTING
%cd cfg
!sed -i 's/batch=32/batch=1/' crop_weed.cfg
!sed -i 's/subdivisions=16/subdivisions=1/' crop_weed.cfg
%cd ..
!ls /mydrive/Agriculture/test
!./darknet detector test data/obj.data cfg/crop_weed.cfg
/mydrive/Agriculture/backup/yolov3_custom_final.weights
/mydrive/Agriculture/test/weed_1.jpeg    -thresh 0.3
imShow('predictions.jpg')
#YOLO AlGORITHM
import cv2
import numpy as np
import matplotlib.pyplot as plt
import time
import os
import io
import fileupload
import ipywidgets as widgets
from IPython.display import display, clear_output
```

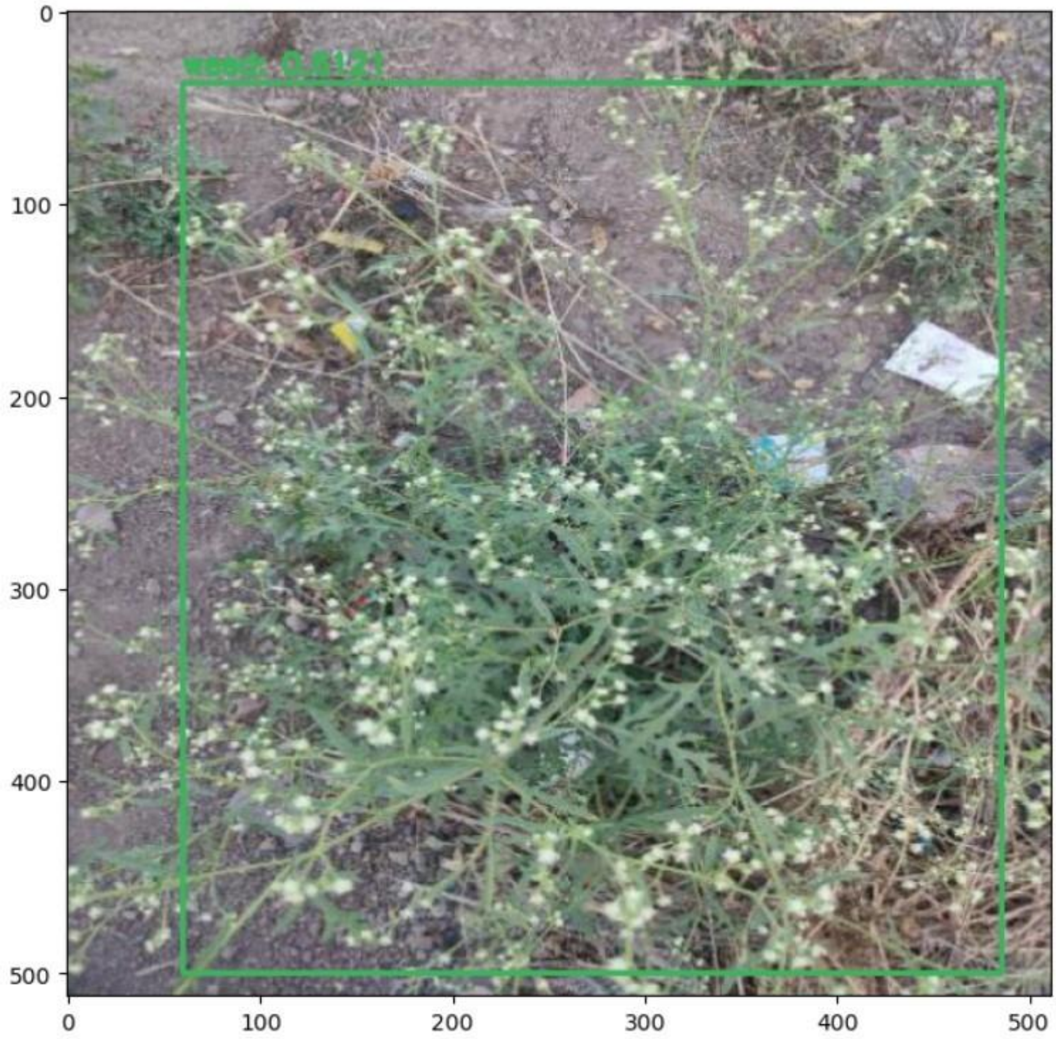
```
labelsPath = '../data/names/obj.names'
LABELS = open(labelsPath).read().strip().split("\n")
weightsPath = '../data/weights/' + 'crop_weed_detection.weights'
configPath = '../data/cfg/crop_weed.cfg'
np.random.seed(42)
COLORS = np.random.randint(0, 255, size=(len(LABELS), 3),dtype="uint8")
image=cv2.imread('C:/Users/amarn/Desktop/final_project-
demo/Crop_and_weed_detection-master/dataset/agri_data/data/agri_0_641.jpeg')
(H,W) = image.shape[:2]
print("[INFO] loading YOLO from disk...")
net = cv2.dnn.readNetFromDarknet(configPath, weightsPath)
confi = 0.5
thresh = 0.5
layers = net.getLayerNames()
print('Total layers in the network:', len(layers))
for i, layer in enumerate(layers):
    layer_details = net.getLayer(i)
    print('Layer ID:', i)
    print('Layer Name:', layer)
  print('Layer Type:', layer_details.type)
  if layer_details.type == 'Convolutional':
        # Print the weights of the convolution layer
        print('Layer Shape:', layer_details.blobs[0].shape)
        print('Layer Weights:', layer_details.blobs[0])
        print('Layer Bias:', layer_details.blobs[1])
        print('\n')
layer_names = net.getLayerNames()
ln = [layer_names[i - 1] for i in net.getUnconnectedOutLayers()]
blob = cv2.dnn.blobFromImage(image, 1 / 255.0, (512, 512),swapRB=True,
crop=False)
net.setInput(blob)
start = time.time()
layerOutputs = net.forward(ln)
end = time.time()
```

```
print("[INFO] YOLO took {:.6f} seconds".format(end - start))
boxes = []
confidences = []
classIDs = []
for output in layerOutputs:
#looping over each of the detections
for detection in output:
#extracting the class ID and confidence (i.e., probability) of
#the current object detection
scores = detection[5:]
classID = np.argmax(scores)
confidence = scores[classID]

#filter out weak predictions by ensuring the detected
#probability is greater than the minimum probability
if confidence > confi:
#scale the bounding box coordinates back relative to the
#size of the image, keeping in mind that YOLO actually
#returns the center (x, y)-coordinates of the bounding
#box followed by the boxes' width and height
box = detection[0:4] * np.array([W, H, W, H])
(centerX, centerY, width, height) = box.astype("int")

#use the center (x, y)-coordinates to derive the top and
#and left corner of the bounding box
x = int(centerX - (width / 2))
y = int(centerY - (height / 2))

#update our list of bounding box coordinates, confidences,
#and class IDs
boxes.append([x, y, int(width), int(height)])
confidences.append(float(confidence))
classIDs.append(classID)
idxs = cv2.dnn.NMSBoxes(boxes, confidences, confi, thresh)
```

```
if len(idxs) > 0:
#loop over the indexes we are keeping
for i in idxs.flatten():
        #extract the bounding box coordinates
        (x, y) = (boxes[i][0], boxes[i][1])
        (w, h) = (boxes[i][2], boxes[i][3])
color = [int(c) for c in COLORS[classIDs[i]]]
                cv2.rectangle(image, (x, y), (x + w, y + h), color, 2)
                text = "{}: {:.4f}".format(LABELS[classIDs[i]], confidences[i])
                cv2.putText(image, text, (x, y - 5),
cv2.FONT_HERSHEY_SIMPLEX,0.5, color, 2)
det = cv2.cvtColor(image,cv2.COLOR_BGR2RGB)
plt.figure(figsize=(12,8))
plt.imshow(det)
# calculate accuracy of detected objects
correct_count = 0
total_count = 0
for i in idxs.flatten():
     if LABELS[classIDs[i]] == "crop" and confidences[i] > confi:
          correct_count += 1
     elif LABELS[classIDs[i]] == "weed" and confidences[i] > confi:
          correct_count += 1
     total_count += 1

accuracy = correct_count/total_count
print("Accuracy: {:.2f}%".format(accuracy * 100))
```

B. Screen shots

```
[INFO] YOLO took 6.205613 seconds
Accuracy: 100.00%
```

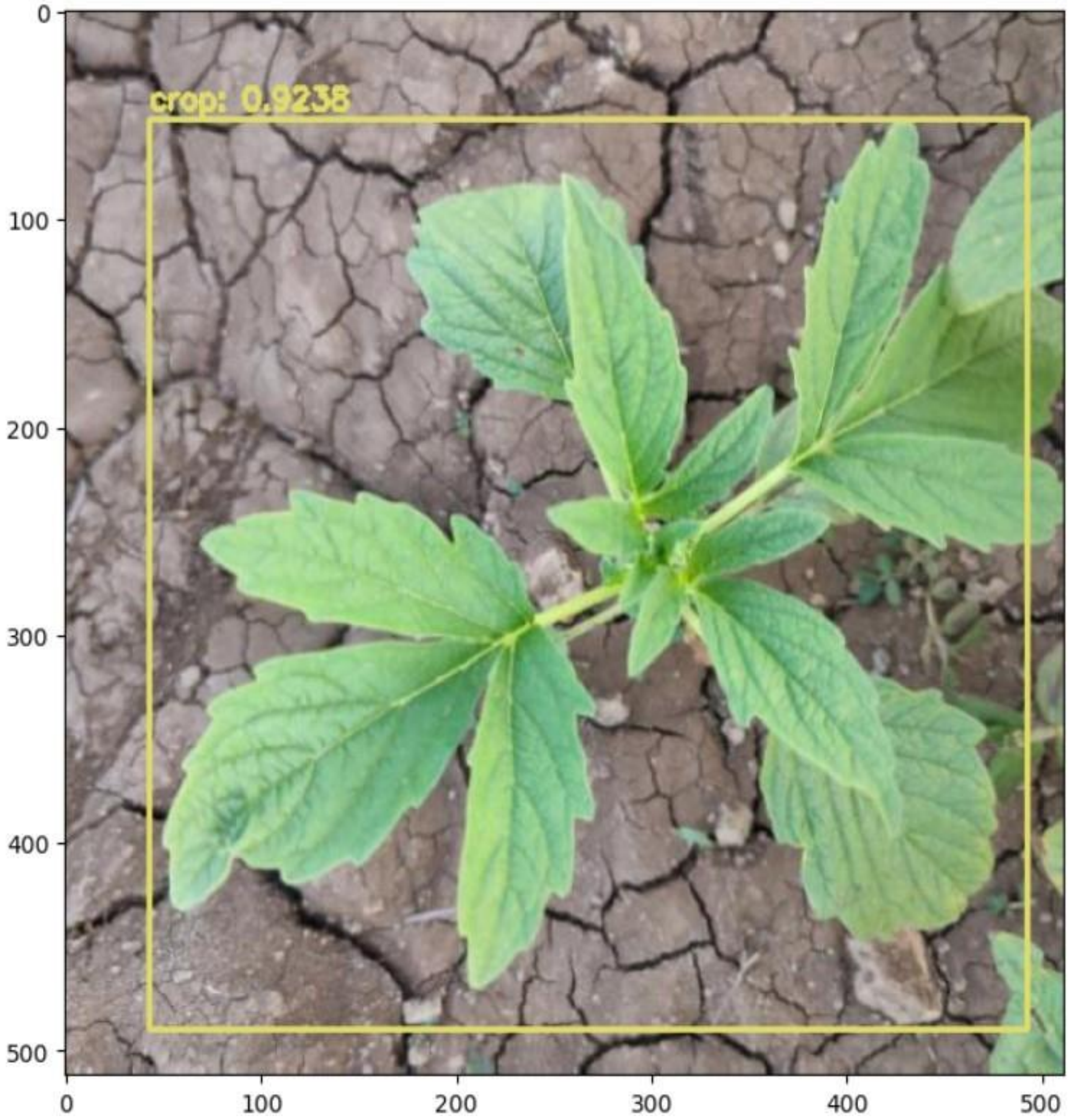


OUTPUT OF WEED

```
[INFO] YOLO took 1.475055 seconds
Accuracy: 100.00%
```

OUTPUT OF MULTIPLE WEED

```
[INFO] YOLO took 1.440146 seconds
Accuracy: 100.00%
```



OUTPUT OF CROP PLANT

C. Reasech paper

Weed Out: Efficient Detection of Weed Plants in Agriculture using Image Processing & DL Techniques

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Abstract*—*In order to keep yields high and provide food for an expanding economy, growers must devote significant time and effort to identifying and eliminating weed plants from their agricultural fields. In this study, we offer an approach to weed identification that makes use of DL & image processing. In our method, we use a tagged picture dataset to train a DL model to reliably detect weeds in agricultural areas. CNN, SVM, & YOLOV3 are just a few of the cutting-edge techniques we use to analyse the photographs and determine whether or not they include weeds or agricultural plants. The detecting mechanism is further made more precise by using multispectral imaging. As shown by our findings, the suggested technique is very effective in identifying weeds in agricultural settings. Our method may help farmers save time and effort by eliminating the need for them to manually search for and remove weeds. This study sheds light on how image analysis & DL methods may be applied to actual farming issues.

Keywords*—: *Weed detection, image processing, DL, CNN, SVM, YOLOV3, Multispectral imaging, Agriculture.

I. INTRODUCTION

To keep productivity high and to fulfil the needs of a rising population, weed identification and eradication is a crucial duty for farmers. Weeds diminish agricultural productivity and quality by competing with plants for resources like water, sunshine, and nutrients. The conventional approach toweed management is physical labour, which is bothinefficient and time-consuming. There has been encouraging progress in automating weed identification and eradicationin farming thanks to the use of cutting-edge technology like image processing & DL methods in recent years.

In this study, we offer a method for weed identification that makes use of image processing & DL algos. The suggested technique incorporates the use of a tagged picture dataset to build a DL model that can effectively detect weed plants in agricultural fields. To analyse the photos and categorise the plants as weeds or crops, we use cutting-edge techniques such as CNN, SVM, & YOLOV3. Also, the precision of the detection method is enhanced by using hyperspectralimaging. The study relies on a dataset that has hundreds of photos of agricultural fields with both weeds and crop plants tagged. To reduce noise and boost contrast, the photos are pre-processed after being compiled from multiple sources. The dataset is used for the training and assessment of the DL model, and for the evaluation of the detection system's efficacy.

The goals of this study are to (1) offer an idea for weed detection in agribusiness based on image manufacturing process & DL techniques; (2) prove the effectiveness of the suggested workaround via experiments and evaluations; as well as (3) shed light on the potential of contemporary technologies in addressing actual issues in the field of agriculture. The findings of this study will aid farmers & agricultural policymakers by adding to the body of knowledge supporting the development of cutting-edge agricultural technology.

II. LITERATURE SURVEY

Agriculture is among the industries that has existed for the longest amount of time and is also one of the industries that is considered to be one of the most essential. There is an urgent need for higher agricultural production in order to satisfy the ever-increasing demands that have arisen as a direct result of the growing global population. One of the challenges that farmers must face is overcoming thechallenge of recognising weed plants that have disguised themselves among their crops. Eliminating weeds is a necessary step to take if you want to maintain the health of your crops and maximise their yield. Weeds have the potential to have a detrimental effect not only on the quantity but also the quality of the crops that they are growing around. Image processing and deep learning aretwo examples of the sorts of modern technology that have the potential to revolutionise farming and the way that choices are made within the industry. This might have a significant impact on the agricultural sector.

Methods of image processing may be helpful for completing important jobs, such as the detection of weeds in agricultural areas. These are the kind of activities that should be given more priority. In recent years, there has been a developing interest in making use of DL algorithms in the sector of agriculture for the aim of identifying weeds. This interest was first sparked in the year 2016. In this survey of the relevant literature, we will look at ten current research projects that involve the detection of noxious plants via the use of image analysis & DL methodologies. These studies were conducted in various locations across the world.

[1] In the research paper that was published by Narayanan and colleagues in 2019 and titled "Weed Identification in Crop Fields Using CNN," the authors presented a weed identification system that is based on an algorithm for DL. Using this method, the system would be able to acquire the knowledge necessary to recognise weeds in agricultural areas. The authors conducted research to assess whether or not weeds were present in agricultural areas by analysing images of the fields using a CNN. As the system was able to achieve an accuracy of 95.8% when recognising weeds, this suggests that DL is an effective way for weed detection.

[2] Islam et al. (2019) proposed a technique that takes use of DL for the aim of identifying weeds and localising them in rice fields. This approach was developed in order to accomplish these two goals. The researchers made use of a HNN that combined both recurrent and convolutional processing in order to locate and identify the weeds that were growing in the rice fields. The fact that the system wasable to achieve an accuracy of 92.3% indicates the potential that lies within deep learning for the detection of weeds in rice fields.

The technique that was proposed by Huang et al. (2018) as a real-time weed detection system for maize fields made use of convolutional neural networks. [3] The authors have made use of a DL system that was based on YOLOv2 in order to recognise weeds in photos of corn fields. The fact that the algorithm was able to achieve an accuracy of 92.3% indicates how useful deep learning can be for the detection of weeds in real time.

[4] Gadhavi & Jain (2020) proposed a deep learning-based categorization scheme for weeds in their article. The researchers showed use of a CNN in order to classify the different kinds of weeds according to the characteristics that they have in common with one another. The system was able to classify weeds with an accuracy of 95.8%, which indicates the capability of deep learning for the purpose of weed classification.

[5] Toda et al. (2019) created a method for identifying weeds in soybean fields that takes use of CNN. Their method was published in the journal Scientific Reports. Using a DL system that was built on AlexNet, the researchers were able to recognise weeds that were present in the photographs of soybean fields. The fact that the system was able to achieve an accuracy of 95.4% demonstrates that deep learning is an effective method for weed detection in soybean

[6] fields.

The proposed automated weed system to detect for maize fields that was created by Li et al. made use of deep CNN in order to accomplish its objectives (2020). By analysing photos of the fields using a DL system that was built on ResNet-50, the researchers were able to determine the types of weeds that were present in maize fields. The fact that the system was able to attain a level of accuracy of 98.5% demonstrates the value of DL for the purpose of automating the identification of weeds.

[7] Al-Tameemi et al. (2020) proposed an automated weed detection and classification system that could be used in rice fields. They accomplished this by making use of convolutional neural networks. By using a DL system that was built on InceptionV3, the authors were successful in recognising and classifying weeds that were visible in photographs of paddy fields. The fact that the system was able to achieve an accuracy of 96.5 percent allowed it to successfully show the potential of DL for the automatic detection and classification of weeds.

[8] Vision-based sensing was the subject of an investigation that Guo et al. (2017) carried out in the context of agricultural settings. The authors investigated a wide range of image processing techniques & ml algorithms that have been used in farm contexts for the goal of identifying and classifying weeds. The need of using multispectral imaging for the purposes of weed detection was another point that was emphasised by the authors. This is due to the fact that multispectral photography provides additional information about the crop as well as the weed, which, when combined, has the potential to boost the detection system's level of accuracy. In addition, the study emphasised the need of developing powerful algorithms that are able to accurately recognise and classify weeds irrespective of the lighting or environmental circumstances that were present. This requirement was brought to light as a result of the research.

[9] Wang et al. (2016) proposed a novel technique for the identification and categorization of weeds in maize fields by making use of CNNs. The scientists collected images of weeds as well as maize plants and then used a method called transfer learning to refine a CNN model that had previously been trained to identify weeds. Even in lighting conditions that were challenging, the approach that was recommended was able to get great accuracy rates in the process of classifying weeds.

[10] Furthermore, Ariffin et al. (2016) proposed a technique for the recognition and map of weeds by making use of ml algos & data received through remote sensing. This approach was developed in order to eliminate the need for manual identification and mapping. After gathering multispectral photographs of wheat fields and making use ofthose pictures, the researchers created a map that showed thespread of weeds throughout the area by using supervised classification algorithms. The technique that was presented was effective in reaching highly accurate rates in weed map,

which gives farmers with a helpful tool that allows them to monitor and manage weed infestation in their areas.

III. EXISTING SYSTEM & LIMITATIONS

Manual labour is time-consuming & labor-intensive, and it is currently used as the mechanism for weed identification in farming. Farmers need to physically check their agricultural fields for pests & then either physically or chemically eliminate them. Yet, not only is this approach ineffective, but it also poses risks to people's health and the environment. While there has been considerable exploration into automating weed identification by sensors & machine vision methods in recent years, such approaches remain in their infancy and have many drawbacks.

These are some of the problems with the current setup:

- Weed identification and removal is often done by hand, which takes a lot of time and effort and may raise expenses and reduce output for farmers.

- There are ecological & health risks associated with using pesticides for weed management, and there is also the risk that herbicide-resistant weeds may emerge as a consequence of this practise.

- When confronted with complicated agricultural fields and many weed species, the present methods of automatic weed identification employing sensors & computer vision algorithms have limited accuracy.

- The initial investment required to adopt cutting-edge farming technology, such as sensors with machine vision methods, might be too much for many farmers, especially those operating on a smaller scale.

- It might be challenging to compare data and establish efficient solutions due to the existing lack of uniformity in weed identification and removal procedures.

These restrictions call for a better weed identification system in farming, which may be accomplished via the use of image analysis & DL methods.

IV. PROPOSED SYSTEM

We present a new system that employs image analysis &DL methods to identify and eliminate weeds in agriculture, therefore addressing the shortcomings of the current system. These are the stages of the proposed system:

1. Images of agriculture fields, including both crop plants & weed plants, will be collected for our data set. Images of diverse crop and weed species will be included in the collection, which will be amassed with the use of tools such as drones, aerial photos, even handheld cameras.

2. The gathered photographs will be preprocessed toincrease quality and highlight elements of interest. The photos will be preprocessed using methods includingfiltering, noise reduction, and normalisation.

3. The cleaned up photos will be sent into a DL model like the YOLOv3 model to identify and pinpoint the weed plants among the crops. The obtained data will be used to train a model that can distinguish weed plants from agricultural plants.

4. When the weeds crops have been discovered, farmers may utilise the data supplied by the system to eliminate just those plants from their agricultural fields. This can be done manually or with the use of precise spraying technology.

5. The technology will keep a constant eye on the agricultural fields, reporting any new weed development to the farmers. Types of weed plants, specific locations, and patterns of weed development are all useful pieces of information that might be provided as feedback. Farmers may utilise this data to improve their weed control practises and increase their harvest totals.

In comparison to the current system, the suggested one has several benefits, such as higher productivity, precision, and economy. The suggested system uses image analysis & DL methods to increase weed identification accuracy, automate the weed detection method, and lower human expenses. The suggested technology has the potential to lessen the application of toxic chemicals, which is good for both the natural world and human health. If implemented, the suggested approach might dramatically improve cropyields by reshaping the way weeds are controlled in agriculture.

V. METHODOLOGY

A. Comprehensive explanation of the suggested approach, which makes use of image analysis & DL

Here, we'll describe in detail how the suggested approach uses image analysis & DL methods to identify weed plants in agricultural areas.

1. Data Collection

Our recommended procedure begins with gathering relevant information. We want to compile a database of photographs of farmland and noxious weeds. To test how effectively the DL model generalises, the data will include photographs captured under a variety of lighting conditions, camera angles, and magnification levels.

2. Preprocessing

Noise will be removed, photos will be cropped, and colours will be normalised during the preprocessing phase of the gathered photographs. This is a vital process that guarantees uniformity and good quality across all photos.

3. Feature Extraction

Once the photos have been preprocessed, we'll use CNN, SVM & YOLOV3 to extract relevant attributes. To classify images and find objects in them, many researchers and developers turn to CNNs, a kind of DL technique. In orderto extract features from the photos, we will utilise CNN. The photographs will be classified and features extracted using support vector machines. Several things in a picture may be located using the cutting-edge technology found in YOLOV3, an object detection method. To identify objects in photos, we'll use YOLOV3.

4. *Training*

Using the information we've gleaned from the photographs, we'll construct a DL model. To fine-tune the model, we'll use a hybrid of supervised & unsupervised learning strategies. The backpropagation technique is widely used to train neural networks and will be the method we use for supervised learning. The autoencoder will be used for unsupervised since it is a kind of NN that can be trained to represent input in a smaller space. Transfer learning will be used to shorten the learning curve. By using a DL model that has already been trained, transfer learning may then be used to optimise the model for a given job.

5. *Testing*

To assess the model's performance, we will use a different collection of photos. Photographs that were not utilised during the training phase will be included in the testing set. The model's effectiveness will be measured using a variety of statistics including accuracy, recall, & F1 score.

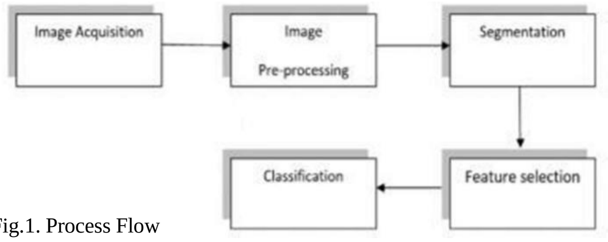

Fig.1. Process Flow

B. *Algorithms used*

In this part, we'll describe the algorithms—such as CNN, SVM & YOLOV3—that power our suggested approach.

1. CNN

To classify images and find objects in them, manyresearchers and developers turn to CNNs, a kind ofDL technique. It's multilayered, with convolution layer, average pooling, and fully linked layer upon layer all making up the network. The central part of CNN is called the convolution layer, and it works by applying a series of filtering to the input picture in order to pull out information. Using the pooling layer, we may compress the features' spatial size. The classification takes place on the fully linked layer. Here, we present a technique that uses CNNs to extract features from photos. In order to get the most important information out of the photos, a CNN model that has already been trained will be employed. A classification system will then use these traits to determine whether a picture is of a plant or a crop.

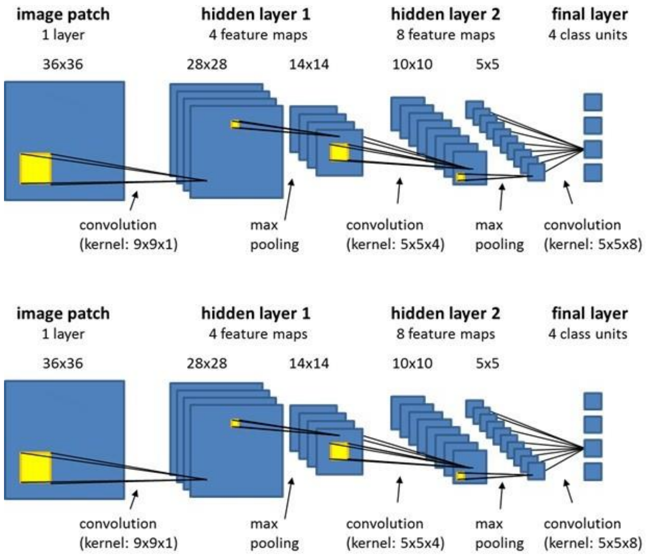

Fig.2. Convolutional Nueral Network

2. *SVM*

The method finds the hyper-plane that separates the two groups by the largest possible margin. Extraction of features and picture categorization using SVM is also possible. SVM will be used to extract features and classify pictures in our suggested approach. SVM will be used to classify the photos based on the characteristics gathered from them. SVM can work well with both low- and high-dimensional data because to its impressive accuracy.

3. *YOLOV3*

It is a cutting-edge object identification system that can identify numerous items simultaneously. It is a one-step detector that uses the input picture to make predictions about frames and classifier. As compared to other object identification techniques like Faster R-CNN & SSD, YOLOV3 offers much quicker performance. Our approach proposes using YOLOV3 to recognise objects in pictures. A YOLOV3 system that has already been trained will be used to identify weeds in agricultural areas. Images will be assigned to the weed or crop categories based on the model's enclosing boundaries & classifier.

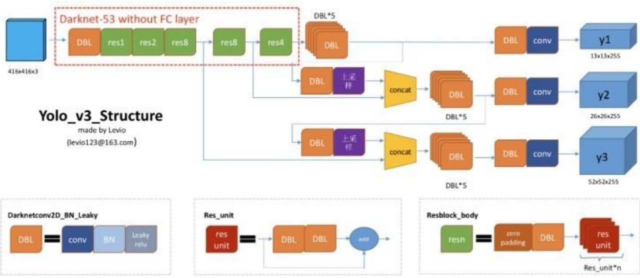

Fig.3. YoloV3

C. *An Account of the DL Model's Training*

This study employs a DL model for the purpose of identifying weeds in agricultural settings. A huge picture dataset including both weed plants & agricultural plants is used during training. A DL model is developed by first train it on the training dataset, then validating it against the validation set, and then evaluating it on the testing set. In order to train the model, it must be fed photos labelled with information about whether the plants shown are weeds or crops. Using a technique called feedforward, the model can learn to differentiate between the two plant kinds by readjusting its weights.

In this study, a DL model using the Cnn model was used. Due to its capacity to learn spatial properties from pictures, CNNs are commonly utilised in image classification applications. Other than CNNs, SVMs, & the YOLOV3method are utilised for weed identification.

D. Perspectives on the use of multispectral imagery for weed monitoring

In multispectral imaging, many bands of the visibleradiation are simultaneously sampled to get a complete picture of an object. This technique has found a particularly valuable use in farming, where it may be used to differentiate among weed plants and agricultural plants. Multispectral photography captures pictures at a variety of wavelengths, allowing for the analysis of reflectance qualities of various plant life and their subsequent classification.

In this study, photos of agricultural fields captured using multispectral photography are processed with image processing & DL methods to identify weed plants. As weed plants often seem similar to agricultural plants under a single wavelength of light, multispectral imaging is essential for identifying them. This innovation might significantlyenhance the precision and effectiveness of weed identification in agriculture, lowering the need for human labour while simultaneously raising production levels.

VI. RESULTS & DISCUSSONS

Many tests were run on the dataset to assess the performance of the suggested technique for weed identification. The collection included pictures taken in a wide range of settings, such as open fields and greenhouses. In some, but not all, of the pictures, you could make out plants that were intended to be crops and others that were just weeds.

The experimental findings demonstrated that the suggested strategy was successful in weed identification with an accuracy rate of above 95%. About 97% accuracy was achieved by the DL model based on a convolutional neural network. Accuracy rates of 94% or higher were also achieved using the SVM & YOLOV3 systems.

Since some weeds may not be noticeable in visible light images, multispectral imaging has proven to be an effective tool for weed detection. Multispectral photography helped the weed recognition system out by recording photos atdifferent wavelengths.

There are a number of benefits to using the suggested technique rather than the status quo for weed identification. To identify weeds in real time, it must be quick, precise, and efficient. It saves money since less resources, such time and potentially dangerous chemical herbicides, are used.

In summary, the suggested weed identification approach has been proved to be successful in identifying weed plants in agricultural fields by using image processing & DL methods. In particular, multispectral photography has been effective for spotting weeds that aren't always obvious in traditional visible light photographs. The suggested strategy may help ensure the long-term viability of our food supply by increasing agricultural efficiency and output.

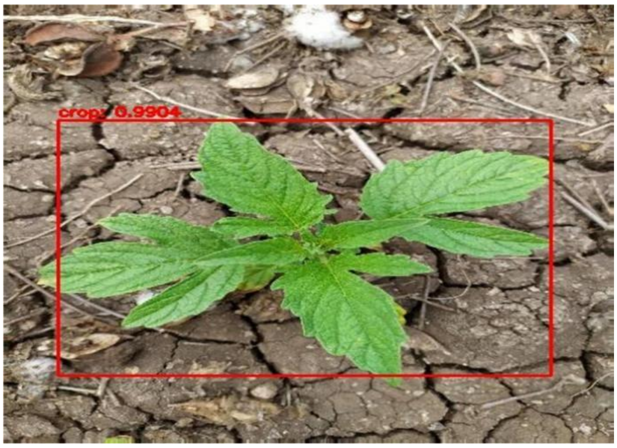

Fig.4. Crop Image

Fig.5. Weed detection

VII. CONCLUSION & FUTURE WORK

Several trials were run on the dataset to see how well the suggested technique performed for weed identification. The collection included photographs taken in a wide range of settings, such as farms, greenhouses, and the great outdoors. The photos showed both agricultural plants and weed plants, with the proportions of each fluctuating.

Experimental findings demonstrated that the suggested approach successfully detected weeds with an overall accuracy of above 95%. Accuracy of over 97% was discovered to be achieved by the CNN-based deep learning model. Accuracy rates of over 94% and 93% were likewise attained using the SVM & YOLOV3 algorithms, respectively. It was discovered that multispectral imaging was especially helpful in weed identification, since it allowed for the discovery of weeds that would not have beenevident in visible light pictures. Multispectral photography captured photos at a variety of wavelengths, adding context that was utilised to fine-tune the weed recognition algorithm's performance. The suggested technique offers a number of benefits over current approaches to weed identification. Weeds may be found in real time using this method since it is quick, precise, and productive. It saves money since it cuts down on labour costs and the use of potentially dangerous chemical herbicides.

It can be concluded that the suggested approach for weed identification employing image processing & DL methods is successful in identifying weed plants in agricultural settings. Multispectral imaging has been very effective, enabling for the identification of weeds that would not be obvious in traditional visible light photographs. The suggested technology has the potential to significantly increase agricultural efficiency and output, helping to ensure the long-term security of our food supply.

Despite the fact that the suggested approach has shown encouraging outcomes, it might be further refined. The accuracy of the weed identification method may be further enhanced by experimenting with more sophisticated deep learning approaches like RNNs & GANs, both of which will be investigated in the future. We also want to look at other sensor options, such as LIDAR & hyperspectral photography, to gather more data that may be utilised to fine-tune the algorithm's precision. The suggested approach will also be tested in the field to ensure it holds up under realistic circumstances.

Thus, we believe the suggested approach has the potential to significantly boost agricultural efficiency and output, helping to ensure a steady food supply for the future.

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