ISSN: 0974-5823 Vol. 7 No. 5 May, 2022

International Journal of Mechanical Engineering

ENHANCEMENT OF CROP PROTECTION BY CLASSIFICATION OF CROPS AND WEEDS USING ALEXNET DEEP LEARNING NETWORK

Sudhir G Hate, Rahul M Pethe, Sahebrao N Patel, Amalraj Shankar

Sudhir G Hate, G H Raisoni University, Anjangaon Bari Rd, Amravati, Maharashtra 444701, India.

Rahul M Pethe, G H Raisoni Institute of Engineering and Technology B-37/39, Hingna Rd, Nagpur, Maharashtra 440028, India.

Sahebrao N Patel, JSPM Bhivarabai Sawant Institute of Technology and Research, Wagholi, Pune, Maharashtra 412207, India.

Amalraj Shankar, G H Raisoni University, Anjangaon Bari Rd, Amravati, Maharashtra 444701, India.

Abstract: The presence of weed in the agriculture farms reduces 30% to 80% of entire production in India. Detection and removal of weeds is essential to improve the production of agriculture yields. In the weed management agrarians are using herbicides or physical man power presently. In order to bypass the adverse effects of herbicides and huge wastage of man power, precision or digital agriculture is preferred by the researchers. This paper deals with the detection and classification of weeds using deep learning algorithm with modified AlexNet Pretrained network. For the training of networks data sets are taken from the agriculture field of Vidarbha region, state of Maharashtra INDIA. It is important to find the optimal value of learning rate for proposed model on the collected data sets using transfer learning approach. Since the optimal learning rate cannot be find out by analytical calculation trial and error method is preferred. From the trial and error method, the proposed modified AlexNet Pretrained network training model gives the optimal value of learning rate 0.002 with classification accuracy of 97.17%.

Keywords: weed classification, deep learning, AlexNet, Convolutional Neural Network

1. Introduction

The rapid increment of population is expected to reach the billions of nine by the year of2050. This leads the obligation of producing agricultural commodities higher than 70% with the present production[1]. In order to achieve such a higher demand, all the scientists and researchers have to cross numerous hurdles like scarcity of water, floods, urbanisation from cultivation of agricultural lands, climate changes and other issues related with nature of soil[2]. Since many of the above said problems are connected with the nature, finding solution is more complex and trivial sometimes. Weeds are one of the biggest threat and continues problem in the agriculture sector[3]. The generation of the weeds in the field of main crop effects in reduction of production by absorbing water, space, sunlight and other nutrients from the soil. So the removal of weeds from the main crop is more essential at any virtue. The removal of weeds are happening in two ways one is using man power and another is using herbicides[4]. The man power requirement to remove weeds alone is between 30-60% from the whole production[5]. To avoid or reduce the man power present farmers are using herbicides. Although herbicides are giving sudden remedy to weeds, it is producing adverse effects like soil infertility and microbial changes[6]. And consecutively it is creating adverse effects in human health like cancer causes, disruption of hormones and other allergies [7]. In order to minimize these adverse effects scientists are prescribing Precision agriculture or digital agriculture to the agrarian society. The precision agriculture involves various technologies like data collection, remote sensing with GPS, robotics and unmanned Ariel vehicle technology etc.[8]. In precision agriculture weed detection is an important and fundamental step[9]. So this paper concentrates more on image processing with deep learning technology to enhance the management of weed with classification of verity of weeds in the region of Vidarbha in the state of Maharashtra, India.

The following section describes briefly about the short history of image processing, machine learning and deep learning in precision agriculture especially weed management system. At first the images are captured from high quality cameras and sensors. The captured images contains the entire information about the presence of the weeds and main crops. To distinguish the weeds from main crop in the precision agriculture image processing technology is used. The image processing is performing the operations of converting images to digital values for the specified operations with desired controlled task. The image process is beginning with the pre-processing of images starting from Image enhancement. And it is the technique used to reduce the noise and increase the contrast. This process is done to improve the quality of the images and to reach maximum accuracy before processing the images[10]. And further the enhanced images are subjected to various steps like feature extraction, Image Restoration, Colour Image Processing, Wavelets and Multiresolution Processing, Compression, Morphological Processing, Segmentation, Representation and Description, Object recognition[11][12][13].

This section gives the glimpse about the applications of image processing in the field of agriculture with some of the researchers. The overall structure and system implementation of a weed detection and removal is well described by Johnson. R Et al [14]. N S Binti Mat et al used HSV Histogram colour-based feature extraction method in banana leaves to find out the diseases. The algorithm used for feature extraction here is K-NN and SVM [15]. Rouhallah A F et al studied the segregation process of mechanically damaged lemon using image processing[16]. Chengquan Z et al have explained the Integrated Skeleton Extraction and Pruning Method for Spatial Recognition in Maize Seedling. Also they described the utilization MGV and UAV data sets in the image processing[17]. Xinda Liu et al have contributed in the plant disease identification using Visual Region and Loss Reweighting Approach. The data sets are taken here is manually and the decision and training is done by the experts[18]. Mark W et al have worked in the crop acreage calculation by Simultaneous usage of Satellite Images with lower and higher resolutions. The key point in that is the higher resolution gives more accuracy in the estimation than the lower estimation[19]. Mohammad R L et al have studied about identification of rice blast disease using KNN algorithm improved by K-Means method[20]. Although several improvement have done in image processing, the computational time is higher due to the complexity of the program. In order to reduce the disadvantages machine learning is introduced by the researchers and the following section briefs about machine learning.

Machine learning is a special application of artificial intelligence and it can give the ability to the system to learn or train itself without higher end complex programs. Machine Learning requires data sets to train on, and it should be inclusive/unbiased with good quality[21]. The development of machine learning algorithm or learning is categorised into supervised, unsupervised, semi-supervised or reinforcement learning algorithms[22][23]. Initially it needs enough time to let the algorithms learn and develop enough to fulfil their purpose with a considerable amount of accuracy and relevancy. In addition with the autonomous nature Machine learning is highly susceptible to errors. The noticeable aspect of machine learning is, it does not require high performance processors. This advantages are inherited by researchers in the same weed management of weed detection. Some of the work of various researchers are described as follows. Siddhesh B et al worked with the cucumber and onion crops. They used convolutional numeral networks and ResNet-50 algorithm for training. The overall accuracy for onion dataset 84.6% and 90% for cucumber crops[24]. Muhammad et al have worked the crop of tobacco. They established weed detection and spray control. The collected data sets from local fields with diverse changes in scale, orientation, background clutter and outdoor lighting conditions. They used SVM classifiers and reached the accuracy of 96% [25]. Abhinav sharma et al have reviewed about machine learning applications in weed detection with various algorithms. They also have taken various crops[26]. Adel bakhshipour have worked with the enhanced classifiers namely Multi-Layer Perceptron (MLP), k-Nearest Neighbors (kNN), Random Forest (RF), and Support Vector Machine (SVM). Four feature filtering techniques including Correlation-based Feature Selection (CFS), Information Gain (IG), Gain Ratio (GR), and OneR were applied to the image-extracted features and 10 of the most significant features were selected and fed into single and boosted classifiers. The RF model trained by IG selected features (IG-RF) was the most appropriate classifier among the evaluated models whether in single or boosted modes. The accuracy, k, and RMSE criteria of this combination on test dataset were 95.00%, 0.9375, and

0.1591, respectively. Although Machine learning having more advantages, it also having certain disadvantages like requirement of refined feature extractions and the requirement of experts for the guidance and learning[27].

Deep Learning is also a subset of artificial intelligence followed by machine learning. Deep learning is a machine learning technique and it learns features and tasks directly from datasets. Deep Learning does not require feature extraction manually and takes images directly as input. Features are automatically deduced and optimally tuned for desired outcome. Features are not required to be extracted ahead of time. This avoids time consuming machine learning techniques. But it requires very large amount of dataset to perform with maximum accuracy compare to other techniques. It is extremely expensive to train the network due to complexity of data models. There is no standard theory to guide the selection of right deep learning tools. Because that requires knowledge of topology, training method and other parameters. The Proposed algorithm will be very much useful in differentiating and categorising the Crops and weeds. There are several research is studied in weed detection using deep learning. And some of the literatures are as follows. Jialin Yu1 et al have studied about turf grass management with four DCNN architectures of i) AlexNet, ii) DetectNet, iii) GoogleNet and iv) VGG-16 (VGGNet). They reordered for various weed detection different architecture is exhibiting higher accuracy[9]. Jialin Yu et al also worked with the same DCNN architectures and they arrived with the maximum accuracy in DetectNet[28]. Ildar Rakhmatuiln et al have reported a survey about the usage various architectures in deep learning[29]. Junfeng Gao et al have reported the identification of Convolvulus sepium (hedge bindweed) from beet root crop. They demonstrated deep learning with deep convolutional neural network (CNN) based on the tiny YOLOv3 architecture[30]. Jiangong ni et al have worked in the indication of freshness of banana using deep learning. They have compared AlexNet, DetectNet, GoogleNet architecture and they have reported accuracy of 98.92% using GoogleNet architecture[31].

The main focus is to find the classification accuracy and time required to train the Alex Net pretrained network. The pretrained network is trained using transfer learning approach by modifying learning rate training options. The performance evaluation of the proposed model using Alex Net pretrained network is observed on the collected labelled datasets. In Vidarbha region of Maharashtra state district like Chandrapur, Washim and Yavatmal the major crops are Soyabean, Cotton and turmeric as compared to other crops. The classification is a requirement between three different types of crops: Soyabean, Cotton, turmeric and major thirteen different types of weeds. For the present dataset the best value of base learning rate is 0.002 with the validation accuracy of 97.17%. Automatic detection and classification of weeds can play an important role in weed management and so contribute to higher yield.

2. Proposed Algorithm for Classification of Crops and Weeds

The steps for proposed algorithm for the classification of crops and weeds shown in Figure 1.

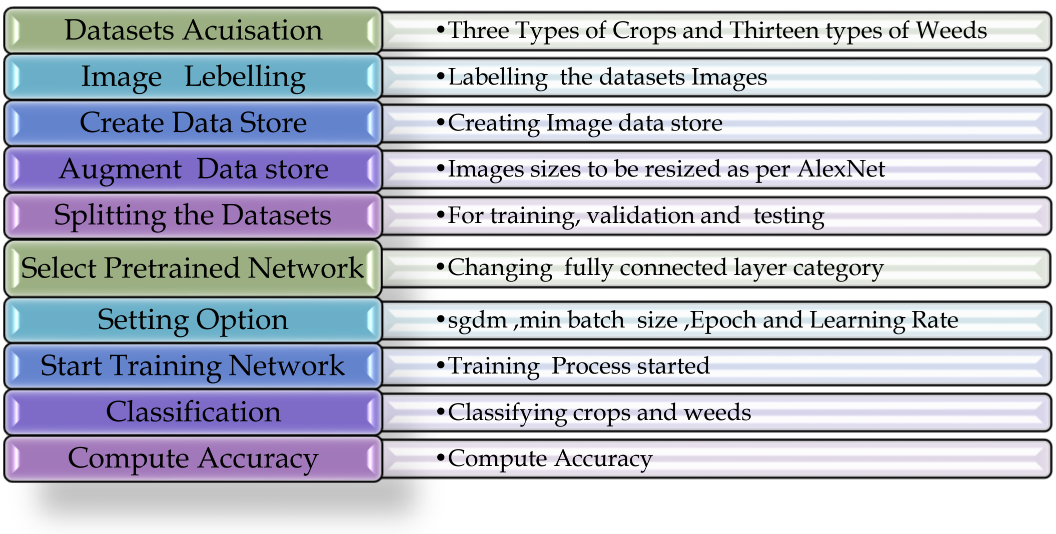

Figure 1: Algorithm Process steps diagram to Classify Crops and Weeds

The proposed model diagram for training of pretrained network using transfer learning is depicted in Figure 2.

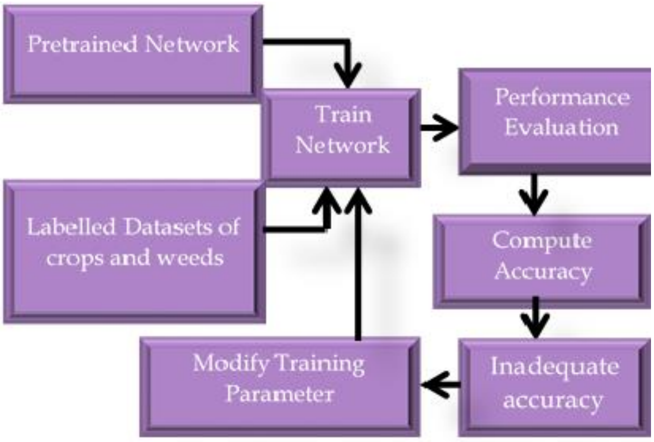

Figure 2: Proposed structure for Transfer Learning

The AlexNet pretrained network used for training purpose. The collection of 3360 images is done from Vidarbha region. All the collected images labelled as per their category. As the work is in progress in this paper the focus is on training of the pretrained network using transfer learning with variation in base learning rate. Using the Pretrained network, Labelled images of three different types of crops and 13 types of weeds are used for training a network. For training purposes setting the training options is important. The options selected to train network are the stochastic gradient descent with momentum optimizer, the mini batch size, the Maximum epoch and Initial learning rate. By changing the learning rate the progress of the training network is observed and finally the classification accuracy for crops and weeds is computed.

Table 1: – Data Sets of Crops and Weeds.

S.N	Name of Crop / Weed	Type	Count	Data sets Source
1	Soyabean	Crop	210	Chandrapur, Washim,
2	Cotton	Crop	210	Washim ,Yavatmal
3	Turmeric	Crop	210	Chandrapur
4	Cynadon dectalon	Weeds	210	Vidarbha Region [33]
5	Bracheria eruciformis	Weeds	210	
6	Cyperus rotundus	Weeds	210	
7	Parthenium hysterophorus	Weeds	210	
8	Dignera arvensis	Weeds	210	
9	Euphorbhia geneculata	Weeds	210	
10	Abitulon indicum	Weeds	210	
11	Commilina benghalensis	Weeds	210	
12	Celocia argentia	Weeds	210	
13	Ergotis minor	Weeds	210	
14	Phyllanthus niruri	Weeds	210	
15	Solanum nigrum	Weeds	210	
16	Amaranthus polygamous	Weeds	210	

For the purpose of doing the training of the pretrained network we performed an extensive dataset acquisition from three different district of Vidarbha regions of Maharashtra, India. We selected three types of crops Soyabean, Cotton and Turmeric. The Soybean Processors Association of India, popularly known as SOPA report says that Maharashtra state securing the first position for soyabean production in India and losses due to weeds for it is 20% - 40% [32]. As per the cotton association of India report 8th Jan 2019 Maharashtra is the second state for production of cotton and losses due to weeds for it are 70-75% [32] . The details of datasets collection from different regions of Maharashtra state see Table 1.

3. Evaluation of Proposed Algorithm

The performance of the proposed algorithm is evaluated using MATLAB 2020 toolbox. As we are using the AlexNet pretrained network for training purposes, the size of input images to be adjusted as per input size, so for it augmentation used to resize the datasets. Then splitting the whole datasets into three categories training, validation and testing. The options for training are selected as sgdm, setting minimum batch size as 64, selecting the epoch 30. The initial learning rate is selected as 0.001 and the pretrained network trained for it. The training progress observed and classification accuracy is computed. The learning rate allows the pretrained network to learn slowly or fast depends on its value. The larger value of learning rate increases the training error and smaller value of it also gives high error. Unfortunately, we cannot analytically calculate the learning rate for a proposed algorithm; instead a good learning rate must be discovered by trial and error method. So selecting three different value 0.001, 0.002 and 0.003 and observes the performance of this pretrained network and compares it.

4. Results and Discussion

The performance evaluation of the proposed model using AlexNet pretrained network on the collected labelled datasets is observed. The performance of the model observed through Training Progress throughout the evaluation. All the parameter details are mention in normalisation table. The confusion chart

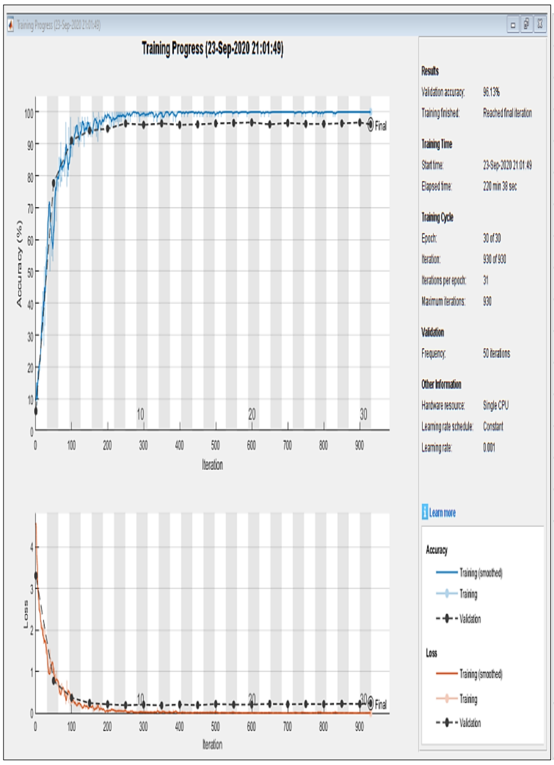

Figure 3:- Training progress for Base learning rate 0.001

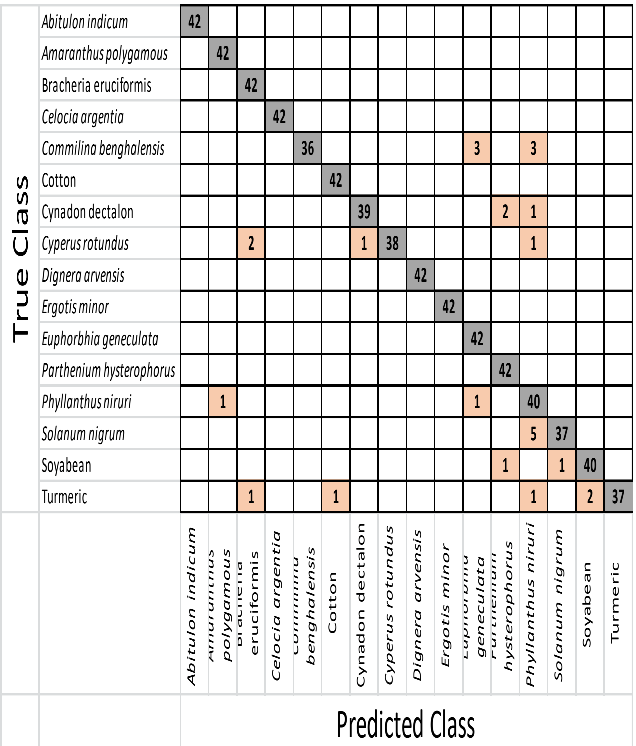

Figure 4:- Confusion Chart for Base learning rate 0.001

Table 2 – Data Normalisation Table for Learning Rate 0.001

Epoch	Iteration	Time Elapsed	Mini-batch Accuracy (%)	Validation Accuracy (%)	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:05:09	9.38	6.10	4.5733	3.309	0.001
2	50	00:28:00	73.44	77.68	0.7357	0.7792	0.001
4	100	00:58:47	89.06	91.07	0.3781	0.3695	0.001
5	150	01:03:37	96.88	94.20	0.1751	0.2412	0.001
7	200	01:08:21	100.00	94.79	0.0348	0.2118	0.001
9	250	01:13:03	96.88	96.43	0.0804	0.1893	0.001
10	300	01:17:27	100.00	95.98	0.014	0.2044	0.001
12	350	01:55:48	98.44	96.43	0.0596	0.1829	0.001
13	400	02:01:06	100.00	95.98	0.0061	0.2076	0.001
15	450	02:06:41	100.00	96.13	0.006	0.1917	0.001
17	500	02:11:45	100.00	96.43	0.0035	0.218	0.001
18	550	02:54:33	100.00	96.58	0.006	0.2044	0.001
20	600	03:00:55	100.00	96.73	0.0043	0.2056	0.001
21	650	03:08:35	100.00	96.13	0.0006	0.2208	0.001
23	700	03:14:53	100.00	96.58	0.0016	0.2111	0.001
25	750	03:20:22	100.00	96.28	0.0026	0.2185	0.001
26	800	03:28:48	100.00	96.28	0.0045	0.2148	0.001
28	850	03:33:20	100.00	96.43	0.0006	0.2249	0.001
30	900	03:37:45	100.00	96.73	0.0011	0.2206	0.001
30	930	03:40:21	100.00	96.13	0.0017	0.2382	0.001

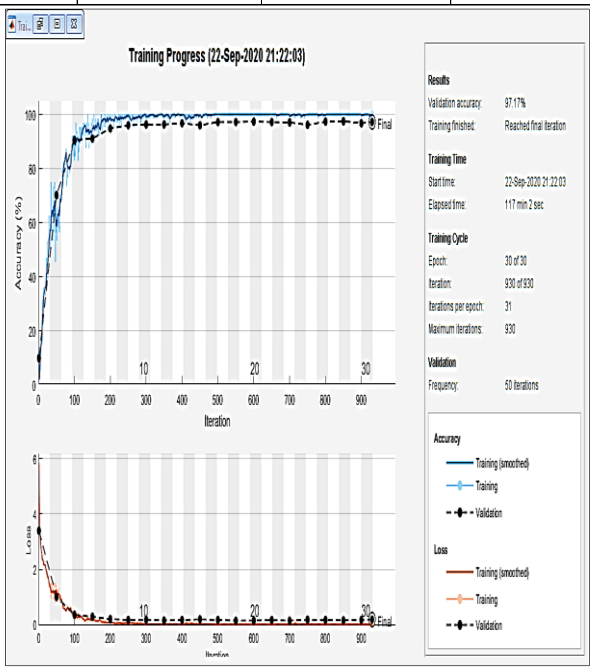

Figure 5:- Training progress for Base learning rate 0.002

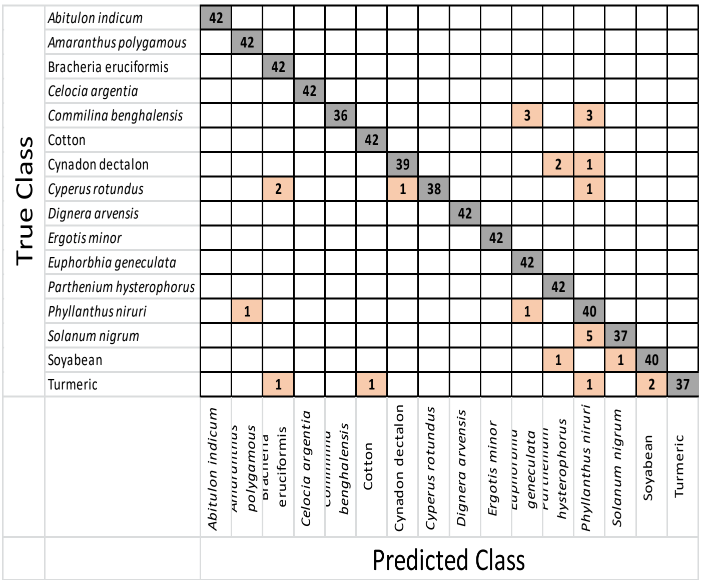

Figure 6:- Confusion Chart for Base learning rate 0.002

Table 3 - Data Normalisation Table for Learning Rate 0.002

Epoch	Iteration	Time Elapsed	Mini-batch Accuracy (%)	Validation Accuracy (%)	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:02:04	7.81	9.67	5.862	3.3969	0.002
2	50	00:09:35	65.63	70.09	1.0172	1.0006	0.002
4	100	00:14:54	82.81	90.48	0.4818	0.3526	0.002
5	150	00:19:41	98.44	91.07	0.1301	0.2817	0.002
7	200	00:24:04	96.88	94.79	0.0745	0.1944	0.002
9	250	00:28:31	98.44	95.98	0.0409	0.1639	0.002
10	300	00:32:45	96.88	96.28	0.0285	0.1752	0.002
12	350	00:37:12	100.00	96.28	0.0035	0.1449	0.002
13	400	00:41:34	100.00	96.73	0.0013	0.1604	0.002
15	450	00:45:40	100.00	95.98	0.0038	0.1864	0.002
17	500	00:49:47	100.00	97.17	0.0024	0.1644	0.002
18	550	00:57:16	100.00	97.17	0.002	0.1384	0.002
20	600	01:02:42	100.00	97.32	0.0002	0.1452	0.002
21	650	01:10:52	100.00	97.17	0.0026	0.1571	0.002
23	700	01:30:04	96.88	97.02	0.0598	0.1405	0.002
25	750	01:36:52	100.00	96.13	0.002	0.1741	0.002
26	800	01:42:42	100.00	97.32	0.007	0.1628	0.002
28	850	01:48:06	100.00	97.47	0.0005	0.1518	0.002
30	900	01:53:16	98.44	96.73	0.013	0.1667	0.002
30	930	01:56:42	100.00	97.17	0.0052	0.1819	0.002

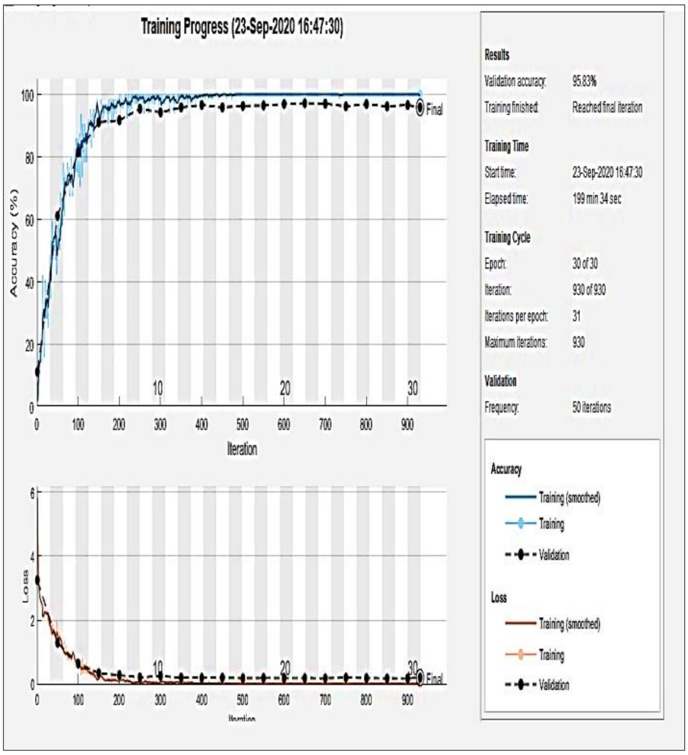

Figure 7:- Training progress for Base learning rate 0.003

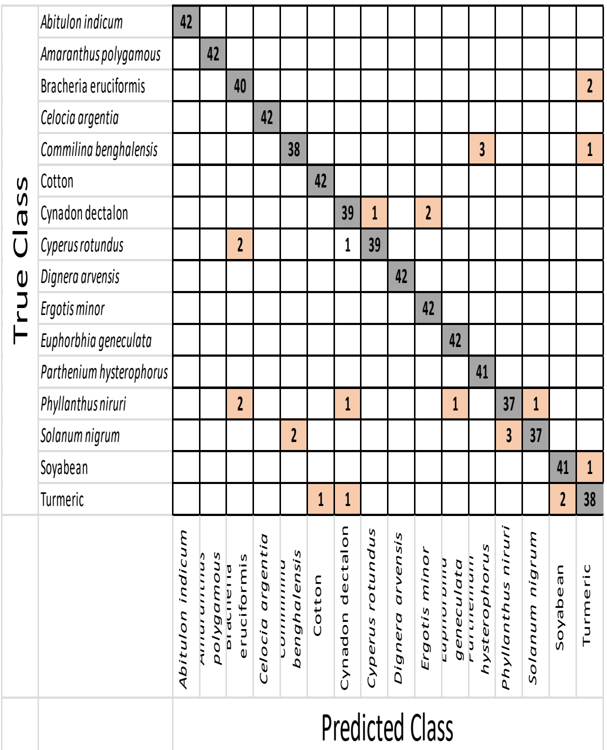

Figure 8:- Confusion Chart for Base learning rate 0.003

Table 4 - Data Normalisation Table for Learning Rate 0.003

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy (%)	Validation Accuracy (%)	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:02:10	7.81	11.01	5.862	3.2518	0.003
2	50	00:53:03	57.81	61.01	1.2933	1.2855	0.003
4	100	01:05:23	79.69	81.40	0.5772	0.6411	0.003
5	150	01:12:35	93.75	91.07	0.1514	0.3366	0.003
7	200	01:18:59	100.00	91.67	0.0586	0.2752	0.003
10	300	02:20:07	98.44	94.20	0.0642	0.2452	0.003
12	350	02:25:46	100.00	95.83	0.0269	0.192	0.003
13	400	02:30:31	100.00	96.58	0.0037	0.1895	0.003
15	450	02:34:43	100.00	95.83	0.0012	0.1907	0.003
17	500	02:38:58	100.00	96.28	0.0018	0.1821	0.003
18	550	02:43:27	100.00	96.43	0.0003	0.1846	0.003
20	600	02:47:43	100.00	96.88	0.0002	0.1836	0.003
21	650	02:52:03	100.00	97.17	0.0001	0.1808	0.003
23	700	02:56:08	100.00	97.02	0.0000	0.1785	0.003
25	750	03:00:31	100.00	96.13	0.0002	0.1947	0.003
26	800	03:07:32	100.00	96.88	0.0001	0.1844	0.003
28	850	03:12:21	100.00	96.13	0.0003	0.1761	0.003
30	900	03:16:37	100.00	96.58	0.0001	0.1757	0.003
30	930	03:19:18	100.00	95.83	0.0001	0.1969	0.003

used to observe false classification from the cells. All three important evaluations tools Training Progress, Normalisation Table and Confusion Chart details discussion mention one by one.

4.1 Training progress:- Training progress is shown in Figure 3, 5 and 7 for learning rate 0.001, 0.002 and 0.003 respectively. These figures consist of two graphs, first graph shows iteration verses accuracy and second graph shows iteration verses losses during training. Iterations are the number of batches needed to complete one epoch, the upper part of graph shows the variation in accuracy for every iteration. The accuracy is below 95% till 400 iterations and second graph shows training losses are more initially up to 200 iterations.

4.2 Normalisation Table: - The table II, III and IV gives the detail information regarding the parameter like time required for iteration, Epochs, mini-batch accuracy, validation accuracy, and mini-batch loss, validation loss and the base learning rate is 0.001. One Epoch is when entire dataset is passed forwarded and backward through the entire network only once. As the more number of epochs increases more number of times the weight are changed. From table we can observe that the increase in validation accuracy with increase in iteration and number of epochs. The training losses decrease for increase in epochs and iteration.

4.3 ***Confusion Chart: -*** Normally shows the image classification between true class and predicted class, Figure 4, 6 and 8 demonstrates the confusion chart for different learning rate. The confusion chart displays the observations in each cell. The diagonal cells of chart indicate correct class and off diagonal cells indicate incorrect class. When the base learning rate is 0.001 the time required to train the pretrained network is three hour and forty minutes while giving the validation accuracy 96.13%, base learning rate is changed to 0.02 then the time required is reduced to one hour and fifty six minutes and validation accuracy is 97.17% and finally for the learning to 0.003, the time required is three hour and nineteen minutes and validation accuracy is 95.83%. From Table II, Table III and Table IV the summary see Table IV.

Table 4– Summary of the results

Sr. No.	Base Learning Rate	Epoch	Validation Accuracy	Validation Losses	Time required for training (hh:mm:ss)
1	0.001	30	96.13%	0.2382	03:40:21
2	0.002	30	97.17%	0.1819	01:56:42
3	0.003	30	95.83%	0.1969	03:19:18

For the present dataset the best value of base learning rate is 0.002 with the validation accuracy 97.17%. This is very much useful as it not only give the good accuracy but also save the time required for training by 50 % as compared with the other two base learning rates timing.

5. Conclusion

The performance evaluation of the proposed training model is done to train the AlexNet pretrained network using the transfer learning approach. For crop and weeds classification on the present data sets validation accuracy of 97.17 % is achieved at a base learning rate of 0.002. The performance evaluation to classify crops and weeds by varying the learning rate to train pretrained network is done using single CPU. The future work is to reduced time required to train model using pretrained network. This proposed model further could be used to remove the weeds using automatic weeding machine.

6. References

[1] P. Radoglou-Grammatikis, P. Sarigiannidis, T. Lagkas, and I. Moscholios, "A compilation of UAV applications for precision agriculture," *Comput. Networks*, vol. 172, no. February, p. 107148, 2020, doi: 10.1016/j.comnet.2020.107148.

[2] S. H. K. Tui *et al.*, "Climate change impacts and adaptation for dryland farming systems in Zimbabwe: a stakeholder-driven integrated multi-model assessment," *Clim. Change*, vol. 168, no. 1–2, 2021, doi: 10.1007/s10584-021-03151-8.

[3] D. D. Patel and B. A. Kumbhar, "Weed and its management: A major threats to crop economy," *J. of. Pharm. Sci. Biosci. Res.*, vol. 6, no. 6, pp. 453–758, 2016.

[4] C. Fischer, F. Riesch, T. Tscharntke, and P. Batáry, "Large carabids enhance weed seed removal in organic fields and in large-scale, but not small-scale agriculture," *Landsc. Ecol.*, vol. 36, no. 2, pp. 427–438, 2021, doi: 10.1007/s10980-020-01157-8.

[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," *Comput. Electron. Agric.*, vol. 122, pp. 103–111, 2016, doi: 10.1016/j.compag.2015.12.016.

[6] M. T. Rose *et al.*, *Impact of Herbicides on Soil Biology and Function*, vol. 136. Elsevier Inc., 2016.

[7] K. H. Kim, E. Kabir, and S. A. Jahan, "Exposure to pesticides and the associated human health effects," *Sci. Total Environ.*, vol. 575, pp. 525–535, 2017, doi: 10.1016/j.scitotenv.2016.09.009.

[8] C. A. Danbaki, N. C. Onyemachi, D. S. M. Gado, G. S. Mohammed, D. Agbenu, and P. U. Ikegwuiro, "Precision Agriculture Technology: A Literature Review," *Asian J. Adv. Res. Reports*, vol. 14, no. 3, pp. 30–34, 2020, doi: 10.9734/ajarr/2020/v14i330335.

[9] J. Yu, A. W. Schumann, Z. Cao, S. M. Sharpe, and N. S. Boyd, "Weed Detection in Perennial Ryegrass With Deep Learning Convolutional Neural Network," *Front. Plant Sci.*, vol. 10, no. October, pp. 1–9,

2019, doi: 10.3389/fpls.2019.01422.

[10] Z. Liu, J. Watson, and A. Allen, “Efficient Image Preprocessing of Digital Holograms of Marine Plankton,” *IEEE J. Ocean. Eng.*, vol. 43, no. 1, pp. 83–92, 2018, doi: 10.1109/JOE.2017.2690537.

[11] H. Ramadan, C. Lachqar, and H. Tairi, “A survey of recent interactive image segmentation methods,” *Comput. Vis. Media*, vol. 6, no. 4, pp. 355–384, 2020, doi: 10.1007/s41095-020-0177-5.

[12] H. Liang, X. Sun, Y. Sun, and Y. Gao, “Text feature extraction based on deep learning: a review,” *Eurasip J. Wirel. Commun. Netw.*, vol. 2017, no. 1, pp. 1–12, 2017, doi: 10.1186/s13638-017-0993-1.

[13] J. A. Lin, C. Te Chiu, and Y. Y. Cheng, “Object Detection with Color and Depth Images with Multi-Reduced Region Proposal Network and Multi-Pooling,” *ICASSP, IEEE Int. Conf. Acoust. Speech Signal Process. - Proc.*, vol. 2020-May, pp. 1618–1622, 2020, doi: 10.1109/ICASSP40776.2020.9054009.

[14] R. Johnson, T. Mohan, and S. Paul, “Weed Detection and Removal based on Image Processing,” *Int. J. Recent Technol. Eng.*, vol. 8, no. 6, pp. 347–352, 2020, doi: 10.35940/ijrte.b3679.038620.

[15] N. S. B. Mat Said, H. Madzin, S. K. Ali, and N. S. Beng, “Comparison of color-based feature extraction methods in banana leaf diseases classification using SVM and K-NN,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 24, no. 3, pp. 1523–1533, 2021, doi: 10.11591/ijeecs.v24.i3.pp1523-1533.

[16] R. A. Firouzjaei, S. Minaei, and B. Beheshti, “Sweet lemon mechanical damage detection using image processing technique and UV radiation,” *J. Food Meas. Charact.*, vol. 12, no. 3, pp. 1513–1518, 2018, doi: 10.1007/s11694-018-9766-8.

[17] C. Zhou, G. Yang, D. Liang, X. Yang, and B. Xu, “An integrated skeleton extraction and pruning method for spatial recognition of maize seedlings in MGV and UAV remote images,” *IEEE Trans. Geosci. Remote Sens.*, vol. 56, no. 8, pp. 4618–4632, 2018, doi: 10.1109/TGRS.2018.2830823.

[18] X. Liu, W. Min, S. Mei, L. Wang, and S. Jiang, “Plant Disease Recognition: A Large-Scale Benchmark Dataset and a Visual Region and Loss Reweighting Approach,” *IEEE Trans. Image Process.*, vol. 30, pp. 2003–2015, 2021, doi: 10.1109/TIP.2021.3049334.

[19] M. W. Liu, M. Ozdogan, and X. Zhu, “Crop type classification by simultaneous use of satellite images of different resolutions,” *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 6, pp. 3637–3649, 2014, doi: 10.1109/TGRS.2013.2274431.

[20] M. R. Larijani, E. A. Asli-Ardeh, E. Kozegar, and R. Loni, “Evaluation of image processing technique in identifying rice blast disease in field conditions based on KNN algorithm improvement by K-means,” *Food Sci. Nutr.*, vol. 7, no. 12, pp. 3922–3930, 2019, doi: 10.1002/fsn3.1251.

[21] L. Vonrueden *et al.*, “Informed Machine Learning - A Taxonomy and Survey of Integrating Prior Knowledge into Learning Systems,” *IEEE Trans. Knowl. Data Eng.*, pp. 1–20, 2021, doi: 10.1109/TKDE.2021.3079836.

[22] P. K. Mallapragada, S. Member, and R. Jin, “SemiBoost : Boosting for Semi-Supervised Learning,” vol. 31, no. 11, pp. 2000–2014, 2009.

[23] S. Hussein, P. Kandel, C. W. Bolan, M. B. Wallace, and U. Bagci, “Lung and Pancreatic Tumor Characterization in the Deep Learning Era: Novel Supervised and Unsupervised Learning Approaches,” *IEEE Trans. Med. Imaging*, vol. 38, no. 8, pp. 1777–1787, 2019, doi: 10.1109/TMI.2019.2894349.

[24] S. Badhan, K. Desai, M. Dsilva, R. Sonkusare, and S. Weakey, “Real-Time Weed Detection using Machine Learning and Stereo-Vision,” *2021 6th Int. Conf. Converg. Technol. I2CT 2021*, pp. 2–6, 2021, doi: 10.1109/I2CT51068.2021.9417989.

[25] M. Tufail, J. Iqbal, M. I. Tiwana, M. S. Alam, Z. A. Khan, and M. T. Khan, “Identification of Tobacco Crop Based on Machine Learning for a Precision Agricultural Sprayer,” *IEEE Access*, vol. 9, pp. 23814–23825, 2021, doi: 10.1109/ACCESS.2021.3056577.

[26] A. Sharma, A. Jain, P. Gupta, and V. Chowdary, “Machine Learning Applications for Precision Agriculture: A Comprehensive Review,” *IEEE Access*, vol. 9, pp. 4843–4873, 2021, doi: 10.1109/ACCESS.2020.3048415.

[27] J. J. Khanam and S. Y. Foo, “A comparison of machine learning algorithms for diabetes prediction,” *ICT Express*, vol. 7, no. 4, pp. 432–439, 2021, doi: 10.1016/j.icte.2021.02.004.

[28] J. Yu, S. M. Sharpe, A. W. Schumann, and N. S. Boyd, “Detection of broadleaf weeds growing in turfgrass with convolutional neural networks,” *Pest Manag. Sci.*, vol. 75, no. 8, pp. 2211–2218, 2019, doi: 10.1002/ps.5349.

[29] I. Rakhmatuiln, A. Kamilaris, and C. Andreasen, “Deep neural networks to detectweeds from crops in agricultural environments in real-time: A review,” *Remote Sens.*, vol. 13, no. 21, 2021, doi: 10.3390/rs13214486.

[30] J. Gao, A. P. French, M. P. Pound, Y. He, T. P. Pridmore, and J. G. Pieters, “Deep convolutional neural networks for image-based Convolvulus sepium detection in sugar beet fields,” *Plant Methods*, vol. 16, no. 1, pp. 1–12, 2020, doi: 10.1186/s13007-020-00570-z.

[31] J. Ni, J. Gao, L. Deng, and Z. Han, “Monitoring the Change Process of Banana Freshness by GoogLeNet,” *IEEE Access*, 2020, doi: 10.1109/ACCESS.2020.3045394.

[32] Y. Gharde, P. K. Singh, R. P. Dubey, and P. K. Gupta, “Assessment of yield and economic losses in agriculture due to weeds in India,” *Crop Prot.*, vol. 107, no. January, pp. 12–18, 2018, doi: 10.1016/j.cropro.2018.01.007.

[33] A. S. Jadhav, “Dominant Weed Flora of Soybean and Cotton in Vidharbha Region of M.S,” vol. 6, no. 1, pp. 729–733, 2017.