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AN ARTIFICIAL INTELLIGENCE BASED WEED CLASSIFICATION USING VGG16 CLASSIFIER AND RMSPROP OPTIMIZER

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ABSTRACT

From the start of farming as a profession, the weeds have been a problem and the problem still continue. The main factors are the competition for nutrients, water, and space and for disease and pesticides. Weed management is becoming popular in crop production with the arrival of high yield varieties and heavier doses of fertilizer application. One important way of improving fertilizer use efficiency is to control weeds in good time. We developed a web application which uses in-depth learning, to capture an input and to detect whether an image is normal or weed image. In this paper VGG16 classifier and RMSPROP optimizers are used for distinguishing a plant and a weed. The dataset is downloaded from Kaggle and Signal handling gathering of the Aarhus. Four plants, common wheat and sugar wheat, common weeds, cleavers with a totality of 942 pictures have been successfully classified. Finally, around 92% precision with a 5.5% rise in current classifications is projected by this work.
***Keywords**: Crop, Weed Classification, VGG16, RMSPROP Optimizer, Deep Neural Networks*

1. INTRODUCTION

Weeds are all around very normal in lakes and gardens. Albeit some might be seen as valuable or attractive, most sorts of pot are viewed as a commotion. Get familiar with weed control and ID assists nursery workers with seeing if these weeds can be endured or not. Consider some normal weed plants and what techniques for weed control might be fundamental. A weed — a plant that works erroneously is called, by definition [2][6].

By far most of these plants are known for their undesirable attributes, as opposed to great ones. Weeds are battling for water, light, supplements and space, battling for your nurseries and turf cultivating [3][5]. Most of them are quick producers and involve a considerable lot of the spaces they lie in. While most weeds flourish in great conditions, native sorts practically all around the world can be found. They can as of now give knowledge into your real conditions in the dirt. For the rancher this is a tremendous issue, as the weed plant burns-through an enormous number of food and water, with the goal that the other plant can't develop accurately.

Legitimate weed distinguishing proof is useful for the right weed control proposal. To keep a rancher from spreading another weed in its field, it is important to remember it quickly. Appropriate recognizing weeds helps with picking the best herbicide to smother a particular plant [10]. It will help you set aside cash in some cases in the event that you have a less exorbitant herbicide. It is important to be exact in recognizing them.

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A few calculations and strategies have been created to take care of this issue. Significant getting the hang of demonstrating, including the Convolution Neural Networks are maybe the most encouraging ongoing strategies for leaf arrangement (CNN)[5][8].

2. LITERATURE SURVEY

The control of weeds is a vital aspect for keeping up with exceptional returns for any harvest. Notwithstanding, there are critical varieties in weed species in conventional harvest weed distinguishing proof systems principally zeroing in on the immediate ID of weeds. The harm caused under such a condition is additionally significant in circumstances where criticism is restricted [11].

Weed misfortunes have been assessed on an alternate premise and reach somewhere in the range of 5 and 24%. As per an investigation did by different farming colleges in the groundnut locale, weed yield misfortune goes from 17% to 19% for corn 9-15% for paddy 10,22% and yield misfortunes for crops like cotton up to half in light of the fact that early development is extremely delayed for cotton crop [12][13].

In [1], a disintegration and enlargement technique are utilized fundamentally for weed discovery in the calculation. By removing the green parts of this picture, the shading picture is changed over into twofold. The measure of white pixels in the locale of interest is resolved and weeds are viewed as regions with a white pixel tally more prominent than the predetermined edge. Otsu's thresholds [11]12] attempt to discover a limit esteem t to limit weighed inside class fluctuation, changing the first picture into a parallel image [2][3]. Creator [4] utilized continuously weed detecting cameras and utilized conventional dissemination splashing strategies to think about the strategy they proposed. The RGB segments of the picture are taken from the grayscale of the image to isolate the vegetation from different segments in the XY area, which compares to the green worth in the picture [5]. In the [6] algorithm proposed, pictures containing uniform enlightenment are handled all the more precisely; pictures that have better brightening. Utilized a UAV splash for herbicide, which diminished the herbicide utilization considerably by around 15-39% [7] [8] presented a strategy for discovery of the significant citrus infections and arrangement. For the putting away of picture highlights with a specific measurement, the CNN utilizes successive convolution layers with a non-linear reLU function [9]. The investigation [12] Support Vector Machine for the Detection of Disease or Flavor Attacks on Blueberry plants was created, the counterfeit neural organizations (ANN), the Random Forest and the CNN. A review of various techniques used to identify and characterize infections of citrus plant blossoms was undertaken [11]. Wide assessment of ground machine vision and weed recognition picture preparing techniques [13][22].

The researchers developed various techniques for classifying the weed from crops using several features for plants and weeds, like size, color, vein pattern, spectral reflectance, shapes, etc [15] [14] [7]. Even though, these approaches are not precisely and reliably executing differentiation process in difficult situations, like high weed density [7][23]. The deep learning model is generally utilized concept in various applications of agriculture. Semantic segmentation techniques, like fully convolutional network are utilized for weed classification from images obtained from Unmanned Aerial Vehicle (UAV) for various crops, namely soybean, rice, and sunflower [17] [16]. Moreover, the utilized approaches use offline image data processing for producing weed map of captured data [16]. Several robotic weed control models are devised on mechanical weeding, electrical discharging, single tactics, flaming discharging, and selective chemical spraying. Furthermore, for differentiating weeds and crops, fuzzy logics, Support Vector Machine (SVM), pattern recognition techniques, Artificial Neural Network (ANN), statistical pattern identification,

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decision tree and so on are developed in 2-dimesnional vision processing. The author in [19] [21] devised and modeled smart sprayer based on artificial intelligence and machine vision for differentiating non-weed and weed crops. The targeted model was combined with precision spraying model, and it is operated with state of art weed identification model and weed mapping scheme for accurate spraying by a robot.

In 2020, Rekha Raja et al. [23] introduced topical marker-based crop signaling approach for weed classification. Here, crop signals of weed were designed for obtaining optical signature, which simplified the classification process. In addition, the spatial position of individual lettuce plant was identified based on computer vision approach. Here, weed and crop mapping approach was employed for weed management in lettuce area. This technique mainly includes decision making and crop mapping process for better weed classification. This weed classification model obtained high success rate, but when the crop plants were overlapped, the classification process is difficult.

In 2020, Mojtaba Dadashzadehet al.[24] devised automated stereo computer vision system for classification of weeds and crops. The stereo video was captured from various crops for differentiating weeds and rice drops. The pre-processing process was applied for input video for removing the noises. After that, the segmentation was carried out for segmenting various regions of frames for better classification. Meanwhile, feature extraction was done for extracting texture and shape features for enhanced classification. Moreover, the significant features were selected and ANN was utilized for classification. Here, Bee Algorithm (BA) and Particle Swarm Optimization (PSO) algorithm were developed for optimizing the ANN classifier. This classification model obtained better classification accuracy, even though failed to utilize effective database.

Table 1: Gives The Overall Methods That Were Discussed By Some Of The Authors.

S/no	Year	Methods
1.	2015	An image processing-based approach is proposed in [1] to differentiate crop Ragi from weeds
2.	2015	Data augmentation is been carried out to enhance the variability among the collected data.
3.	2015	Here, it is converted into a binary image using Otsu's threshold which tries to find a threshold value t which minimizes the weighted within class variance given in the equations 2 and 3.
4.	2016	Used real-time cameras for weed sensing and compared their proposed method with conventional broadcast spraying techniques.
5.	2016	Taking advantage of the RGB components of the image, all the components in the XY space that correspond to the green value in the image, are subtracted from the grayscale image to separate the vegetation from the other components.
6.	2016	The proposed algorithm considers the processing of images that contain uniform illumination; images with better illumination are processed with greater precision.
7.	2017	Used a UAV for herbicide spraying which resulted in a substantial reduction in herbicide usage of about 15-39%.

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8.	2017	Presented a method for detecting and classifying the main citrus diseases.
9.	2017	The CNN uses successive convolutional layers with a nonlinear ReLU function for storing the features of an image having a specific dimension.
10.	2017	UAV based crop and weed classification.
11.	2018	As a continuation of [2], Jamil Ahmad et al. in [3] exploited boosted visual features, local shape, and texture, of images that consisted of weeds for improving the performance of their weed classifier.
12.	2018	Conducted a survey on various methods used for the detection and classification of diseases in the leaves of citrus plants.
13.	2019	Used Support Vector Machine (SVM), Artificial Neural Networks (ANN), Random Forest, and Convolutional Neural Network (CNN) for detecting disease or pest attacks on blueberry plants.
14.	2019	Broad review of ground-based machine vision and image processing techniques for weed detection was given.
15.	2020	Used CNN method for Crop and Weed Recognition.

3. PROPOSED METHODOLOGY

This section outlines our methods, from the preparation to the arrangement of images of plants using profound learning. In this segment also, the importance of key preprogramming, preparation and testing tasks will be examined. The photos are prefabricated with photos from two plants and two weeds, and the yields are grouped, irrespective of whether the image is of a plant or of a weed.

Deep learning calculations get acquainted with every layer of the image of the neural network. The neural network is an AI classification calculating method. The weight vector (W) and bending (B) are two types of neural network. The CNN is a deep neural organization class used mostly to evaluate visual pictures in deep learning. It has a layer of information and yield, as well as other hidden levels. Each layer is made up of a group of neurons, and each layer is totally connected to the one before it. The yield layer is responsible for the yield expectation. A picture as input is taken by the convolutionary layer and a number of maps are generated.
The components of the CNN are two:

1) Feature extraction part: as the network carries out a number of convolutionary and pooling operations, features are found.

2) Classification part: extracted features are provided to a completely linked classifier layer.
The majority of the time, CNNs are used to group image data. The first step is to prepare the image. The following methods should be used to construct the model:

- Data Acquisition
- Image preprocessing
- Model Building using VGG16
- Optimization using RMSPROP

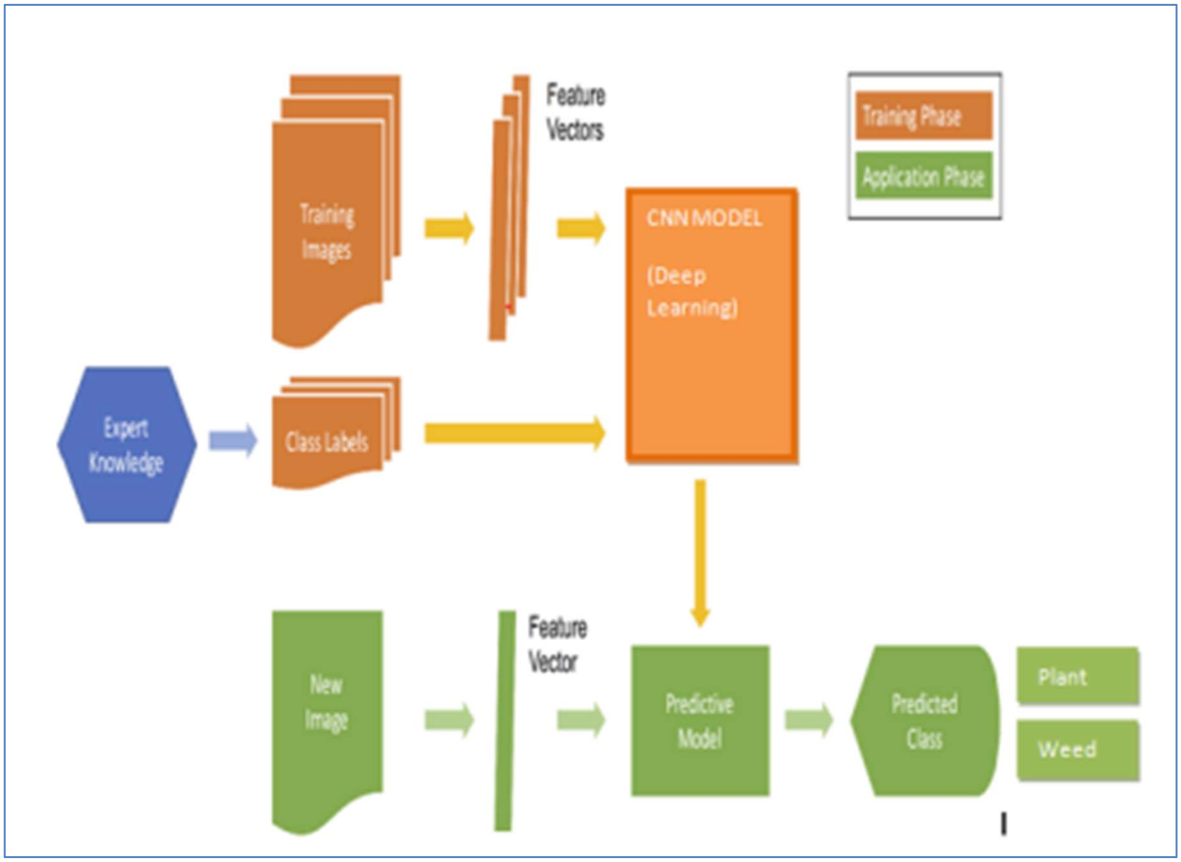

Figure 2: Proposed Work To Classify The Given Input Image Is Plant Or Weed

The proposed architecture is applied in the Jupiter note pad of the boa constrictor and is subsequently connected to the cup system. The methods utilized to do this include protecting information (image information), CNN model construction and forecasting. The flagon system is built to predict whether the image consists of plants or weeds.

3.1 Data Acquisition

An image database of around 4,234 distinct plants from the Aarhus University, featuring a place for 12 plant species in various growth stages. It contains famous RGB photos with approximately ten pixels per mm of the actual target. They are pictures of the seedlings on which they are based. The collection includes the Kaggle and four other species: common wheat, sugar wheat, common weeds and cleavers. Info indexes available for download. All of the photographs are 942.

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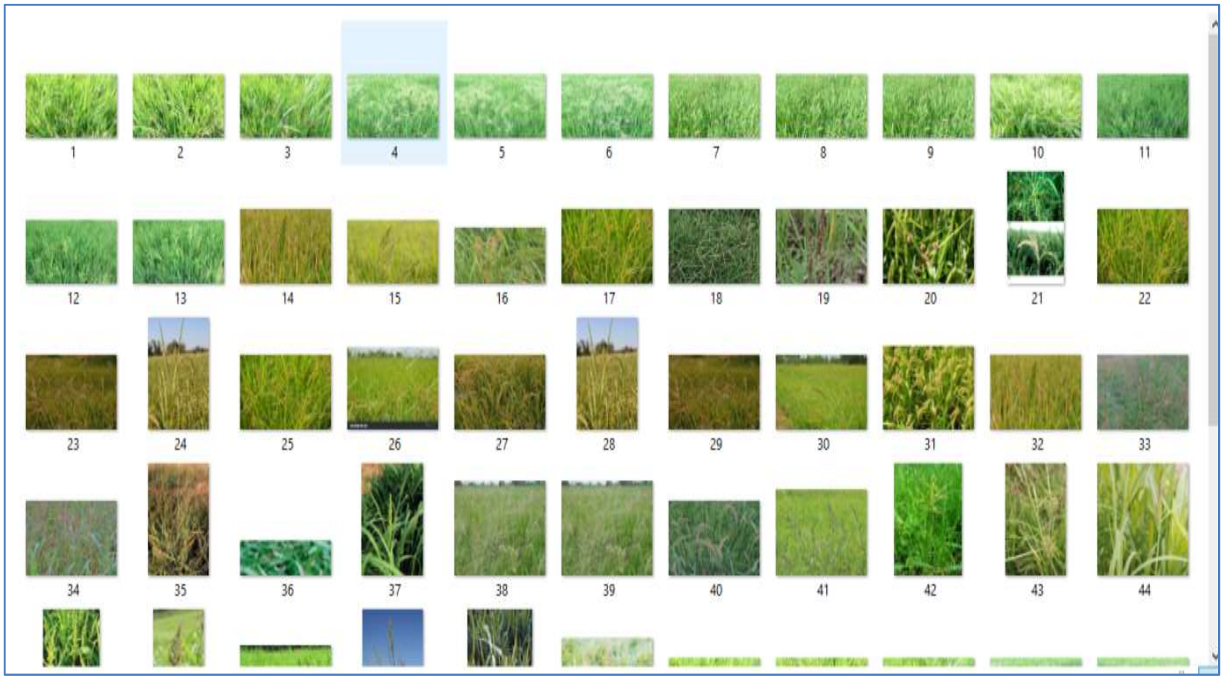

Figure 3: Crop And Weed Images In Database

3.2 Image Pre-Processing

During the pre-production stage of the photograph, we used shadow space transformation and image optimization. In order to analyses shading and light layers we have altered shading space and work on visual analysis at now. Due to the images that have been scaled from 54x54 to 3991x3557, the MxN record configurations are changed. Picture size should be MxM, with the same image size being advanced with a deep learning model to prepare, validate and test. In 224x224 RGB color format, all photos are reworked. A new image would be returned from the edited image with a two-element row and column vector number.

3. 3 Model Building Using Vgg16 Classifier

VGG16 is an engineering CNN that assists ILSVR in winning the 2014 events (ImageNet). It is considered to be one of the best model views of the time. Instead of developing numerous hyper-border systems, VGG 16 is remarkable since it concentrates on 3x3 channel convolutions with stage 1 employing only a coiling layer and a 2x2 strand 2 Maxol canal. The entire engineering process is followed by this process of convolution and max pool layers. At the end, it has 2 FC (full-associated layers). The 16 is a 16-layer load in VGG16.

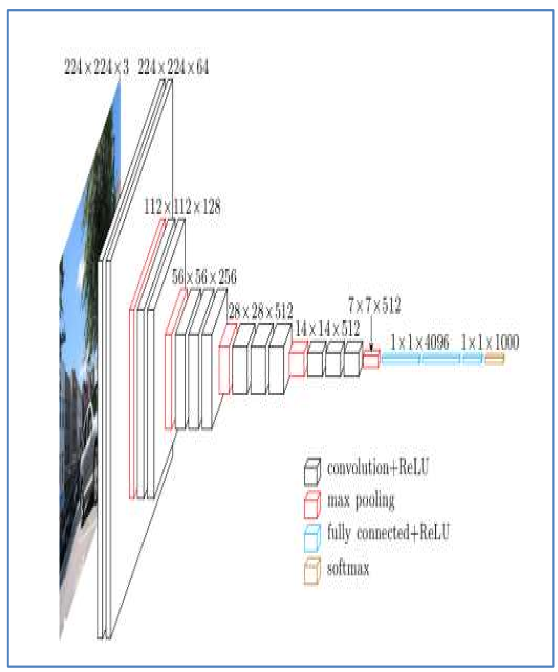

Figure 4: Architecture Of VGG16

The functioning strategy in the convolution networks is clarified in the above figure.
The loss function that we used for a single training example in our fully connected network was:

$$\mathcal{L}(\hat{y}, y) = -y log(\hat{y}) - (1-y) log(1-\hat{y})$$

And the loss function that we use for a single training example for VGG16 is very similar:

$$\mathcal{L}(\hat{\mathbf{y}}, \mathbf{y}) = -\sum_{i=1}^{1000} y_i log(\hat{y}_i)$$

The gadget has 32x1 layers, with the principal layer, Image Data, using 224x224x3 data sources. Progressive layers are linked without jeopardizing the combination or standardization elements. The final segment of the organisation execution estimation grouping formation is coordinated to levels that are all related and have varied execution loads and boundaries. Convolution is divided into three levels. After assembly and combination in the last location, the created amount is moved to three completely associated layers of neurons.

3.4 Optimization Using RMSPROP

To increase the yield, three streamlining agents are used those are RMSPROP, ADAM, and ADAGRAD. These calculations are based on the angle thrust improvement rule. Aside from RMSPROP, combining with VGG16 yields the greatest results.

4. RESULTS AND DISCUSSION

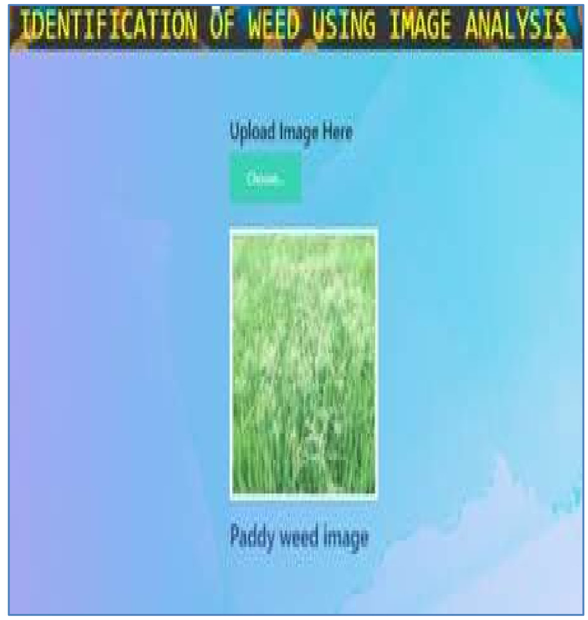

Figure 5: Screenshot Of Work For Test Input Image.

Figure 6: Distinguishing Normal Paddy Image With Weed

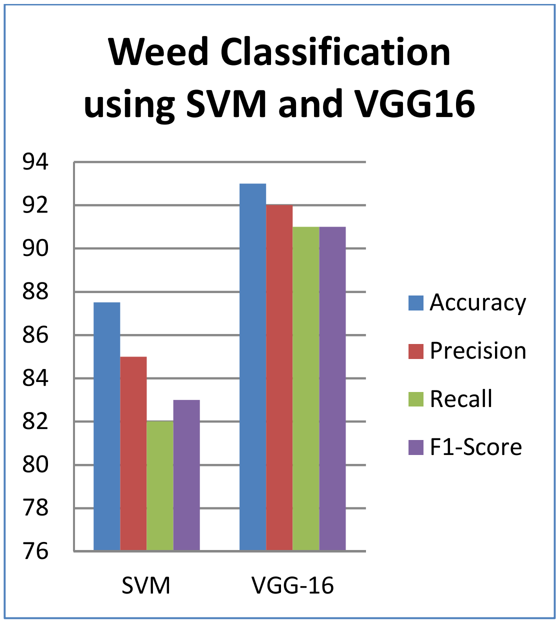

Figure 7: Comparison Of VGG16 Classifier With SVM Classifier

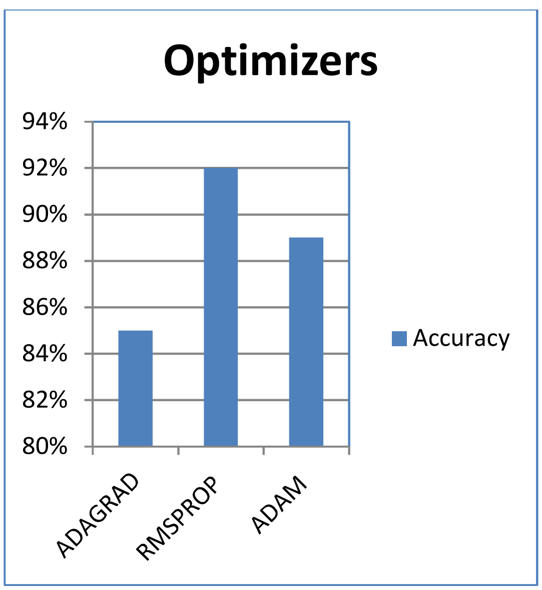

Figure 8: Various Optimizers For Increasing The Accuracy

The analyzers ADAM, RMSPROP, and ADAGRAD are used throughout the model planning process. For each of the layers, relu enactment work is used, and SoftMax work is chosen for the final layer. The misfortune is borderline entropy. We discovered that RMSPROP enhancer with 0.005 learning rate model outperforms all other models by achieving 92 percent accuracy. This research is compared to the SVM classifier. With the aforesaid analyzers, VGG16 places precise orders.

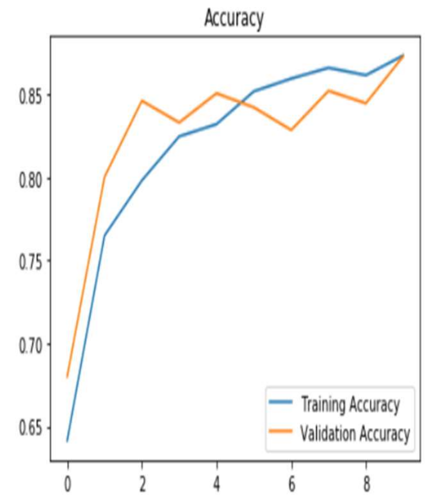

Figure 9: Training Accuracy Vs Validation Accuracy

The above chart shows how the preparation information and approval exactness increments with number of cycles.

Once we fit the data to the model, we can predict the weed in the crop. The major problem of neural network is it over fits data to the model. If it suffers over fitting, it works well with the training test but it does not predict the rating accurately while testing data. So, we split testing dataset into testing data and cross validate data. Here we check the predicted rating and actual rating of the cross validate dataset. So that we know whether the model suffers overfitting or not.

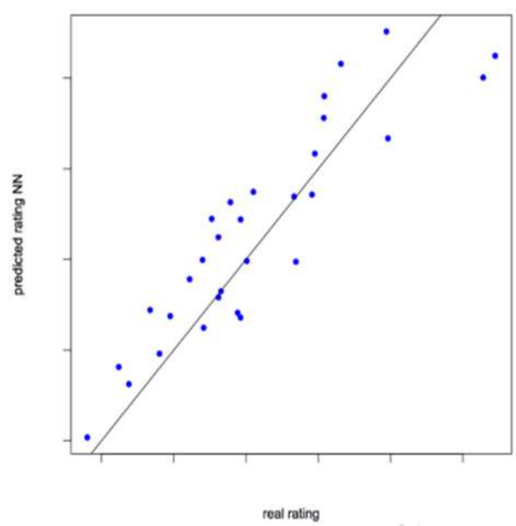

Figure 10: Predicted Rating Vs. Real Rating Using Neural Network

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In traditional machine learning models, the error decreases with increase of length of the data up to some extent once it reaches to a point if we increase the length of the data set the model is unable to learn hidden patterns from the data and error does not varies with length of data. Whereas in Neural Networks, Accuracy increases with the increase of length of data.

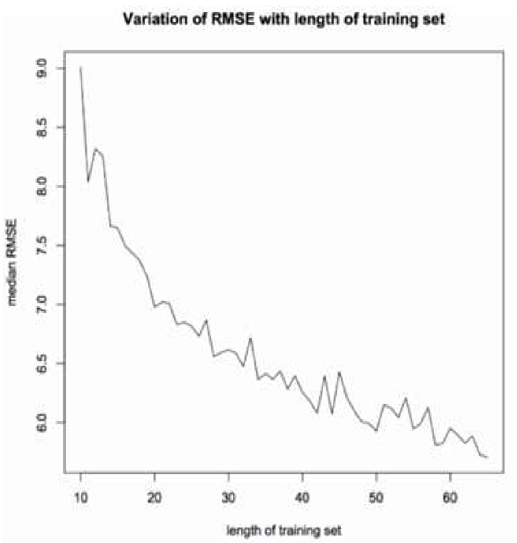

Figure 11: Variation of RMSE

5. CONCLUSION AND FUTURE WORK

This work was particularly useful for weed identification. The strategies used are Convolutional Neural Network computations. With these approaches, we are able to separate weeds from regular photos in a paddy field. Under the constraints of the prescient displaying issue, including picture order, the construction of convolutional neural organizations is the capability, to consequently get proficiency with a few channels in the same, explicit to the informational index preparation The result is a set of very unique highlights that can be found in any input photo. It also aids clients in identifying various sorts of weed in a crop. In addition, the prior can be supplied extra information. This could be accomplished with robots; for example, the weed may be removed from the yield instantly, saving time and money.

REFERENCES:

[1] Aravind R, Daman M and Kariyappa B S, "Design and Development of Automatic Weed Detection and Smart Herbicide Sprayer Robot", IEEE Recent Advances in Intelligent Computational Systems, pp. 257-261, 2015.

[2] Na Zhao, Shi-Kai Sui and Ping Kuang, "Research on Image Segmentation Method Based on Weighted Threshold Algorithm", International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP), pp. 307-310, 2015.

[3] Chaoyun Zhang, Pan Zhou, Chenghua Li and Lijun Liu, "A Convolutional Neural Network for Leaves Recognition Using Data Augmentation", IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable Autonomic and Secure Computing; Pervasive Intelligence and Computing, pp. 2143-2150, 2015.

[4] K.H. Dammer, "Real-time variable-rate herbicide application for weed control in carrots", Weed Research, vol. 56, pp. 237-246, 2016.

[5] J. L. Tang, X. Q. Chen, R. H. Miao and D. Wang, "Weed detection using image processing under different illumination for site-specific areas spraying", Computers and Electronics in Agriculture, vol. 122, pp. 103-111, 2016.

[6] M. A. Molina-Villa and L. E. Solaque-Guzmán, "Machine vision system for weed detection using image filtering in vegetables crops", Facultad de Ingeniería Universidad de Antioquia, vol. 80, pp. 124-130, 2016.

[7] F. Castaldi, F. Pelosi, S. Pascucci and R. Casa, "Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize", Precision Agriculture, vol. 18, pp. 76-94, 2017.

[8] H. Ali, M. Lali, M.Z. Nawaz, M. Sharif and B Saleem, "Symptom based automated detection of citrus diseases using color histogram and textural descriptors", Computers and Electronics in agriculture, vol. 138, pp. 92-104, 2017.

[9] Guosheng Lin, ChunhuaShen, Anton van den Hengel and Ian Reid, "Exploring Context with Deep Structured models for Semantic Segmentation", IEEE Transactions on Pattern Analysis and MachineIntelligence, vol. 33, no. 2, pp. 536-551, April 2017.

[10] P. Lottes, R. Khanna, J. Pfeifer, R. Siegwart and C. Stachniss, "UAV-based crop and weed classification for smart farming," 2017 IEEE International Conference on Robotics and Automation (ICRA), Singapore, pp. 3024-3031, doi: 10.1109/ICRA.2017.7989347, 2017.

[11] J. Ahmad, K. Muhammad, I. Ahmad, W. Ahmad, M. L. Smith, L. N. Smith, et al., "Visual features based boosted classification of weeds for real-time selective herbicide sprayer systems", Computers in Industry, vol. 98, pp. 23-33, 2018.

[12] 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 Robotics and Automation Letters, vol. 3, no. 1, pp. 588-595, 2018.

[13] Huang H, Deng J, Lan Y, Yang A, Deng X, Wen S, Zhang H, Zhang Y, "Accurate weed mapping and prescription map generation based on fully convolutional networks using UAV imagery", Sensors, vol.18, no.10, pp.3299, October 2018.

[14] Kunz C, Weber J F, Peteinatos G G, Sökefeld M, Gerhards R, "Camera steered mechanical weed control in sugar beet, maize and soybean", Precision Agriculture, vol.19, no.4, pp.708-20, Ref No. : 182021007980 | Page 19 of 35, August 2018.

[15] Nguyen TD, Khan JY, Ngo DT, "A distributed energy-harvesting-aware routing algorithm for heterogeneous IoT networks", IEEE Transactions on Green Communications and Networking, vol.2, no.4, pp.1115-27, May 2018

[16] Bakhshipour A, Jafari A, "Evaluation of support vector machine and artificial neural networks in weed detection using shape features", Computers and Electronics in Agriculture, vol.145, pp.153-60, February 2018.

[17] Chen Z, Chen Y, Wu L, Cheng S, Lin P, "Deep residual network based fault detection and diagnosis of photovoltaic arrays using current-voltage curves and ambient conditions", Energy Conversion and Management, vol.198, pp.111793, October 2019.

[18] C. Sullca, C. Molina, C. Rodríguez and T. Fernández, "Diseases Detection in Blueberry Leaves using Computer Vision and Machine Learning Techniques", International Journal of Machine Learning and Computing, vol. 9, no. 5, 2019.

[19] A. Wang, W. Zhang and X. Wei, "A review on weed detection using ground-based machine vision and image processing techniques", Computers and electronics in agriculture, vol. 158, pp. 226-240, 2019.

[20] Partel V, Kakarla SC, Ampatzidis Y, "Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence", Computers and Electronics in Agriculture, vol.157, pp.339-50, February 2019.

[21] Kumar, K. K., Srikanth, B., Kasiviswanadham, Y., Subbarao, C. D., Indira, D. N. V. S. L. S., & Pratap, N. L. (2021). The importance of light-weight encryption cipher in restricted IoT systems to make intelligent technology safer for devices. *Applied Nanoscience*, 1-11.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[22] Kumar, K. K., Ramaraj, E., & Geetha, P. (2021). Multi-sensor data fusion for an efficient object tracking in Internet of Things (IoT). *Applied Nanoscience*, 1-11.

[23] Ramaraj, E., & Indira, D. N. V. S. L. S. (2021, February). Data Fusion Method and Internet of Things (IoT) for Smart City Application. In *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)* (pp. 284-289). IEEE.

[24] Ch, G., Thirumal, S., Ramesh, R., Satyanarayana, D. S. S., & Asadi, S. (2021). Association of vaccine medication for the efficacious COVID-19 treatment. *World Journal of Engineering*.