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Smart weed monitoring system

Abarna R [1*], Ajishiya R [2], Janani R [3], Dr. P Anandraj [4]
[1-4] Department of CSE, EGS Pillay Engineering College, Nagapattinam, Tamil Nadu, India

* Corresponding Author: **Abarna R**

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Abstract
Smart weed monitoring system can be said as an aborning topic in this new technological era. A weed plant can be described as a plant that is unwanted at a specific location in the given time. Due to the enormous usage of fertilizers and pesticides the weeds have also got increased in the agricultural fields. So in this paper we will bring the idea to detect the weeds effectively and also increases the productivity of the crops. In this article we can explore the scope of sustainable weed management, growing concerns on herbicide resistance, environmental and health hazards on using pesticides including herbicides and declining profitability are the major challenges of 'high input' agriculture. It also makes use of machine learning and image processing methods to efficiently detect the weeds present along with the crops. The Farmers have fought against the weed density as long as land has been used for food production. Automation in weed detection is one of the viable solutions for effective exclusion or reduction of chemicals involved in crop production. This study discusses and compares the weed control method and allows farmers to reduce the cost and expenses spent for the man power and manage these in an environmentally and economically sustainable manner.

Keywords: weed detection, Machine Learning, Convolution Neural Network (CNN), increase productivity, reduce environmental hazard

1. Introduction

The agriculture sector is a central pillar of the Indian economy, employing 60% of the nation's workforce and contributing to about 17% of its Gross Development Product (GDP). Productivity remains a challenge, which includes poverty and malnutrition in rural areas. To address these problems, this project proposes a novel machine learning technique, in particular the architecture of Convolutional Neural Networks (CNN) for identification of weed plants. Weeds are plants which are undesirable, damaging and persistent that interferes in the growth of other crop plants thus affecting agriculture, human activities, natural processes and economy of the whole country. Weeds that grow along with the crops would compete with crops for resources such as nutrients, water, and sunlight. Weeds can significantly reduce crop yields and quality, leading to economic losses for farmers. Additionally, some weeds can serve as hosts for pests and diseases, which can further harm the crops. Crop weeds can cause several problems, including,

- Competition for resources
- Reduced form productivity
- Crop damage
- Pest and disease transmission
- Environmental impact
- Economic impact

Controlling weeds is therefore an important aspect of crop management. Farmers may use a variety of methods to control weeds, including mechanical methods such as hand weeding or tillage, as well as chemical methods such as herbicide application.

In recent days the usage of herbicides is being drastically increased, which results in environmental and health issues. So by using this system we can control the usage of herbicides.

2. Literature Review

1. Durgesh raghuvanshi, Apurva Roy, Vaibhav Panwar [1] developed a “Smart Agricultural System” with the concept of Internet of Things (IoT) using soil moisture sensor and temperature sensor. Some of the disadvantages are increased usage of chemicals, uneven water distribution, reliance on organic fertilizers, and increase food miles.
2. Iwin Thanakumar Joseph Swamidason, Shanthini Pandiyarajan, Karunakaran Velswamy, P.Leela Jancy [2] implemented a “Futuristic IoT based Smart Precision Agriculture” and analyzed various environmental parameters such as water level, humidity, soil moisture, air quality, UV level, rain etc. which are highly essential for the fruitful yield of any nutritious crops. Here the inconvenience includes difficulties during implementation in rural areas because of multiple reasons like land differences, ownerships, and infrastructure, it is costly also not a freehand agriculture method.
3. Avtar Singh, R.Kaur, J.Kang, Gurpreet Singh [3] discussed about “Weed Dynamics in Rice, Wheat Cropping System” using Weed dynamic resistance, Conservation tillage. The drawbacks include Puddled translated rice when following a wheat crop exposes the hidden organic matter to air and results in its oxidation, thus leading to structural degradation of the soil. Th intensive tillage results in the annihilation of large aggregates, which leads to low crop yields.
4. Santoshachandra Rao karanam, Y.Srinivas, M.Vamshi Krishna [4] implemented “Deep Learning for Image Processing” and established a complete understanding on the usage of Deep Learning in Image Processing and Image Segmentation that brings out the various fields where Deep Learning can be considered. Some issues are, it requires very large amount of data in order to perform better than other techniques, it is extremely expensive to train due to complex data models, more over deep learning needs valuable GPUs and hundreds of machines. This increases cost to the users.

3. Existing System

The existing system is used to detect the different kinds of leaves by using various approaches in Machine Learning such as.

A. Active Contour Model (ACM) filter

Active contour model (ACM) is a technique which have been widely applied to image segmentation. It can obtain closed object contours as segmentation results, which can be conveniently used for shape recognition and analysis.

B. Hierarchical Vector Quantization (HVQ)

Computed aided detection (CADe) of pneumonic knobs is being considered as a basic for helping radiologists in early recognizable proof of lung tumor from computed tomography (CT) examines. This paper proposes a novel CADe framework in view of a progressive vector quantization (VQ) plot. Contrasted and the regularly utilized straightforward thresholding approach.

C. Rule-based filter

It is a flexible and powerful technique as fuzzy inference system that can be adapted for detecting nodules. Therefore, rule-based system is subsequently optimized based on training data.

D. LDA

Linear Discriminant Analysis (LDA) is a idealogy for finding linear combination of variables which effectively separates two or more classes. LDA is not a classification algorithm, though it makes use of class labels. However, the result of LDA is used as part of a linear classifier. Its use is making a dimension reduction before using nonlinear classification algorithms.

E. K-Nearest Neighbor Classifier

K Nearest Neighbor classifier is Supervised classification method. In the time of training, without having any previous information about the structure of the dataset it can classify the training set based on the k value. As there is no training phase, K Nearest Neighbors keeps all training data and uses it during the testing phase. The outcome of this algorithm is a discrete value which is based on the majority of votes from its neighbors. The k value is directly proportional to the confidence in predictions.

F. Artificial Neural Networks (ANN)

An ANN is a computational model which is based on the underwater obstacle. It contain some nodes that are connected through weights. Each and every node receives data from its previous nodes, adds it together and produces the output data through a nonlinear function, and then it propagates data to proceeding nodes. The two phases in the ANN actions are training or learning phase and test phase. In the first phase, input data are presented to the ANN and weights are adjusted and fixed. The next phase is about testing.

G. Support Vector Machines (SVMs)

SVM is one of the Supervised machine learning algorithms that predicts an optimal hyperplane in an n- dimensional space to divide the training set into multiple classes. Different kernel functions can be specified for the decision function based on them problem. They could be used to implement a multi-class classification on a dataset, providing in advance a subset of labeled data that are needed for model training.

H. Random Forest (RF)

RF is also a supervised machine learning algorithm which uses the statistical resampling technique bootstrapping when creating an ensemble of decision trees. In this procedure, the training dataset is sampled with alternatives for each tree present in the forest and random subsets of features are used at each decision split. Final prediction of the forest depends on which label was classified most by all trees when predicting new data.

4. Proposed System

A. Region Proposal Network

This region proposal network takes convolution feature map that is produced by the backbone layer as inputs and outputs the anchors given by sliding window convolution is applied on the input feature map.

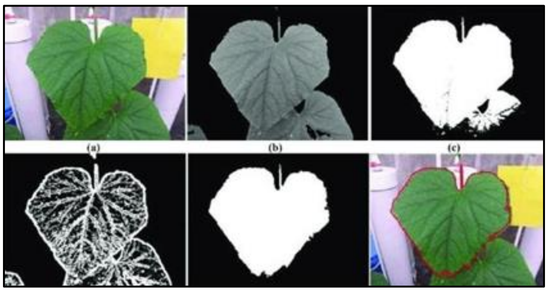

Fig 1: Convolution feature map

B. Gray Level Co-occurrence Matrix

Gray Level Co-occurrence Matrix (GLCM) based texture analysis of the kidney diseases for parametric variations. The study were done using three Pyoderma variants (Boil, Carbuncle, and Impetigo Contagiosa) using GLCM. GLCM parameters were extracted for each color component of the images was taken for the study. The correlation, contrast, energy and homogeneity represent the linear dependency, coarseness, textural uniformity, and pixel distribution of the texture respectively. The approach can be used for the identification of CKD diseases with accuracy by employing a suitable deep learning algorithm.

C. Convolutional Neural Network (CNN)

A CNN is a kind of deep learning technique used to analyse visual scenes. It is portrayed by having one or more hidden layers, which extracts the attributes in videos or images, and a fully connected layer to produce the desired output. In case of computer, the image is a 3D array (width× height × depth) of values ranging from 0 to 255. It is simply pixels of colour; if the number of channels is one, the image is grayscale, black, and white. Besides, the channels are three colours (if images are RGB). CNN has several layers in an hierarchical structure.

5. Methodology

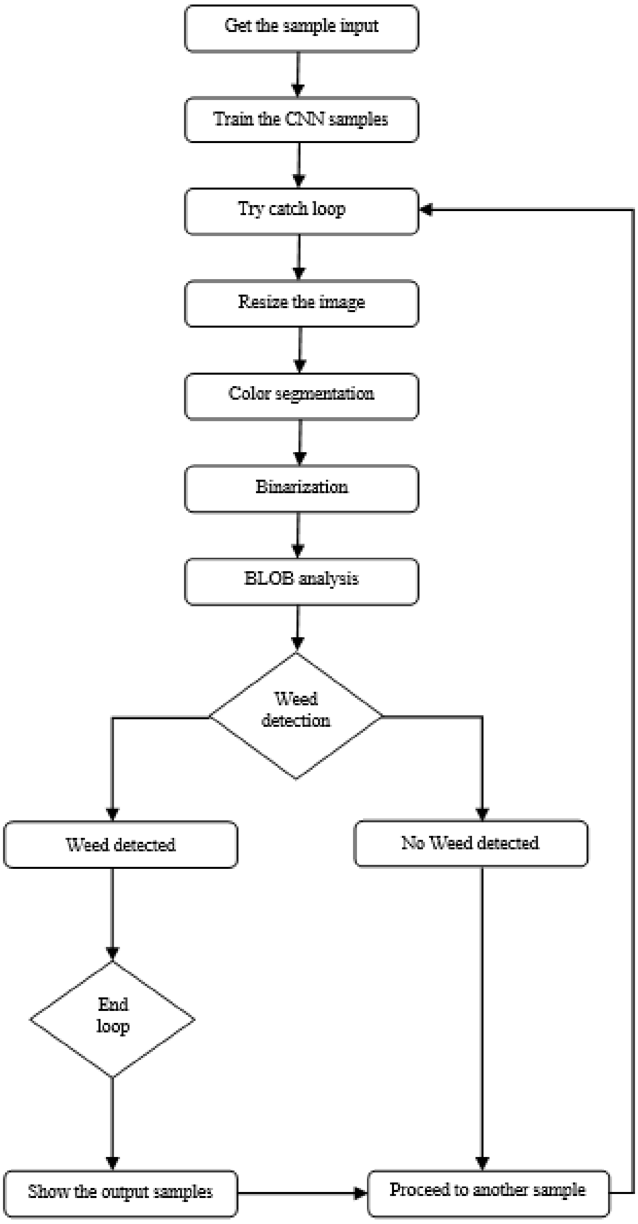

Fig 2: Data flow diagram

The weed dataset that is used in training and preprocessing of weed images, as well as the deep CNN model of weed identification system that has been used for identification and classification of plant species through a given weed image. Initially images transform into a suitable form in which feature extraction become easy, it is done using image pre-processing techniques, after that features are extracted using different layers of CNN and at last by using these features finally it classifies plant.

6. Algorithm

Input

train_x,train_y: features and labels of Leaf and their Species Name Training Set

test_x,test_y: features and labels of Leaf and their Species Name Test Set

Output

W^l b^l,: weights and bias of Convolution and Pooling Neural Network(CPNN)

W^l $b^l_{jk,}$: weights and bias of Full Convolution Neural Network(RPN,FRCNN,FCNN have 3 layers)

Required parameters

max_time: maximum value n of nACs in every ISP

target_error: when the current training error is less than target error, the training is finished

η_CPNN: the learning rate of CPNN

Initialization work

Wl ij,b l j,wjk,bjk: weights and scaling parameters of CNN(RPNN+FCNN) are set as random numbers.

t:t is the current simulation time,which is initialized as t-1 before the training loop.

L(t):L(t) is the mean square error at simulation time t.L(t) is initialized as L(1)=1>target_error.

Begin

1. Set the required parameters and complete the initialized work
2. while ttarget_error
3. for all trainingSet:
4. time_p (prediction of label) is calculated according to train_x and forward calculation formula 1-9
5. end for
6. L (t) is re-calculated as L (t)= $\frac{1}{2}\sum_{n=1}^{N}(train_{p(n)} - train_{y(n)})$ 2, N is the total number of training Set.
7. Δwl, Δbl, Δw-1 ij, Δb-1 j
8. wl (t),bl (t),wijlbj -1 (t)
9. t++
10. End while

7. Future Enhancement

Future work will be conducted to identify weeds in videos. Meanwhile, it would also be interesting to evaluate the accuracy reached in the detection of crops by optimizing the machine learning model. Even though the Weed detection System is good enough, we can use drones with automatic sprayer of Herbicides, through which the usage of Herbicides can be reduced and can harvest quality crops. Also Better Cameras can be used in order to capture much better images to overcome from the problem that may arise due to Sunlight variation and shadows.

8. Conclusion

In this project, we have proposed an approach to identify weeds in crop plantation using machine learning based CNN algorithms. Grey Level Co-occurrence Matrix algorithm for feature extraction was used to avoid model over fitting problems and lower the memory requirements in computation for the CNN model classifier. Transfer learning approach and data augmentation were used to build the VGG16 model classifier due to the small data size. The algorithm used in this project can also be used for robotic weeding, e.g. chemical weeding or mechanical weeding. Given the high-level performance in this project, it was demonstrated that the proposed method is suitable for the ground-based weed identification in crop plantation under various conditions, including varied illumination, complex backgrounds as well as various growth stages and has the application of the sustainable development in the crop industry. The average precision was 91.8%, 92.4%, and 92.15% respectively, which indicated that the proposed dataset has the capability for further development of precise weed identification models, which would contribute to the application of intelligent weed control technology in practice.

8. References

1. Durgesh Raghuvanshi, Apurva Roy, Vaibhav Panwar. Iot Based Smart Agriculture System IJRES. 2021, 9(6).
2. Iwin Thanakumar Joseph Swamidason, Shanthini Pandiyarajan, Karunakaran Velswamy, P.Leela Jancy, Futuristic IoT based Smart Precision Agriculture, River Publishers, in press.
3. Avtar Singh, R Kaur, J Kang, Gurpreet Singh. Weed Dynamics in Rice, Wheat Cropping System, Current agriculture research Journal, 2017.
4. Santoshachandra Rao karanam, Y Srinivas, M Vamshi Krishna. Deep Learning for Image Processing, IJMTE, in press, 2018, 8(12).
5. YH Kim, KR Park. MTS-CNN: Multi-task semantic segmentation-convolutional neural network for detecting crops and weeds, Comput. Electron. Agricult., in press, 2022, 199.
6. S Imran Moazzam, US Khan, WS Qureshi, MI Tiwana, N Rashid, A Hamza. *et al*. Patch-wise weed coarse segmentation mask from aerial imagery of sesame crop, Comput. Electron. Agricult. In press, 2022, 203.
7. S Shorewala, A Ashfaque, R Sidharth, U Verma. Weed density and distribution estimation for precision agriculture using semisupervised learning, IEEE Access, in press, 2021, 9:27971-27986.
8. SMM Hasan, F Sohel, D Diepeveen, H Laga, MGK Jones. A survey of deep learning techniques for weed detection from images, Comput. Electron. Agricult, in press, 2021, 184.
9. S Xie, C Hu, M Bagavathiannan, D Song. Toward robotic weed control: Detection of nutsedge weed in bermudagrass turf using inaccurate and insufficient training data," IEEE Robot. Autom. Lett. in press. 2021, 6(4):7365-7372.
10. K Zou, X Chen, F Zhang, H Zhou, C Zhang. A field weed density evaluation method based on UAV imaging and modified UNet, Remote Sens. In press. 2021; 13(2):310.
11. I Sa, Z Chen, M Popovic, R Khanna, F Liebisch, J Nieto, *et al*. WeedNet: Dense semantic weed classification using multispectral images and MAV for smart farming, IEEE Robot. Autom. Lett. 2020; 3(1):588-595.

12. K Hu, G Coleman, S Zeng, Z Wang, M Walsh. Graph weeds net: A graph-based deep learning method for weed recognition, Comput. Electron. Agricult. In press, 2020, 174.
13. K Osorio, A Puerto, C Pedraza, D Jamaica, L Rodríguez. A deep learning approach for weed detection in lettuce crops using multispectral images, Agri Engineering. In press. 2020; 2(3):471-488.
14. M Aparna, D Radha. Detection of weed using visual attention model and SVM classifier, Proc. Int. Conf. ISMAC Comput. Vis. Bio-Eng. In press. 2019; 30(1):243-253.
15. X Ma, X Deng, L Qi, Y Jiang, H Li, Y Wang, *et al*. Fully convolutional network for rice seedling and weed image segmentation at the seedling stage in paddy fields, PLoS One. in press, 2019, 14(4).
16. A Farooq, X Jia, J Zhou. Texture and shape features for grass weed classification using hyperspectral remote sensing images, Proc. IGARSS IEEE Int. Geosci. Remote Sens. Symp. In press, 2019, 7208-7211.