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WEED DETECTION AND CLASSIFICATION

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Abstract: In the agricultural sector, weed detection and categorization are of critical technical and financial relevance. It is possible to automate various processes, such as shape, colour, and texture, in weed control systems. Building a machine vision weed control system that can locate weeds in real-time is the aim of this article. The system is designed to categorise photos into wide and narrow classes for on-the-fly spraying of selective herbicides. The developed Edge Link Detector-based algorithm has been put to the test on weeds in various areas, and the results have revealed how good the algorithm is at identifying weeds. Additionally, the outcomes demonstrate a very trustworthy performance on weeds under various field circumstances. Over 240 sample photos (wide, narrow, and no or little weeds) including 100 samples from broad weeds, 100 samples from narrow weeds, and the remaining 40 samples from no or little weeds were classified with over 93 percent accuracy, according to the results analysis.
Keywords: detection of weeds, CNN, ML.

I. INTRODUCTION

Weed control is a vital aspect of farming and has a big impact on crop productivity. Herbicides are crucial for controlling weeds, however their application is criticized for being overused and having unintended consequences. Numerous studies indicate that patch spraying significantly lowers the use of herbicides. For the majority of farm operations, manual scouting for patch spraying is not a practical alternative because it uses a lot of resources. Using distant sensing and machine vision, numerous researchers have tried Patch spraying with varying degrees of effectiveness. While remote sensing can be used on a plot-by-plot basis, machine vision technologies are best for applying herbicides at the plant scale. In essence, image processing and image acquisition are needed for both of these systems. The processing time varies from 0.34 seconds to 7 seconds depending on the image resolution, crop and weed type, method employed, and device specifications. Image sizes typically range in the order of megabytes. The machine vision-based solution combines individual or combined shape, texture, colour, and location-based data to distinguish between weed and crop. For these traits and their combinations, the studies report a variety of results. There are numerous ways to use image sensors, which are a crucial part of practically every weed detection and classification system. With either spectral or colour imaging, individual plant classification has been effectively shown. Typically, the spatial resolutions of spectral systems are insufficient for precise detection of individual plants or leaves. However, colour imaging techniques with greater spatial resolution do not provide the crucial extra information that spectral data does. Herbicide is sprayed on roadside vegetation by Caltrans to keep the weeds from posing a summertime fire risk.Classifying the pixels is the initial stage in weed detection in an image. The classification of the pixels will include a point operation. The classification of a pixel will not be influenced by its surroundings. To determine how much plant matter is present in a particular location, the image is segmented into plant and background pixels. An herbicidal spray treatment is made to a specific region when the amount of plant material reaches a predetermined threshold. The percentage of background pixels that are incorrectly identified as plant matter restricts the spray threshold. Herbicide will be wasted spraying background if the spray threshold is set too close to the background misclassification rate. As a result, the smallest plant that may be recognized without spraying the background is constrained by a higher misclassification rate. It would be considerably more effective and cause less environmental harm to have a system that could use the geographical distribution data in real-time and only apply the necessary amounts of herbicide to the weed-infested area. For site-specific weed management, a high spatial resolution, real-time weed infestation monitoring system appears to be the answer.

II. PROBLEM STATEMENT

Weed plant detection is a recent research issue in agriculture that seeks to use computer science to detect unwelcome weed development alongside other crops and plants. Usually in farming, when farmers plant something because of the characteristics of the soil and already existing micro seeds, extra weed development occurs, which ruins the actual results of farming because they stunt the growth of planted plants. Weed detection then involves properly locating the weeds so that specified regions can be sprayed with the least amount of spraying on other plants of interest. Precision agriculture is gaining more and more attention from experts in recent years as the world population has increased and the amount of available land and natural resources has reduced. The use of image processing techniques could be used to address this issue.

III. LITERATURE SURVEY

Imaging tools are helpful in agriculture for spotting heterogeneities in the field. Remote sensors may be included into a variety of vehicles, including tractors, agricultural engines, aircraft [3, 2], or satellites, depending on what we want to view (a leaf, a plant, for example) and to enable the features to be displayed. Herbicide treatments need special consideration for sustainable agriculture because they are the main agricultural pollutants and site-specific weed spraying in crop fields might significantly reduce herbicide consumption. As a result, numerous researchers have created various vision systems to identify weed plants in crops and map them in real-time so that contaminated areas can be sprayed specifically [7, 8]. These systems might be built around optical sensors called photodiodes, which could be used to classify or distinguish between different types of plants (narrow plants versus broad plants) based on their reflection spectra. Their spectrum of reflectance. The most well-known ones are Weed Seeker and Spray Vision, but these systems can't tell weeds from crops. Recently [9, 10], a robot that intends to mechanically eradicate weeds in the interred was built with two vision systems guided by crop rows. However, this detection technique is only applicable to crops drilled, like sugar beet and salad. Data are collected in a single pass using an off-line approach, which is then examined in the office. In a subsequent pass, an agricultural engine in the crop field is managed using the weed mapping.

As an illustration, a multi-spectral imaging system was created and integrated onto a tiny aircraft that flew over a crop of sunflowers. With spatial image processing based on Gabor filtering, which detected crop rows by their frequency, this was able to distinguish between inter-row weeds and crop. Weeds within the crop row weren't found, nevertheless. Many precise techniques have been developed for the detection of weeds, including principal component analysis, the wavelet transform, which can distinguish between crops and weeds in perspective agronomic photos. Other scholars have looked into biological morphology, such as the identification of leaf shapes, or textural traits. Therefore, many quick algorithms have been created in real time for the identification and classification of crop rows in photographs. Some of them are based on the Hough Transform, others on the Fourier Transform, others on the Kalman filter or linear regression. For automatic steering in crop fields, the Hough Transform is typically used [20, 21]. As a result, there are now a variety of vision systems for mechanical weed removal on autonomous weed control robots.

IV. PROPOSED SYSTEM

Figure 1 below shows the system's overall layout. It displays the various modules used to construct the system, such as [1] For more accuracy, images of weed were captured in RGB format using a high resolution camera in a crop field or from an online dataset. Each acquired image is saved in its appropriate size and as a jpg file. [2] Various elements, including as noise, illumination changes, low image quality, and undesirable background, have an impact on the photos that are obtained.The conversion of RGB to grayscale, the conversion of grayscale photos to binary images, and the use of filtering techniques to eliminate background noise are all examples of pre-processing tools. [3] The given dataset must be separated into two sets of data: Test dataset and Train dataset, following pre-processing. Following the dataset division, the training data will be utilised to train the specified network using the CNN algorithm. The test data is tested in the network after training. [4] The system generates a final model based on the dataset collected after testing the network using test data. This final model is then compared with the user input from the front end, and the output will be displayed following the comparison.

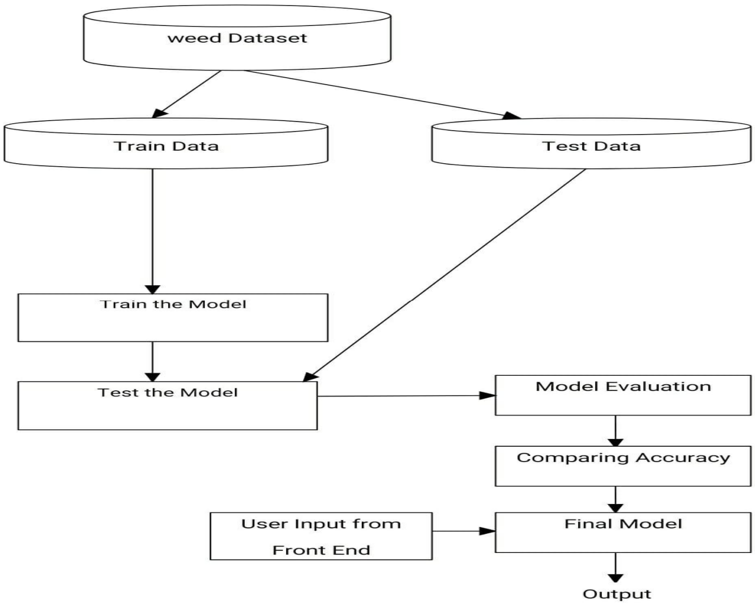

Fig 1. System Architecture

V. RESULTS

The suggested methodology is examined using the RGB photos from Section. Using the ARCGIS and Labelme tool boxes, preprocessing of pictures such as background segmentation and manual labelling are carried out. The dataset is split into training and test sets, with corresponding sizes of 85% and 15%. Images are enhanced and divided into smaller tiles for training after the train-test split. NVIDIA GPU GeForce GTX 1080 Ti with 11 GB memory is used to quicken the model training.

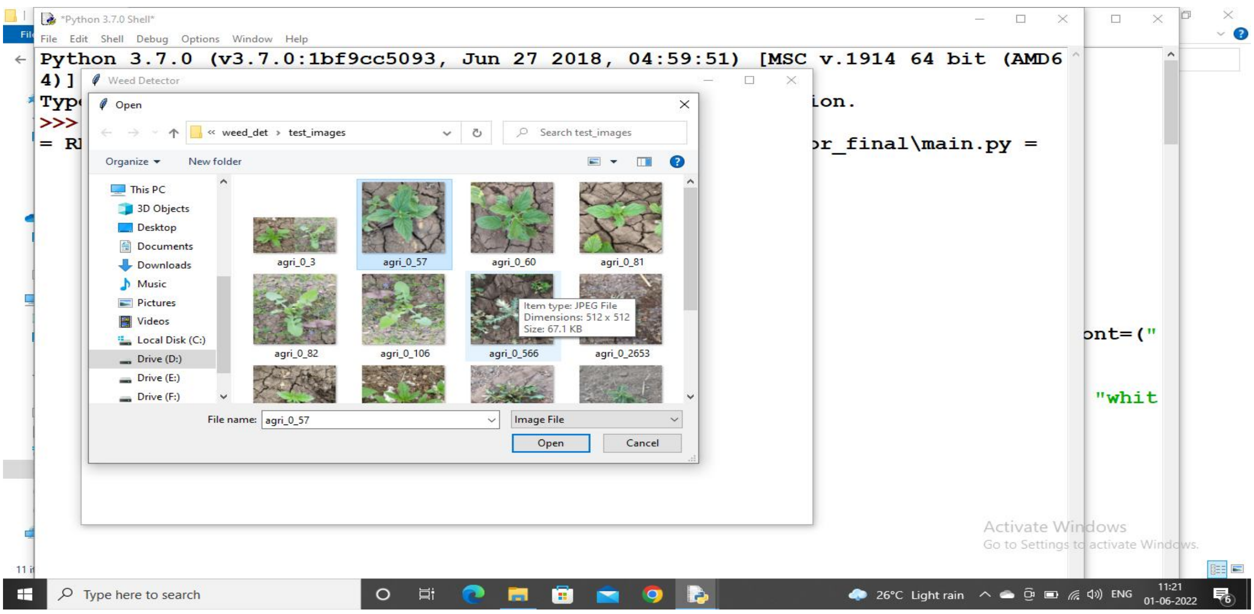

Fig 2. Folder images

Fig 2. shows image folder with multiple images from which one image can be selected for prediction.

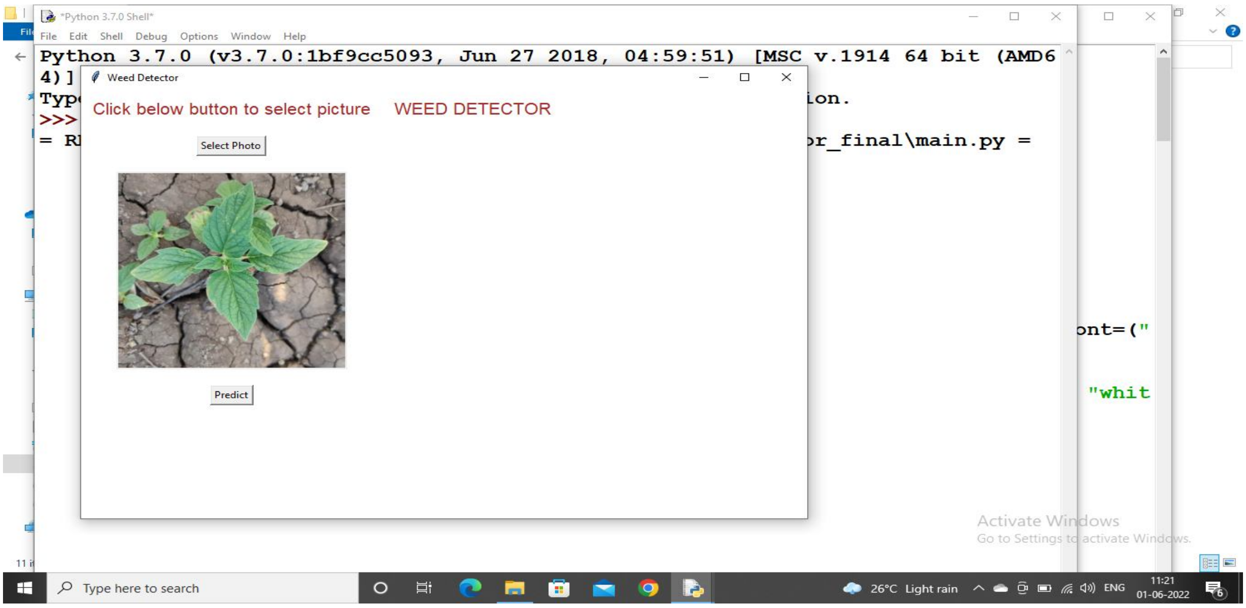

Fig 3.Image Uploaded

Fig 3 shows the window displayed after image selection and there is a predict button.

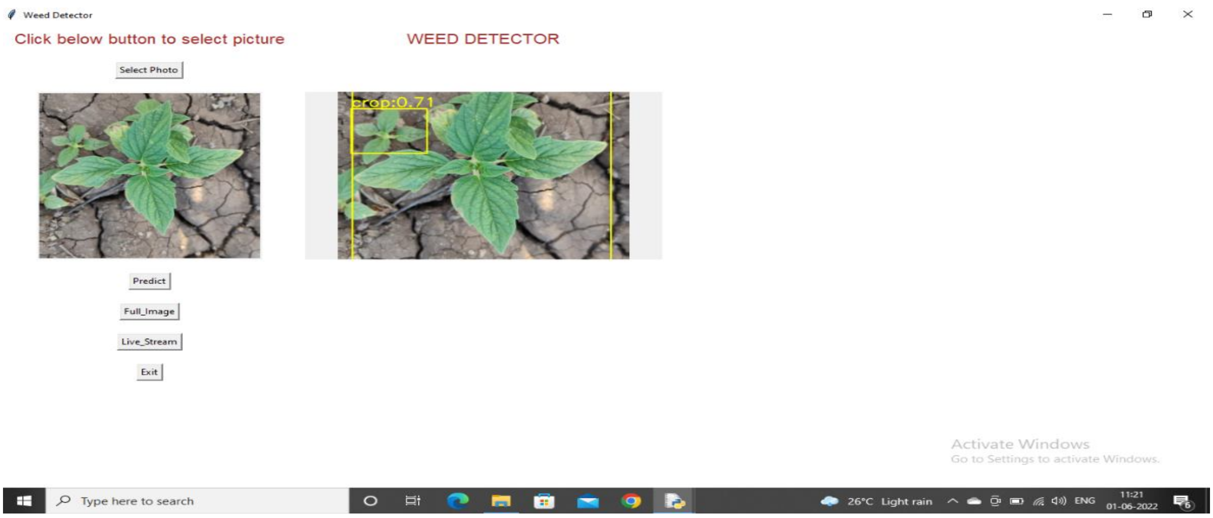

Fig 4 Predicted image

Fig 4 shows the predicted image with name as weed or crop accordingly.

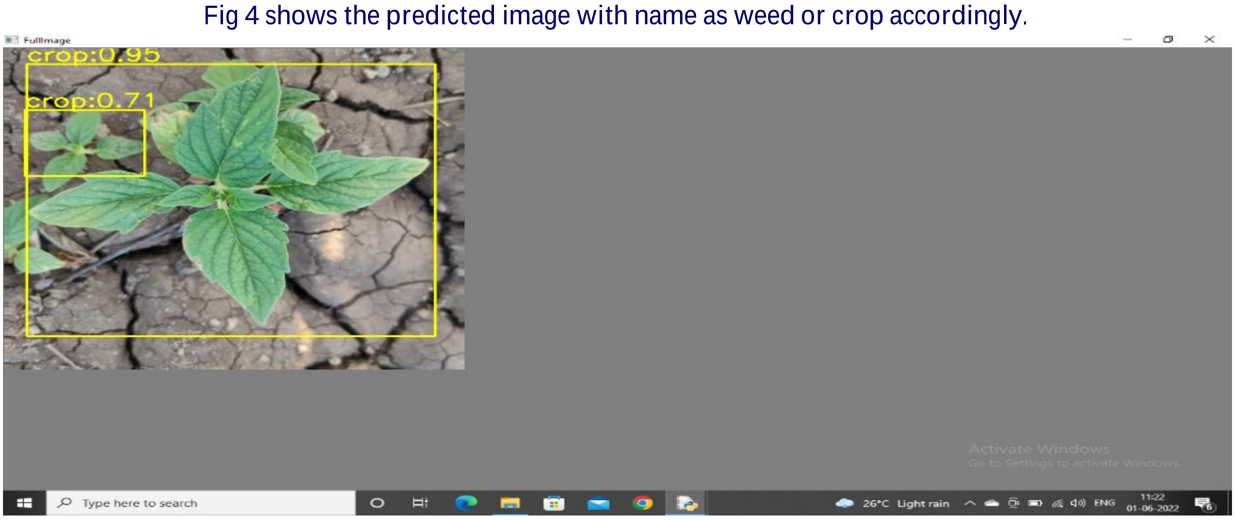

Fig 5 Full Screen image

Fig 5 shows the full screen image of the detected crop. The image has the detected crop image with text saying crop along with the accuracy value.

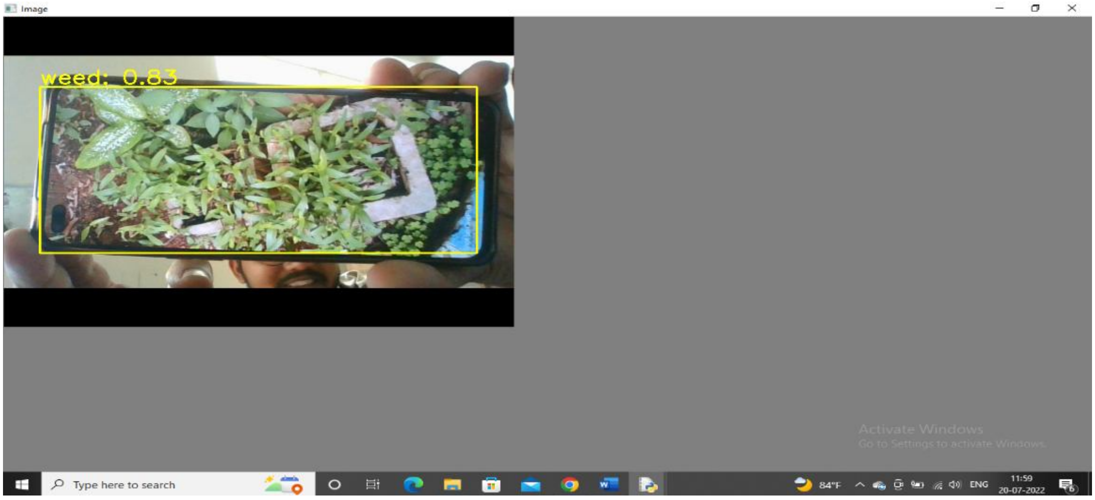

Fig 6 Live stream detection

Fig 6 shows the live stream detection of the weed present in the given input live stream. The output has text weed displayed along with accuracy.

VI. CONCLUSION

To fulfil the demands of the weed detection in the broadacre cropping areas, the mechanism of picture acquisition was created to attain higher speed. In order to reduce the use of herbicides and increase the effectiveness of weed control in the broadacre no-tillage farming setting, this research created a machine vision system that can identify weeds. As feature extractors, deep CNN architectures offer superior performance and facilitate quicker application development. In the future, more hybrid models that combine deep learning and traditional image processing are anticipated.

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