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Weed detection using Machine Learning

Anupuri Sai Priya
priya.anupuri@gmail.com
Sai Vidya Institute of Technology, Rajanukunte, Karnataka

Nadimpalli Lavanya
nadimpallilavanya2000@gmail.com
Sai Vidya Institute of Technology, Rajanukunte, Karnataka

Pallavi K.
pallavik.17cs@saividya.ac.in
Sai Vidya Institute of Technology, Rajanukunte, Karnataka

G. Nithyasree
nithyasreegowram99@gmail.com
Sai Vidya Institute of Technology, Rajanukunte, Karnataka

Santhosh Reddy P.
santhosh.r@saividya.ac.in
Sai Vidya Institute of Technology, Rajanukunte, Karnataka

Abstract— Agriculture is one amongst the world's oldest sources of human nourishment. To satisfy the strain of an ever-increasing population, agricultural output must be greatly enhanced. People employed natural techniques to enhance production within the past, like utilising garbage as a fertiliser within the fields, which increased output sufficiently to fulfil the population's needs. Following this epoch, the utilization of lethal chemicals like herbicides skyrocketed. As a result, we've got made extra money while also causing greater environmental damage. the most important goal of this research is to use image processing to detect and take away weeds.So, in this project, we've created a way to decrease herbicide consumption by only spraying them where weeds are present. Using image processing, we were able to locate weeds in the site photos and classify them based on their area and aspect ratio.

Keywords—weed, image, productivity, agriculture, increase

1. INTRODUCTION

Weed detection and classification system, and there are a variety of ways to use one. Using either spectral or colour imaging, individual plant categorization has been effectively shown. Spectral methods' spatial resolutions are generally insufficient for reliable individual plant or leaf detection. Color imaging techniques with better spatial resolution, on the other hand, do not give the critical extra information that spectral data does. During the summer, Caltrans sprays roadside plant material with pesticide to prevent weeds from becoming a fire danger. The classification of pixels is the initial stage in recognising weeds in a picture. A point operation will be used to classify the pixels. A pixel's categorization will not be influenced by its surroundings. The goal of segmenting the picture into plant and background pixels is to determine how much plant material is present in a given region. The region is targeted for herbicidal spray treatment if the amount of plant material reaches a certain level. The proportion of background pixels misclassified as plant stuff limits the spray threshold. Herbicide will be spent spraying background if the spray threshold is set too near to the background misclassification rate.

Weed management is a crucial farm activity that may have a big impact on crop output. Herbicides are essential for weed management, although their usage has been criticised due to concerns about overuse and associated side effects. Patch spraying has been shown in several trials to significantly reduce pesticide consumption. Manual scouting for patch spraying wastes a lot of time and money, therefore it's not a viable alternative for many farms. Patch spraying has been studied by several researchers with varying degrees of success utilising remote sensing and machine vision. Machine vision systems are ideal for applying herbicides at the plant level, although remote sensing is frequently used on a plot level. Both of these technologies need the capture and processing of images. Processing time varies from 0.34 seconds to 7 seconds, depending on picture resolution, crop and weed type, method utilised, and system settings . To distinguish between weed and crop, the machine vision-based method employs form, texture, colour, and location-based characteristics separately or in combination. The studies show a wide range of results for these characteristics and their combinations.
An image sensor is an important part of nearly any

As a result of the higher misclassification rate, the smallest plant that may be identified without spraying the background is limited. A system that could use real-time spatial distribution information to administer just the appropriate amounts of herbicide to the weed-infested region would be considerably more efficient and less harmful to the environment. As a result, for site-specific weed control, a high spatial resolution, real-time weed infestation detection system appears to be the solution.

2. LITERATURE SURVEY

Crop/weed detection and classification based on variable real-time machine learning. Precision Agriculture Spraying Rate: This research shows a vision-based agricultural sprayer. The system consists of a crop and weed detection module based on real-time computer vision and application hardware for spraying. The vision system is first trained using an offline data set, which includes various images of crops, weeds, and other objects. Pulse width modulation technology is used to control the flow rate of agrochemicals. After many experiments, the conclusion is that the system works well in real time under different environmental conditions.

Use a deep learning convolutional neural network to detect perennial ryegrass weeds: This study demonstrates the feasibility of using DCNN to detect perennial ryegrass weeds. By training a neural network with a training data set that contains a single weed species, AlexNet and VGGNet perform similarly in detecting E. coli. Maculata and G. hederacea grow on perennial ryegrass. AlexNet and VGGNet reduce the recovery value used to detect iron skins in TD 2, but overcome this problem by training a multi-species neural network. VGGNet consistently showed the highest MCC value in the multi-species neural network from the two training data sets.

Deep Learning of Unsupervised Data Labeling for Linear Crop Weed Detection in UAV Imaging: We will design a fully machine learning method that uses convolutional neural networks and collection of data sets from unsupervised training, used to detect bean and spinach fields in weeds in UAV images. The results obtained show a performance close to the labeling of supervised data. The difference in area under the curve (AUC) between the spinach field and the bean field is 1.5% and 6%, respectively. Supervised tagging is a costly task for human experts. Given the difference in accuracy between supervised and unsupervised marking, this method may be a better option for detecting weeds, especially when crop rows are widely spaced. The proposed method is interesting in terms of flexibility and adaptability, because the model can be easily trained with new data sets.

Multi-class weed species image data set for deep learning: This paper presents the first large-scale multi-class weed species image data set collected entirely from Australian ranches in if you. Deep weeds contains eight weeds of national importance to Australia, spanning eight geographic locations in northern Australia. We used the CNN models of Inceptionv3 and ResNet50 to demonstrate strong benchmark performance on the dataset, achieving average sort returns of 95.1% and 95.7%, respectively.

Performance comparison of weed detection algorithms: Weed and Crop Classification is used for weed recognition, helping to automate the weed removal process. Shape features provide different attributes for the classification of weeds and crops. The performance of classifiers based on SVM, ANN and CNN is analyzed. Compared with SVM and ANN, CNN has been observed to provide better performance because of its deep learning ability to learn image related features.

Detection of broadleaf weeds in grasses: Here we examine different methods to achieve high detection accuracy and robustness in practical applications. Various methods have been proposed and implemented. The results show that the traditional machine learning method can obtain the ideal high precision when exploring the image texture information, and the local binary mode and the secondary support vector machine achieve the highest precision rate of 89.4 %. Using CNN's deep learning method to further increase accuracy to 96.88%.

3. SYSTEM REQUIREMENTS

OpenCV:

OpenCV is a computer vision library that is free to use. The library works on Linux, Windows, and Mac OS X and is developed in C and C++. Interfaces for Python, Ruby, Matlab, and other languages are in active development. OpenCV was created with an emphasis on real-time applications and computing efficiency. OpenCV is developed in efficient C and is multicore CPU compatible. You may purchase Intel's Integrated Performance Primitives libraries, which provide low-level optimised routines in a variety of algorithmic areas, if you want further automated optimization on Intel architectures.

If the relevant IPP library is present, OpenCV will utilise it automatically during runtime. One of OpenCV's aims is to provide a simple-to-use computer vision infrastructure that allows individuals to easily create rather complex vision applications. Over 500 functions in the OpenCV library cover a wide range of vision topics, including industrial product inspection, medical imaging, security, user interface, camera calibration, stereo vision, and robotics. Because computer vision and machine learning are frequently linked, OpenCV includes a comprehensive Machine Learning Library. The statistical pattern recognition and clustering are the emphasis of this sublibrary. The MLL is very beneficial for the vision problems at the heart of OpenCV's purpose, but it may be used to any machine learning issue.

Numpy:

We have lists in Python that act as arrays, however they are sluggish to parse. NumPy attempts to deliver a 50- times quicker array object than standard Python lists. The array object in NumPy is named ndarray, and it comes with a slew of helper methods to make dealing with it a breeze. In data research, when speed and resources are critical, arrays are commonly utilised. NumPy arrays, unlike lists, are kept in a single continuous location in memory, allowing programmes to access and manipulate them quickly. In computer science, this is referred to as location of reference. This is the primary reason why NumPy outperforms lists. It's also been tweaked to operate with the most recent C versions.

Tensorflow:

TensorFlow is a machine learning software library that is free and open-source. It may be used for a variety of applications, but it focuses on deep neural network training and inference. Tensorflow is a dataflow and differentiable programming-based symbolic math toolkit.

Tkinter:

Tkinter is a built-in Python package for creating graphical user interfaces. Because it is simple and straightforward to use, it is one of the most widely used modules for developing GUI applications in Python. You don't need to bother about installing the Tkinter module individually because it's already included with Python.

4. SYSTEM REQUIREMENTS

The first component of building a deep learning network is to gather our initial dataset. We need the images themselves as well as the labels associated with each image. These labels should come from a finite set of categories. Now that we have our initial dataset, we need to split it into two parts:

I. A training set
II. A testing set

A training set is used by our classifier to "learn" what each category looks like by making predictions on the input data and then correct itself when predictions are wrong. After the classifier has been trained, we can evaluate the performing on a testing set.

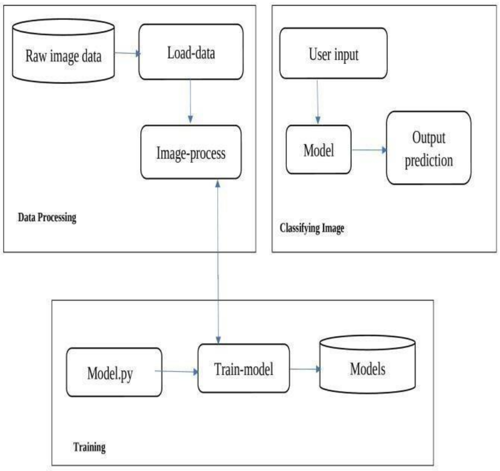

Fig 1 : Block Diagram for Proposed System

The goal here is our network must learn to recognise each of the categories in our labelled data in order to achieve this aim. When the model makes a mistake, it learns from it and continues to improve. Finally, we must assess our well-trained network. We show each of the photos in our testing set to the network and ask it to guess what the label of the image should be. The model's predictions for a picture in the testing set are then tabulated. Finally, the ground-truth labels from our testing set are compared to the model predictions. The picture category is represented by the ground-truth labels. We can then compute the number of correct predictions our classifier made, as well as aggregate reports like precision, recall, and f-measure, which are used to characterise the overall performance of our network.

5. SYSTEM FLOW

A flow chart is a sort of diagram that depicts a process or activity. It's also a visual depiction of the method, with a step-by-step approach to demonstrate the work. To begin, information about the relevant data set is extracted from the crop image data set, which is the first stage in the data set's preparation.

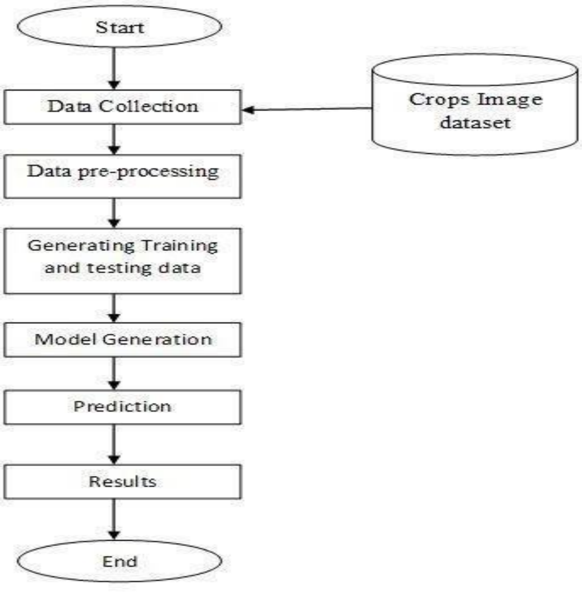

Fig 2 : Flow chart for proposed System

The crop picture will be recorded by the camera during preprocessing. It may contain brightness-related problems. Image enhancement techniques are used to improve the visual look of images or convert them to a format that is more suitable for human or machine interpretation.

We must partition the dataset into a 70:30 ratio in the training and testing model, which is based on the scaling procedure. The correctness of the trained model will be verified by testing. We will evaluate the correctness of the weed categorization and discover the correct form of the weed using appropriate model generation.

5. IMPLEMENTATION AND RESULTS

Fig 3 : Original Image of Crop and Weed

We loaded the data sets at the start of the project and then trained them with Convolutional Neural Networks. The picture is then categorised as 4 and retrained. Finally, the data is validated, and Models are generated. This algorithm prepares an image for more sophisticated processing by loading it from the source and detecting edges. Color segmentation is a technique for distinguishing the crop from the background. The technique aids in the separation of all clearly distinct hues.

After colour segmentation, the required image has both crop and weed, making it suitable for the next step in the process, edge detection. A curve in an image that follows a route of rapid change in image intensity is called an edge. The borders of items in a scene are frequently linked with edges. Edge detection is a technique for identifying the edges in an image and preparing it for the next step, filtering.

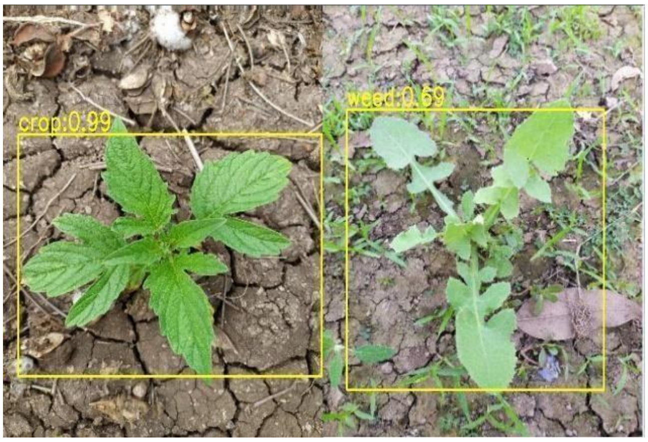

Fig 4 : Detecting both weed and crop

In a CNN, each layer uses a separate set of filters. It is made up of three layers, each of which has a distinct role. In the first layer, detect edges from raw pixel data. In the second layer, use these edges to detect forms. Use these shapes to identify higher-level characteristics in the network's top layers, such as face structures, automobile parts, and so forth.

6. CONCLUSION

We've devised a method for detecting marijuana that combines image processing and machine learning. We can identify and distinguish weeds from agricultural plants using this method. The goal of this research is to identify weeds and repurpose land that has been contaminated by a high concentration of chemicals. We can manage less spraying by detecting weeds, which helps to preserve the environment as well as money.

As a result, we may deduce that the image collection mechanism was developed to attain better speed and accuracy in order to satisfy the needs of weed detection in broad-acre cropping areas. The proposed method, which is based on the CNN algorithm, must be tested on weeds in various places and has proved to be highly successful in weed detection. In the future, more hybrid models combining deep learning and traditional image processing are predicted.

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BIOGRAPHY

Santhosh Reddy P
Assistant Professor, Dept of CSE,
Sai Vidya Institute of Technology, Rajanukunte , Bangalore, Karnataka, India

Anupuri Saipriya
Student
Sai Vidya Institute of Technology, Rajanukunte , Bangalore, Karnataka, India

Nadimpalli Lavanya
Student
Sai Vidya Institute of Technology, Rajanukunte , Bangalore, Karnataka, India

Pallavi K
Student
Sai Vidya Institute of Technology, Rajanukunte , Bangalore, Karnataka, India

Nithyasree G
Student
Sai Vidya Institute of Technology, Rajanukunte , Bangalore, Karnataka, India