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# Convolutional Neural Networks for Use in Weed Detection

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**ABSTRACT**

Today, weed detection and plant detection in plants are increasingly challenging. Vegetable planting weeds have not received much attention thus far. Although the differences in weed species are significant, traditional methods for weed identification focused mostly on directly identifying weed. This work proposes an alternative approach that combines deep learning with image technologies. The dataset was initially trained using the CNN model. Once the training is finished, we can identify and predict whether the input image is a crop or a weed.

Keywords: Weed Detection, Deep Learning, CNN.

## I. INTRODUCTION

A plant that is "in the wrong location" is referred to as a weed in this context. Common examples are plants that are undesirable in human-controlled environments like farm fields, gardens, lawns, and parks. A plant that is a weed in one context may not be a weed when it grows in a situation where it is desired, and where one species of plant is a valuable crop plant, another species in the same genus may be a serious weed, such as a wild bramble growing among cultivated loganberries. According to taxonomy, the term "weed" has no botanical significance. In a future crop, volunteer crops (plants) are treated the same way as weeds. Numerous plants that are commonly thought of as weeds are also produced on purpose in gardens and other cultivated areas, in which case they are also referred to as helpful weeds.

Any plant that grows or reproduces invasively outside of its natural habitat is also referred to as a weed. More broadly, the term "weed" is sometimes used pejoratively to describe organisms beyond the plant world that are able to thrive in a variety of conditions and procreate swiftly; in this sense, it has even been used to describe people. The management of weeds is crucial in agriculture. The use of hoes by hand, cultivators with power, mulching or soil solarization, smothering, and fatal wilting with high heat, burning, or chemical attack with herbicides are some of the techniques.

Some types of weeds have similar adaptations to harsh settings. In other words, disturbed habitats that offer weeds an edge over valuable crops, pastures, or decorative plants, such as those where soil or natural vegetative cover has been harmed or often gets damaged. Which weed populations dominate will depend on the characteristics of the ecosystem and any disruptions to it.

Plants that are suited to naturally occurring disturbed settings like dunes and other windswept places with shifting soils, alluvial flood plains, river banks and deltas, and areas that are regularly burned are examples of such ruderal or pioneer species. Some weeds are efficiently preadapted to grow and proliferate in human-disturbed regions such as agricultural fields, lawns, roadsides, and construction sites because human agriculture methods frequently mirror these natural settings where weedy species have developed.

The weedy nature of these species frequently gives them an advantage over more desirable crop species because they frequently grow quickly and reproduce quickly, they frequently produce seeds that persist in the soil seed bank for a long time, or they may have brief lifespans with multiple generations in the same growing season. Contrarily, permanent weeds frequently have creeping stems that root and spread out across the ground, like ground ivy (Glechoma hederacea), or underground stems that extend beneath the soil's surface.

According to the "natural enemy's hypothesis," plants liberated from these specialised consumers may become dominant when transferred to other habitats since the creatures in their native habitat that compete with them or feed on them are missing. The Klamath weed is one such instance. Once being unintentionally introduced to North America, it endangered millions of hectares of prime grain and grazing area, but after some of its natural enemies were brought in during World War II, it was quickly reduced to a rare roadside weed.

Weeds have more resources available for growth and reproduction in areas where predation and competitive interactions are absent. The "novel weapons hypothesis" is a theory that suggests that some species that are introduced into new ecosystems become weedy because they produce allelopathic substances to which native plants are not yet acclimated. The growth of mature plants or the germination and development of seeds and seedlings may be hampered by these substances.

Even if a plant is harmless in and of itself, its ecological role may still classify it as a weed if it harbours a pest that depends on it for survival. For instance, Berberis species serve as intermediate hosts for stem rust fungi, which causes serious damage to wheat crops when they are grown close to fields.

For a variety of reasons, both native and non-native plants are undesirable in a certain area. Functionality is a significant one; they must be controlled to prevent crop yields from being lost or reduced when they interfere with the production of food and fibre in agriculture. They obstruct other cosmetic, decorative, or recreational objectives, such as those in lawns, landscape design, playing fields, and golf courses, which is another significant factor. They can also be problematic for environmental reasons, such as when introduced species outcompete preferred endemic plants for resources or space. Weeds cause problems in horticulture (both functionally and aesthetically) and the environment because of these factors:

- Providing hosts and vectors for plant pathogens, giving them greater opportunity to infect and degrade the quality of the desired plants.
- competing with the desired plants for the resources that a plant typically needs, namely direct sunlight, soil nutrients, water, and (to a lesser extent) space for growth.
- Providing food or shelter for animal pests like seed-eating birds and Tephritid fruit flies that would otherwise struggle to survive seasonal shortages.
- Causing root damage to engineering works like drains, road surfaces, and foundations; obstructing streams and rivers.
- Causing irritation to the skin or digestive tracts of people or animals, either physically through thorns, prickles, or burs, or

chemically through natural poisons or irritants in the weed.

Even while the name "weed" is typically associated with undesirable plants, many of them can actually be useful. Many weeds are edible, and their leaves or roots can be used as food or herbal medicine. Examples include the dandelion (Taraxacum) and lamb's quarter. Burdock is widespread over much of the world, and in East Asia, it is occasionally used in soup and medicinal. Some weeds draw advantageous insects, and these insects in turn can shield crops from damaging pests. Weeds can also deter pest insects from locating a crop because their presence alters the frequency of helpful indications that pests use to identify food. The ground cover provided by weeds can serve as "living mulch," reducing moisture loss and preventing erosion.

Dandelions, for instance, use their tap root to draw up elements like calcium and nitrogen from deep below the soil, and clover has nitrogen-fixing bacteria living in its roots, which directly fertilise the soil. Weeds can help increase the fertility of the soil. The dandelion is one of many plants that help crops develop deeper root systems by breaking up hardpan in overly-cultivated fields. Some garden flowers were selectively selected for their garden-worthy flowers or leaves after emerging as weeds in farmed areas. The corn cockle (Agro stemma githago), which was once a common weed in European wheat fields but is now occasionally grown as a garden plant, is an example of a crop weed that is grown in gardens.

## II. RELATED WORKS

This model highlights an existing methodology that was created utilising some image processing techniques that will split the image and identify the weed portion of the crop.

[1] T. W. Berge, A. H. Aastveit, and H. Fykse:

The use of site-specific weed management in cereals has been impeded by a lack of automatic weed detecting technologies. SINTEF ICT (Oslo, Norway) developed a preliminary object-oriented approach for the automatic detection of broad-leaved weeds in wheat, which was evaluated. The near-ground red-green-blue images are used by the algorithm (called "Weed Finder") to assess the total density and cover of broad-leaved weed seedlings in cereal fields. Using images from two wheat fields that had been sown with the typical 0.125-meter-apart row spacing for the area, "Weed Finder" was tested for its ability to predict "spray" or "no spray" decisions in accordance with a model for spray decision-making for spring cereals that had previously been proposed. Using the decision model as a straightforward look-up table, "Weed Finder" correctly identified which weeds to spray in 65 to 85% of the test photos. Comparable mean rates using discriminant analysis ranged from 84 to 90%. Future versions of “Weed Finder” must be more accurate and accommodate weed species recognition.

[2] E. Hamuda, M. Glavin, and E. Jones: The survey first focuses on segmentation, then briefly examines picture pre-processing. In the segmentation phase, plants are segmented against backgrounds (identifying plant from a background of soil and other residues). There are three main plant extraction strategies that are covered: segmentation based on colour index, segmentation based on threshold, and segmentation based on learning. This review primarily focuses on colour index-based methods because they are prevalent in the literature. Therefore, based on studies from the literature completed in the recent past, particularly from 2008 to 2015, a full assessment of the segmentation performance of colour index-based techniques is offered.

[3] H. Mennan, K. Jabran, B. H. Zandstra, and F. Pala: Our lives would not be complete without vegetables, which also have enormous commercial and nutritional importance. In addition to lowering vegetable yield, weeds also lower crop quality. Both organic vegetable production and achieving environmentally sustainable weed management

depend on non-chemical weed control. According to estimates, weed-vegetable competition can cause a 45%–95% reduction in vegetable yield. Vegetable weed control without chemicals is preferred for a number of reasons. Vegetables, as an example, are more likely to be contaminated by herbicide residue than grains or pulse crops. Due to environmental contamination, the development of herbicide resistance in weeds, and a significant preference for organic vegetable cultivation, non-chemical weed management in vegetables is also required. Although there are a number of non-herbicide weed control methods, cover crops are a desirable option since they offer satisfactory and long-lasting weed control as well as a number of other advantages (such as soil and water conservation).

| S. No | Journal Type with year | Authors | Title | Outcomes |
|---|---|---|---|---|
| 1 | 2014 | Olfa Mzoughi, Itheri Yahiaoui, Nozha Boujemaa, Ezzeddine Zagrouba | Multiple leaflets-based identification approach for compound leaf species | Compound leaf species identification |
| 2 | Elsevier-2016 | Guillermo L. Grinblat, Lucas C. Uzal, Mónica G. Larese, Pablo M. Granitto | Deep learning for plant identification using vein morphological patterns | Vein morphological patterns |
| 3 | Elsevier, 2017 | Sue Han Leea , Chee Seng Chana,∗ , Simon Joseph Mayo b , Paolo Remagninoc | How deep learning extracts and learns leaf features for plant classification | Deep learning for leaf features for plant classification |
| 4 | International symposium on Computer Vision and Internet (VisionNet'15), Elsevier Procedia Computer Science 58(2015) 740-747.-2015 | Trishen Munisami, Mahess Ramsurn, Somveer Kishnah, Sameerchand Pudaruth | Plant Leaf Recognition using Shape features and colour Histogram with K-nearest Neighbor classifiers | Plant Leaf Recognition |

## III. METHODOLOGY

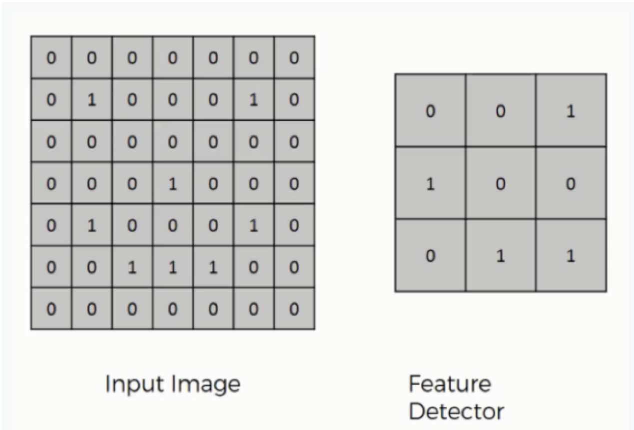
In our suggested approach, we use the CNN algorithm built on deep learning to categorise the crop and weed from the input image under consideration. The dataset images, which include crop and weed photos in addition to the weed, were first trained using the CNN model. Once the training is finished, we can submit the input image to test the image and determine if it is a crop or a weed. Below is a block diagram of our suggested model.

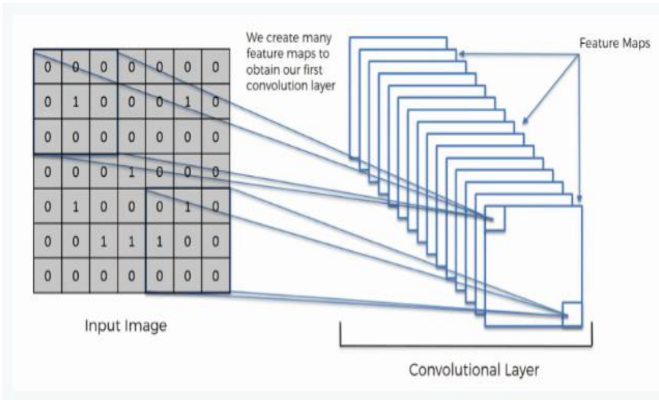
### 1. Convolutional Neural Network

**Step1: convolutional operation**

The first building block in our plan of attack is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters. We will also discuss feature maps, learning the parameters of such maps, how patterns are detected, the layers of detection, and how the findings are mapped out.

The Convolution Operation

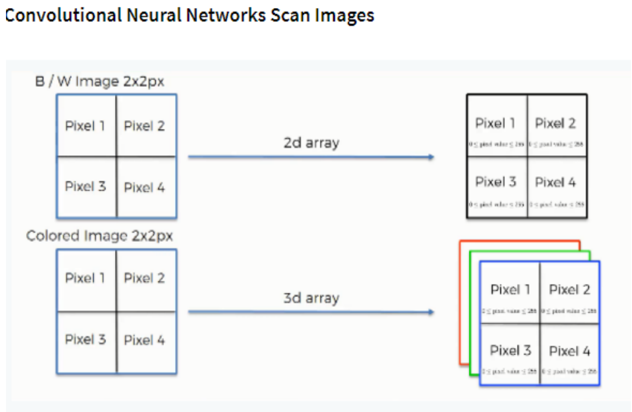



**Step (1b): ReLU Layer**

The second part of this step will involve the Rectified Linear Unit or Relook. We will cover Relook layers and explore how linearity functions in the context of Convolutional Neural Networks.

Not necessary for understanding CNN's, but there's no harm in a quick lesson to improve your skills.




## Step 2: Pooling Layer

In this part, we'll cover pooling and will get to understand exactly how it generally works. Our nexus here, however, will be a specific type of pooling; max pooling. We'll cover various approaches, though, including mean (or sum) pooling. This part will end with a demonstration made using a visual interactive tool that will definitely sort the whole concept out for you.

## Step 3: Flattening

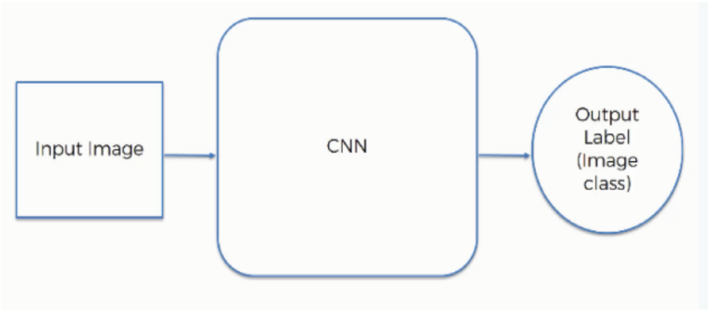
This will be a brief breakdown of the flattening process and how we move from pooled to flattened layers when working with Convolutional Neural Networks.

## Step 4: Full Connection

In this part, everything that we covered throughout the section will be merged together. By learning this, you'll get to envision a fuller picture of how Convolutional Neural Networks operate and how the "neurons" that are finally produced learn the classification of images.

## Summary

In the end, we'll wrap everything up and give a quick recap of the concept covered in the section. If you feel like it will do you any benefit (and it probably will), you should check out the extra tutorial in which Softmax and Cross-Entropy are covered. It's not mandatory for the course, but you will likely come across these concepts when working with Convolutional Neural Networks and it will do you a lot of good to be familiar with them.



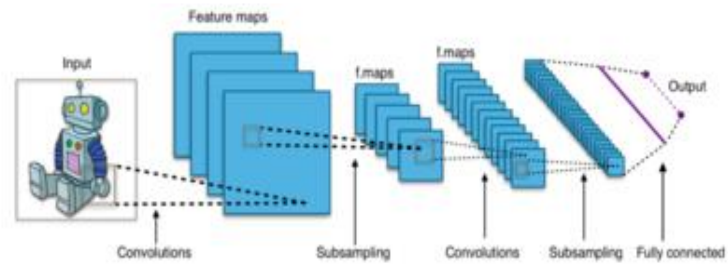




Fig 2. CNN Architecture

## SOFTWARE DEVELOPMENT LIFE CYCLE – SDLC:

In our project we use Agile model as our software development life cycle because of its step-by-step procedure while implementing.

- Requirement Gathering and analysis: All possible requirements of the system to be developed are captured in this phase and documented in a requirement specification document. System requirements will be mainly focused here.
  - The requirement we gathered here is mainly of the dataset which is of crop and weed images are collected from the kaggle website.
  - The dataset containing images of crop and weed which are taken from the

kaggle and to be classified is split into training and testing dataset with the test size of 30-20%.

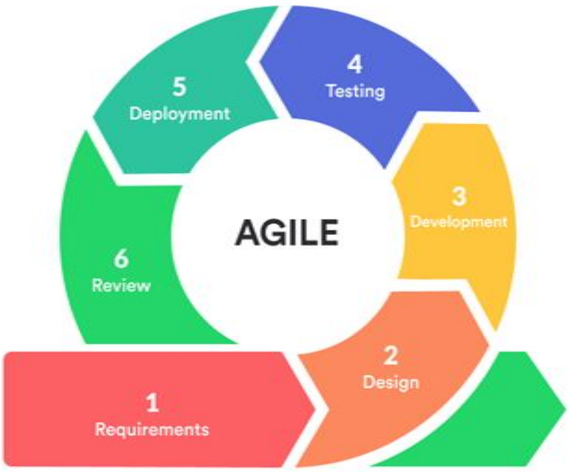



**Fig 3**: Agile Model

- System Design: The requirement specifications from first phase are studied in this phase and the system design is prepared. This system design helps in specifying hardware and system requirements and helps in defining the overall system architecture.
    - At first we gather the information regarding the dataset and then that is splitted into training and testing.
    - After the data splitting the data is pre-processed and used for the training with the algorithm.
    - For the training process, we use the deep learning algorithm and the model is saved once after the training.
    - The saved model is used further for testing.
- Development: With inputs from the system design, the system is first developed in small programs called units, which are integrated in the next phase. Each unit is developed and tested for its functionality, which is referred to as Unit Testing. Here the development is done using the deep learning based algorithm.
    - The algorithm here we are using is the CNN algorithm of deep learning.
    - A convolutional neural network consists of an input layer, hidden layers and an output layer. In any feed-forward neural network, any middle layers are called hidden because their inputs and outputs are masked by the activation function and final convolution. In a convolutional neural network, the hidden layers include layers that perform convolutions. Typically this includes a layer that does multiplication or other dot product, and its activation function is commonly ReLU. This is followed by other convolution layers such as pooling layers, fully connected layers and normalization layers.
- Testing: All the units developed in the implementation phase are integrated into a system after testing of each unit. Post integration the entire system is tested for any faults and failures. The testing will be implemented using the flask framework, where the classification is performed for testing.
    - Once after training with the algorithm and saving the model we will go for testing, where we test for the cases either they are showing the accurate classification or not.
- Deployment of system: Once the functional and non-functional testing is done; the product is deployed in the customer environment or released into the market.
    - Once after the testing the application will be deployed and it will be released into market where user can use the application.

- Reviews: Once after the deployment, the reviews can be considered from the customer environment, that which can be used for the further modifications and for better extensions
    - Once after the deployment we will be consider reviews from the user that helps in the further extension or for the better modifications.

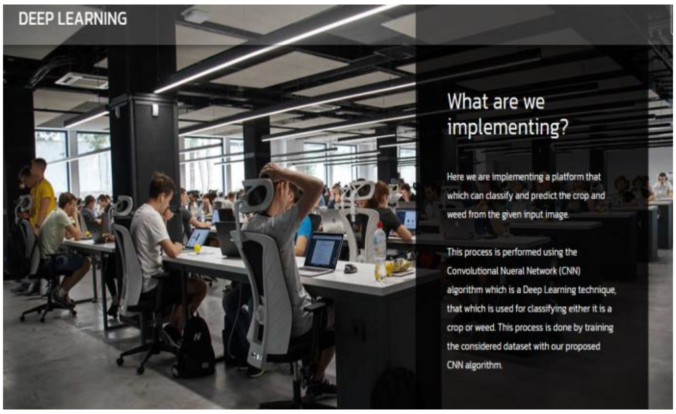
## IV. Results and Discussions

**Home:**

In our project, we are classifying the crop and weed with the help of deep learning.

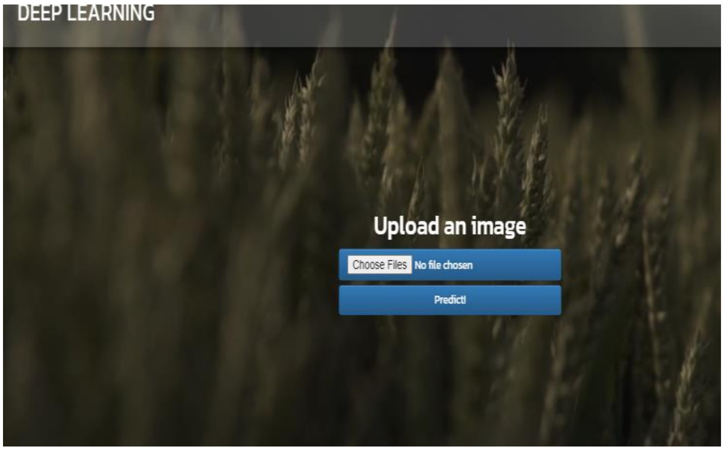

**About Project:**

Here the user will get a breif idea about the project.



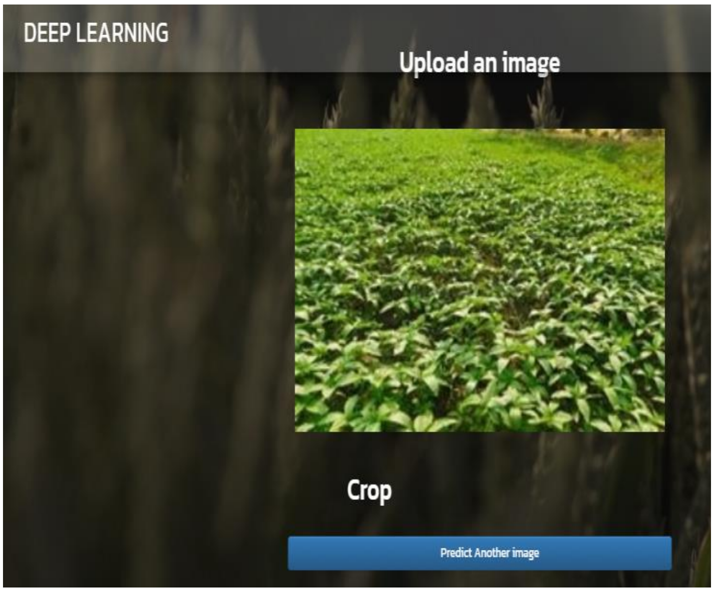

**Upload Image:**

Here the images can be uploaded those which are to be classified.



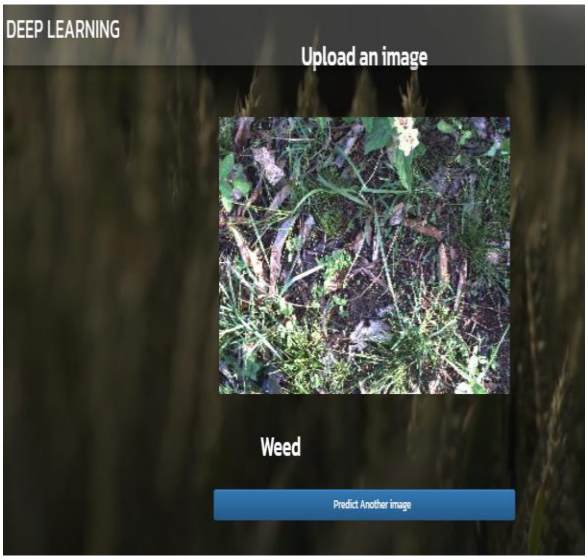

**Classified output:**

The uploaded image is classified as the crop.




**Classified output:**

The uploaded image is classified as the weed.



## V. CONCLUSION

In this project we have successfully created a system that which is able to classify the weed or crops using the CNN model of the deep learning. Here we will use the CNN model for training dataset. Post training, testing is performed where the classification and detection of weed and crop is performed.

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