

WEED IDENTIFICATION USING KNN ALGORITHM FOR PADDY FIELD BASED ON MACHINE VISION

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More than 30 to 40 percent of the population in the world choose agriculture as a primary occupation, due to labor shortages and an increased need to feed the global population. In India, most of the cultivation is rice and wheat. One of the major problems faced by Indian farmers is weed growth. Farmers are not able to remove the weed from the root one by one around the cultivation land. Because of the weed growth on the cultivation land, the soil and growth rate of the crops are damaged and reduced respectively. To overcome this problem, we propose to invent a system that can be used to identify the weed around the cultivation land and remove them from the land. In this paper, three algorithms have been used to train the sample images to get accuracy rates of detection. KNN algorithm was the best among the other algorithms. With the help of a webcam, weed identification was accomplished and identified in the paddy field. The classification and the accuracy are determined and done in Matlab and converted into Python. The geographical location of the weed will be stored in the cloud systems. With proper implementation, the increase in the growth rate of crops with improve profit for farmers.

1. Introduction

Today the environmental effect in agricultural production may be very a whole lot that specializes in its needs to growth increase within the manufacturing respectively. Worldwide, more than 40 percent of people choose agriculture as their primary career. But in India, there are 70% of people are dependent on agriculture. The agricultural techniques should be enhanced through Innovative thoughts. The problem changed into recognized at the same time as journeying the agriculture area. The Indian farmers are going through fundamental troubles with the weed boom. Because of the weed boom, the yield decreases, and the fertility of the soil is damaged closely. Weed elimination is the technique to expel the weeds. Weeds are unwanted flowers that advanced alongside treasured harvests. Weeding is needed because weeds are aggressive plants as they decrease the treasured harvest yield via getting space, manures, and dietary supplements from the dust. Because of the weed growth in cultivation land, the yield ratio is high and the productiveness of rice or wheat inside the paddy discipline is low. The yield ratio is a 1:2 ratio, wherein 1/2 of the cultivation land is covered with weed boom in very small plantations and the opposite 1/2 is with the crop. So, they advanced an image processing device to discover the distinction between weed and crop. Numerous weeds that develop among crops and in nurseries were presented either unintentionally or intentionally by early British pilgrims. They incorporate groundsel (*Senecio vulgaris*), chickweeds (*Stellaria media* and *Cerastium spp.*), fathen (*Chenopodium collection*), nightshade (*Solanumsp.*), (*Amaranthus spp.*), and willow weed (*persicaria*) – plants that develop promptly and develop, blossom and organic product rapidly to deliver bountiful seeds.

At times weeds debase gathered harvests. For instance, dark nightshade berries might be gathered alongside peas. Weeds can likewise have ruinous bugs, for example, aphids, caterpillars, parasitic decays, and infections.

By implementing the KNN algorithm as an image processing system in any agricultural robot, we can successfully identify weeds present in a specific area of crop growth extending an additional protective measure to farmers. The comprehensive application developed for farmers not only reduces the physical hardship and time spent on different agricultural activities but also increases the overall land yield, reduces the possibility of losses due to failure of crops in a particular soil, and lessens the chances of damage caused to crops by weeds. As the work starts from groundwork which is a field study of multiple terrains of soil and spacing of the crops in paddy fields around India will help to build a strong foundation for this image processing system.

2. Literature Review

Gurpreet Khurana, et. al [1] have addressed that picture processing is the most important technique concerned within the agricultural fields. The yield and subsequent profit may be enhanced by way of detecting and coping with the troubles associated with crop yield signs in the early degree. The crop yield signs including weeds may be detected and eliminated by using specific manual and automated strategies. The technique of textural characteristic evaluation and morphological scanning is carried out on the sugar beet plants in this paper. At remaining, a KNN classifier is carried out which can classify weed plant life from subject plants. We have taken the sugarcane field as our primary attention. The results of the weed detection are analyzed in terms of accuracy of 60% and execution time.

In Ishita Dasgupta, et. al [2], with the help of IoT gadgets, AI techniques are combined for faster and more powerful advice of suitable crops to farmers based on a list of factors considered. So, for detection of undesirable flowers on plants, specifically, weed detection, is applied with the frame-shooting drone and deep getting to know strategies. Naïve Bayes algorithm for crop recommendation based on several elements detected utilizing WSN sensor nodes has been used, resulting in an accuracy of 89.29%, which has proved to be better than numerous different mentioned algorithms within the paper, like regression or aid vector system.

Nahina Islam, et. Al [3] have explored the capability of the system to get to know algorithms for weed and crop categories from UAV photos from drones. The identification of weeds in vegetation is a hard project that has been addressed via ortho mosaicing of pictures, feature extraction, and labeling of images to train gadget studying algorithms. In this paper, the performances of several systems getting to know algorithms, random woodland (RF), aid vector system (SVM), and okay-nearest neighbors (KNN), are analyzed to detect weeds the usage of UAV drone pix accumulated from a chili crop area positioned in Australia. The assessment metrics used within the comparison of performance were accuracy, precision, bear in mind, fake-nice rate, and kappa coefficient. MATLAB is used for simulating the system learning algorithms, and the weed detection accuracies are 96% using RF, 94% using SVM, and 63% using KNN. Based on this study, RF and SVM algorithms are efficient and sensible to use and can be applied effortlessly for detecting weed from UAV photos.

Lars Grimstad, et. al [4] reported the advanced work vehicles and other edge machines driving over the homestead field harm the dirt structure to conquer this issue the farm haulers are made to be more modest and lighter with the goal that they don't hurt the dirt. For this reason, the mechanical framework utilizes the re-arrangement of the aluminum outline and various modules to make a robot of various sizes and with various properties, and modifying the robot is brisk and simple.

Gulam Amer, et. al [5] proposed a hexapod robot that can autonomously walk in any direction, avoiding objects with its ultrasonic proximity sensor. Its walking algorithms allow it to instantly change direction and walk in any new direction without turning its body. An underbody sensory array allows the robot to know if a seed has been planted in the area at the optimal spacing and depth. Agribiont can then dig a hole, plant a seed in the hole, cover the seed

with soil, and apply any pre-emergence fertilizers and/or herbicides along with the marking agent. Agribiont can then signal to other robots in the immediate proximity that it needs help planting in that area or that this area has been planted and to move on by communicating through Wi-Fi.

R.shah, S.ozcelik, et. al [6] discussed the limitation of height is the primary requirement in robot design, yet this can be overwhelmed by utilizing substantial pressure-driven and pneumatic frameworks. They utilized a winding lift to change the stature of the portable robot stage. Winding lift is the most recent innovation to lift hefty burdens in enterprises utilizing low force and basic components. At ideal conditions, the conservativeness of the winding lift empowers us to keep the robot at its insignificant size. By contemplating distinctive versatile robots and systems. They will plan and investigate robots utilizing the winding lift in cutting-edge CAD programming - SolidWorks. They have utilized I-Lock 75 due to its lock system and smallness. I-Lock 75 in light of its lock component and smallness.

Gokhan Bayar, et. al [7] discussed that while creating different applications for portable robots, a researcher feels the requirement for a configurable robot that can adequately work both inside and outside, onto which different equipment can without much of a stretch be introduced and taken out Como RAT is created with this viewpoint, to be a little Size versatile robot. Reasonable for scholastic exploration running on a restricted financial plan. The footing framework can be designed to utilize wheels, tracks, or both. The body of the robot gives the conclusion to batteries, engine drives, and principle PCs. Extra equipment can without much of a stretch be introduced both inside and outside of the robot. The centralized computer is built from an aluminum profile that has forests to encourage the expansion of equipment without any problem.

Tommy Ertbolle Madsen, et. al [8] have addressed the natural effect of agricultural creation, especially in the center, while the opposition requests high effectiveness. A few years back, weeding was done physically without the utilization of pesticides. With the improvement of a self-sufficient rural vehicle with sensors for weed identification, it will again be conceivable to maintain a strategic distance from pesticides. The vehicle utilizes high exactness GPS (RTK), encoders, compass, and tilt sensors, to situate itself and follow waypoints. The vehicle has 4-WD and 4-WS, which makes it conceivable to test diverse controls. The vehicle is exceptionally intended for in-column driving; this has been accomplished with the utilization of wheel engines. The vehicle can drive in column crops with a line separation down to around 250 mm and with 500 mm high yields.

M.J. Aitkenhead, et. Al [9] discussed a method that included the utilization of a straightforward morphological trademark estimation of leaf shape, which had to change adequacy in separating between the two sorts of plants, with the various subject to plant size. The second included a self-sorting out of the neural system more organically conceivable than numerous regularly utilized NN techniques. While the last didn't give results, they demonstrated that a neural system-based strategy exists which permits the framework to learn and separate between species to a precision surpassing 75% without predefined plant portrayals being essential.

Victor Alchanatis, et. al [10] discussed an algorithm that was created utilized phantom reflectance properties to highlight the weed discovery. Soil-crop division was finished with two spectral channels from the hyperspectral sensor. Weed identification depended on surface highlights, extricated from the fragmented pictures. The calculation was applied to a database of pictures of cotton plants and weeds, in their beginning times of advancement. The outcomes indicated a decent location capacity. The event of weeds was distinguished in all pictures; the weed-plagued zone was assessed with a 14% mistake, and the bogus location rate was 15%.

Latha, et. al [11] proved that the recognition of weed is done by utilizing edge recognition. Picture division utilizes the way that the edge frequencies and veins of both the harvest and the weed have distinctive thickness properties. The picture after both shading division and edge discovery is left with the edges and veins of both the harvest and the weed in white and the rest of the part dark. Sifting is utilized for perceiving districts in which edges show up with a recurrence in a particular range (weed recurrence extend).

C. Chaisattapagon, et. al [12] have proposed three unique methodologies, such as the shading examination, shape investigation, and surface investigation were utilized in the investigation. For the shading examination approach, proportions of pixel dim levels in pictures taken utilizing chosen shading. Channels were valuable in grouping pixels into five unique classifications—wheat leaf, weed leaf, weed stem, soil, and sand. Five shape parameters, unconventionality, smallness, and three invariant minutes were utilized to fit as a fiddle examination. For the surface investigation approach, the Fourier spectra of chosen windows inside leaf regions of wheat and weed species were broken down. A record of fineness was characterized by utilizing the spectra. Bends of standardized outspread otherworldly vitality were gotten from the spectra. Leaves with unmistakable directionality highlights, for example, weed species can be recognized utilizing parameters characterized utilizing these bends.

Kishore C. Swain, et. al [13] have proposed a keen distinguishing proof method that takes a shot at the idea of 'dynamic shape demonstrating' to recognize weed and yield plants dependent on their morphology. The robotized dynamic shape coordinating framework (AASM) method comprises, a Pixelink camera; an LTI picture preparing library, and a pc with the Linux OS. A 2-leaf development organizational model for nightshade is created from 32 portioned preparing pictures in Matlab programming conditions. Utilizing the AASM calculation, the leaf model was adjusted and set at the focal point of the objective plant and a model distortion process was completed. The parameters utilized for model twisting were evaluated, refreshed and an improved model was contrasted with the objective plant shape to acquire the best fit. Around 90% of the nightshade plants were distinguished effectively with AASM. The time required for recognizing the objective plant as nightshade was around 0.053 s and a non-distinguishing proof procedure required 0.062 s for eight cycles with the Linux stage utilized.

F. Ahmed, et. al [14] addressed that a real-time framework can be utilized by distinguishing and splashing just the weeds. This paper explores the utilization of an AI calculation called bolster vector machine (SVM) for the successful arrangement of harvests and weeds in advanced pictures. To assess if a good arrangement rate can be gotten when SVM is utilized as the characterization model in a mechanized weed control framework. A sum of fourteen highlights that portray harvests and weeds in pictures were tried to locate the ideal mix of highlights that gives the most elevated characterization rate. Investigation of the outcomes uncovers that SVM accomplishes above 97% exactness over a lot of 224 test pictures. Significantly, there is no misclassification of yields as weeds and the other way around.

A.J.Perez et. al [15] has reported the improvement of close ground picture catch and handling methods to recognize broadleaf weeds in oat crops, under genuine field conditions. The proposed techniques utilize the two hues and shape examination systems for separating harvests, weeds, and soil. The exhibition of calculations was evaluated by contrasting the outcomes and human order, giving a decent achievement rate. The investigation shows the potential of utilizing picture handling strategies to produce weed maps.

C.C. Yang, et. al [16] reported that the initial phases of the advancement of a picture preparing a framework to identify weeds, just as a fluffy rationale dynamic framework to figure out where and how much herbicide to apply in a farming field. The framework utilized a camera and an individual PC. In the image processing stage, the green articles in each picture were distinguished utilizing the greenness strategy that looked at the red, green, furthermore, blue (RGB) powers. The RGB network was decreased to a paired structure by applying the accompanying paradigm. If the green power of a pixel was more prominent than the red and the blue powers, at that point the pixel has relegated to an estimation of one; in any case, the pixel was given an estimation of zero. The subsequently paired grid was utilized to register the greenness region for weed inclusion and greenness dissemination of weeds (weed fix). The estimations of weed inclusion and weed fix were contributions to the fluffy rationale dynamic framework, which utilized the participation capacities to control the herbicide application rate in every area.

Irshad Ahmadet, et. al [17] have discussed an algorithm that was developed based on erosion followed by a dilation segmentation algorithm. The algorithm can identify weeds and order them. The algorithm is tried on two sorts of weeds expansive and tight. The created algorithm

has been tried on these two kinds of weeds in the lab, which gives truly solid execution. The calculation is applied to 240 pictures put away in a database in the lab, of which 100 pictures were taken from broadleaf weeds and 100 were taken from slender leaf weeds, and the staying 40 were taken from no or little weeds. The outcome appeared over 89% results.

Brian L. Steward, et. al [18], attempted to grow ongoing machine vision weed recognition innovation for open-air lighting conditions. The EASA (environmentally adaptive segmentation algorithm) was created with the target of constant procedure on an installed PC-based framework. The EASA utilized a bunch of examinations to gather pixels of homogenous shading locales of the picture together which framed the reason for picture division. The performance of a few varieties of this algorithm was estimated by looking at divided field pictures delivered by the EASA, fixed-shading HSI locale division, and ISODATA bunching with hand-fragmented reference pictures. Affectability and foundation affectability were utilized as execution measures

Arman Arefi, et. al, [19] has reported that the identification of four significant weed seeds, that are generally found in ranches was finished by computerized picture examination. In this way, the recognition of weed seed species is the initial step. By utilizing a pack of imaging, some uniform pictures of tests were gained. At that point, a program was coded in Matlab programming for the segmentation of the samples. The recognition of weed seeds depended on morphology and shading. For perceiving shading highlights, we utilized RGB and HSI. These shading highlights were mean and fluctuation of the immersion part. Acknowledgment of cleavers was finished by two morphology highlights, Shape factors. The absolute grouping exactness was 98.40%.

M. S. El-Faki, et. al, [20] discussed the shading contrasts among weeds, and harvests have been utilized to build up a picture-based sensor to identify weeds. The principal factor was soil dampness content. Pictures of weeds and soil at 10 distinctive dampness substances were examined utilizing a measurable strategy. Subsequently, varieties in soil dampness content didn't cause noteworthy misclassification among soil and weeds. The subsequent factor was brightening. Pictures of standard RGB essential shading plates were taken at nine distinctive light forces. The varieties of the list esteem followed perceptible examples, which could be utilized in shading file alignment. The third factor contemplated was spatial goals. Nine diverse spatial goals of weed pictures were accomplished by taking pictures at various camera-plant separations. The classifier was recognized with CCRs of 40.2% and 54.9%.

Overall, most of these papers have used image processing in various fields such as fruits and vegetable cultivation but only a few papers have tested in the paddy field. The application of image processing for weed identification is mostly used in drones, and mobile robots but haven't been shown in actual-sized robot and some robots are manually controlled but not haven't used any new technologies such as autonomous control, IoT, etc. Moreover, in all of these papers, if the computational power is high then the timing for identifying is less and vice-versa. For higher computational power, the cost of the component is more which is not recommended and feasible to get.

3. Methodology

To discover the weed inside the field the usage of the drive can be found. Few images are taken to extract the capabilities. The functions used are edge detection, coloration threshold, ROI coloration, and photo labeler. The photo is converted into a 2-dimensional matrix, so the photo can be in grayscale. From grayscale, they extracted each feature information and compiled it into one file. Once the data have compiled, the facts are dispatched to the category learner. The type of learner could be processing the records in multiple algorithms to get the accuracy of detection. The maximum accuracy might be exported as a Matlab function. The functions are generated which will be converted to a C++ or Python program to apply the set of rules in raspberry pi. A webcam is hooked up to the raspberry.

From the above reference, the most common and famous features used for weed detection have been taken to model this proposed system, they are; Edge Detection; Region of Interest; Color Threshold; and Image Labeler.

3.1 *Feature Extraction*

The samples have been taken, a few are from the internet and the rest is taken from the field. So, the images have first converted into a grayscale image that is of the same size. Some of the images are converted into a grayscale image with some simple commands and saved in the workspace and are imported into Matlab. Then the converted image is used in different features. Once the output is given from the feature which has been in the form of a table. The table has been taken and saved as an excel file. Till now the sample data taken is nearly 12 lakh data with all four features. The size of the image for training data for detection is 1280x720 pixels.

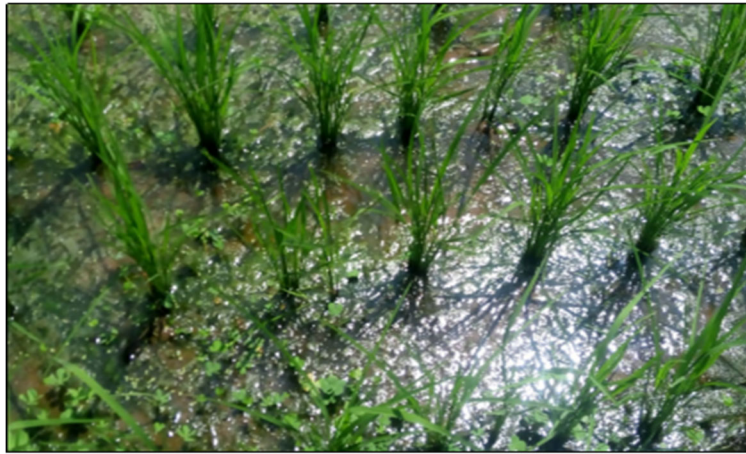


Figure 1. Crop with Weed in Paddy Field

3.2 *Edge detection*

Edge detection will be done for an image to find the boundaries in the image. In this image, both weeds' boundaries will be in both cylindrical, circular shapes because most of the edges of the weeds will be circular.

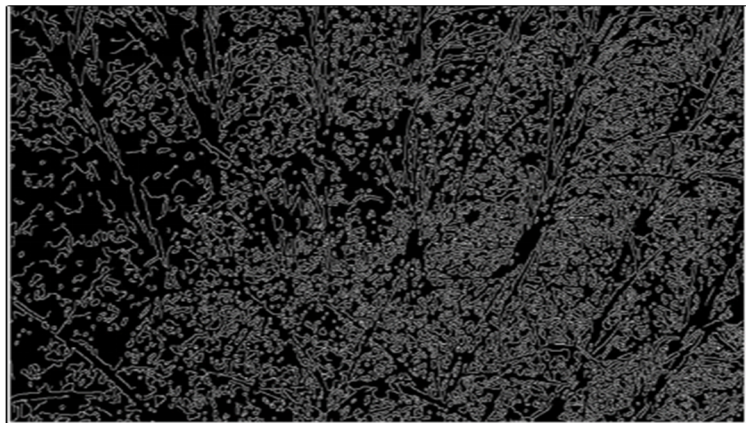


Figure 2. Edge Detection

Edge identification incorporates an assortment of scientific techniques that target distinguishing focuses on a computerized picture at which the picture splendor changes strongly or, all the more officially, has discontinuities.

The focuses at which picture brilliance changes strongly are ordinarily sorted out into a lot of bent line fragments named edges. Sobel channel is utilized in picture preparing and PC vision, especially inside edge location calculations where it makes a picture accentuating edges.

3.3 *Region of Interest (ROI)*

A region of interest is sampled within a data set identified for a particular purpose. A district of intrigue (ROI) is a segment of a picture that you need to channel or work on here and there. The tool stash underpins a lot of ROI protests that you can use to make ROIs of numerous shapes, such as circles, ovals, polygons, square shapes, and hand-drawn shapes. The binary image is the same size as the image you want to process with pixels that define the ROI set to 1 and all other pixels set to 0.



Figure 3. Region of Interest

3.4 *Color Threshold*

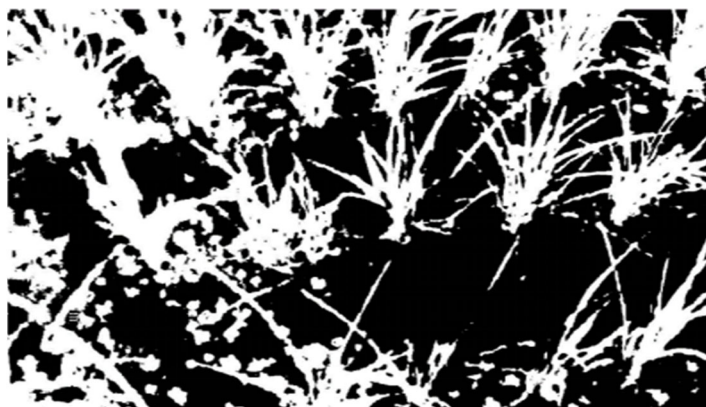


Figure 4. Color Threshold

The Color Threshold module is utilized to evacuate portions of the picture that fall inside a predefined shading range. This module can be utilized to recognize objects of reliable shading esteems. The color threshold is done to this image because the weed is going to identify. The weed will be green in color. So, with the help of this feature, the separation of the green shaded areas in the paddy field. These features have two options and, in this paper, $L^*a^*b^*$ has been used.

3.5 *Image Labeler*

Image labeling is done to make the ground truth information. Ground truth permits picture information to be identified with genuine highlights and materials on the ground. The assortment

of ground truth information empowers adjustment of remote-detecting information and helps in the translation and investigation of what is being detected. In this, the pixel selection is done manually and the line option for doing labeling because the crops and weeds are not in the shape of a rectangle.

4. Classification Algorithm

Most journal papers and some experimental robots in the agricultural field have mostly used these three algorithms, around the world. So, the implementation of this identification is also done in these three algorithms.

4.1 Naive Bayes Algorithm

Naive Bayes (NB) is 'Naive' because it makes the suspicion that highlights of estimation are autonomous of one another. Presently if rather makes the credulous suspicion that all highlights are autonomous of one another, at that point they don't need to depend on precise copies in our preparation of information collection to make a characterization.

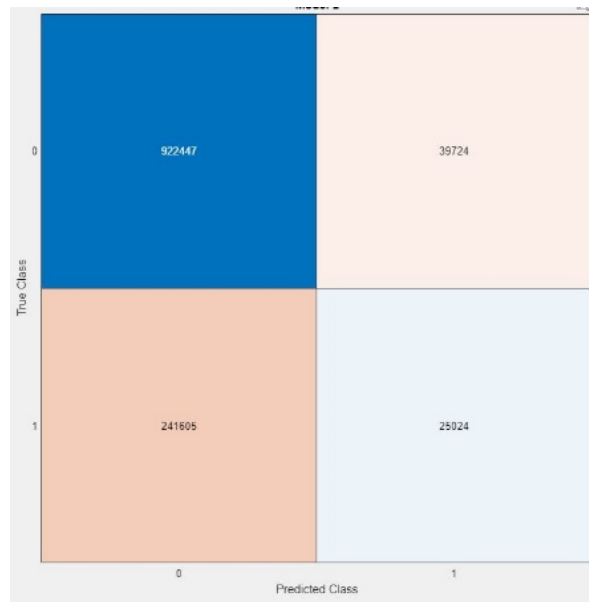


Figure 5. Confusion Matrix of Naive Bayes Algorithm

The Naive Bayes is a grouping calculation that is reasonable for paired and multiclass order. Naive Bayes performs well in instances of clear-cut info factors contrasted with numerical factors. It is valuable for making expectations and anticipating information dependent on verifiable outcomes. The algorithm leverages the Bayes theorem and assumes that the predictors are conditionally independent, given the class. Naive Bayes classifiers assign observations to the most probable class. The estimations and the densities of the predictors within each class are done. Models posterior probabilities are possible according to the Bayes rule. Under the observations of the given sample data, the accuracy rate is 76% in all three types of Naïve Bayes algorithms.

4.2 Decision Tree Algorithm

Choice trees, or arrangement trees and relapse trees, anticipate reactions to information. To foresee a reaction, follow the choices in the tree from the root (starting) hub down to a leaf hub. The leaf hub contains the reaction. Order trees give reactions that are ostensible, for example, 'valid' or 'bogus'. Relapse trees give numeric reactions. Measurements and Machine Learning Toolbox trees are parallel. Choice trees, or arrangement trees and relapse trees, anticipate

reactions to information. To foresee a reaction, the choices in the tree started from the root (starting) hub down to a leaf hub. The leaf hub contains the reaction.

Order trees give reactions that are ostensible, such as 'true' or 'false'. The training data was given to all four types of this algorithm and the results of the accuracy rate are 78.1% in Medium Tree, but the rest of them came near to 77.1%.

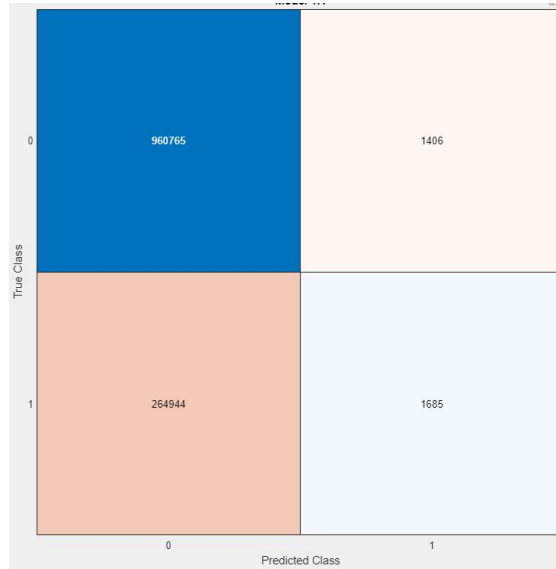


Figure 6. Confusion Matrix of Decision Tree Algorithm

4.3 KNN Algorithm

K nearest neighbors is a straightforward calculation that stores every accessible case and groups new cases dependent on a likeness measure. KNN has been utilized in measurable estimation and example acknowledgment as of now at the start of the 1970s as a non-parametric strategy. KNN is a non-parametric, sluggish learning calculation. Its motivation is to utilize a database where the information focuses are isolated into a few classes to anticipate the characterization of another example point. Only for reference, this is "the place" KNN is situated in the calculation rundown of sci-kit learn.

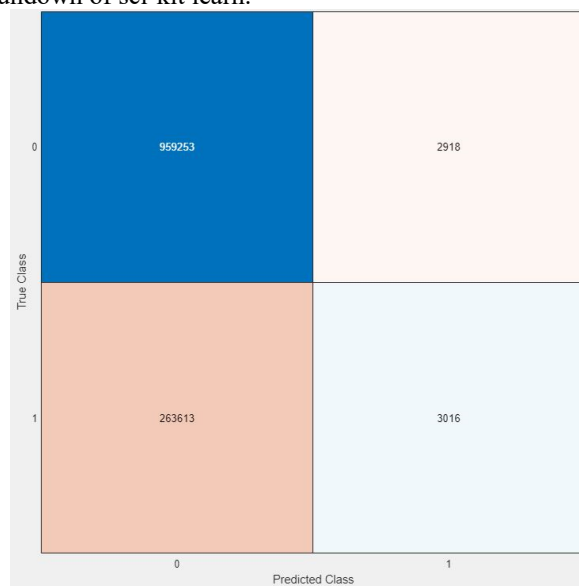


Figure 7. Confusion Matrix of KNN Algorithm

K-Nearest Neighbor (KNN) search and find the k closest points in X to a query point or set of points Y . The KNN search technique and KNN-based algorithms are widely used as benchmark learning rules. KNN model can alter both the distance metric and the number of nearest neighbors. Because a KNN classifier stores training data. The model was used to compute resubstituting predictions. Then the model was used to classify new observations using the predict method. The accuracy rate of this algorithm gave 78.3% with the training data.

5. Result

In a comparison with the Decision Tree algorithm and the KNN algorithm, the correct prediction accuracy rate is 78.3% in the KNN algorithm, and the decision tree is around 77.1%. But the accuracy of the KNN incorrect classification percentage is around 1.8% whereas, more than 2% for the decision tree algorithm. The comparison with the Naïve Bayes algorithm and the KNN algorithm, the correct prediction accuracy rate is 76% in the naïve Bayes algorithm and 78.3% in the KNN algorithm. The accuracy rate of the naïve Bayes incorrect classification percentage is nearly 2.3% which is higher than the KNN algorithm. So, our selection for weed identification is the KNN algorithm.

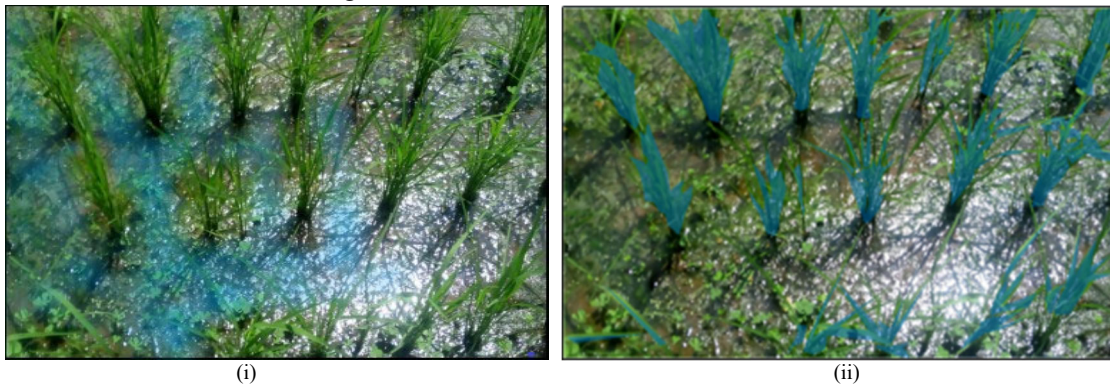


Figure 8. (i) Real-Time Input Image, (ii) Identification Outputs

As a result, comparing the results acquired from our paper and results from various journal papers, we can conclude that the KNN algorithm is much superior to any other algorithms because the KNN requires fewer sample data with a high accuracy rate above 78% and can achieve the result of detection in less computational time.

6. Conclusion & Future Scope

As our country is recognized, that approximately 70% of the population lives in villages & their foremost profits depends on the rural source. In this paper, detection may be prolonged by introducing tracking the weed detection and removal everywhere, in any area, at any time. Upgrading the features extraction from 4 to eight to 12 to get a higher accuracy rate percentage. The computational time for processing the real-time and taking the output will be reduced, which makes the cutting procedure undying. With the help of IoT connectivity, we can access information everywhere.

As it turned into expected to provide you with some solutions that can be implemented to boom the performance of production almost with the aid of weed detection the use of a place-based feature to discriminate from weed to crop. This era will be applied in our robotics can be one of all the largest breakthroughs in agriculture aids proving to quickly end up a farmer's great pal that takes out his worst enemy.

References

1. G. Khurana and N.K. Bawa. in *Advances in Electromechanical Technologies, LNME, Springer Cham.* (2021).
2. I. Dasgupta, J. Saha, P. Venkatasubbu and P. Ramasubramanian. *Arab. J. Sci. Engg.* **45**:11115-27.(2020)
3. N. Islam, Md. M. Rashid, S. Wibowo, C.Y. Xu, A. Morshed, S. A. Wasimi, S.Moore, and Sk M. Rahman, *Agriculture.* **11(5)**:387. (2021).
4. L. Grimstand and P. J. From. *IFAC PapersOnLine.* **50(1)**: 4588-93. (2017).
5. G. Amer, S.M. Mudassir and M.A. Malik. in. *International conference on industrial instrumentation and control.* (2015).
6. R. Shah, S. Ozcelik and R. Chaloo, *Procedia Computer Science. Elsevier Ltd.* **12**:170-5. (2015).
7. G. Bayar, A. B. Koku and E.I konuksevn, *Int. J. of Math. mod. and met. in app. sci.* **4(3)**:366-73. (2009).
8. T.E. Madson and H.L. Jakobsen. *T.U. Denmark.* (2001).
9. M.J. Aitkenhead, I.A.Dalgetty and C E. Mullins. *Comp. and Elec. in Agri., Elsevier Ltd.* **39(3)**. (2003)
10. V. Alchanatis, L. Ridel, A. Hetzoni and L. Yaroslavsky. *Comp. and Elec. in Agri., Elsevier Ltd.* **47(3)**. (2005)
11. Latha, A. Poojith, B.V.A. Reddy and G.V. Kumar. *Int. J. Inno. Res. in Elec. Elect. Ins. and Cont. Engg.* **2(6)**. (2014).
12. N. zhang and C. Chaisttapagon. *Trans. of the ASAE.* **38(3)**: 965-74. (1996).
13. K.C.Swain, M. Norremark, R.N. Jorgensen, H.S. Mitiby and O. Green. *Bio. Sys. Engg.* **110(4)**: 450-57. (2011).
14. F. Ahmed, H.A. Al-Mamun, A.S.M.H. Bari, E. Hossain and P. Kwan. *Crop Protection.* **40(98)**:104. (2012).
15. A.J. Perez, F. Lopez, J.V. Benlloch and S. Christensen, *Comp. and Elec. in Agri., Elsevier Ltd.* **25(3)**:197-12. (2000).
16. C.C. Yang, S.O. Phraser, J.A. Landry, J. Perret and H.S. Ramaswamy, *Cand. Agri. Engg.* **42(4)**: 195-00. (2000)
17. M. H. Siddiqi, I. Ahmad and S. Bt. Sulaiman, in *Int. Conf. on Edu. Tech. and Comp. IEEE.* (2009).
18. B. L. Steward and L. F. Tian, in *SPIE Conf. on Prec. Agri. and Bio. Qty.* (1999).
19. A. Arefi and A. M. Motlagh, *J. of Food Agri. and Env.* **9(1)**:379-383. (2011).
20. M. S. El-Faki, N. Zhang and D. E. Peterson. *Trans. of the ASAE.* **43(4)**:1001-9. (2000).