IJCSE International Journal of Computer Sciences and Engineering Open Access

Research Paper Vol.-6, Issue-8, Aug 2018 E-ISSN: 2347-2693

An Experimental Analysis on Texture Based classification Using Learning Algorithms

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Available online at: www.ijcseonline.org

Accepted: 13/Aug/2018, Published: 31/Aug/2018

Abstract- In this digital era, with the advancements of technology a major role is being played by Information and Communication Technology in agriculture. Especially the issues related to agriculture such as real-time crop detection and monitoring, leaf identification is still a challenging task for the researchers and practitioners. Automatic detection of the crop type and its growth by analysing the colour and size of the leaves helps the farmers to take immediate advice from the botanical domain expert. The work in this paper deals with study and implementation of texture based classification and annotation of groundnut crop leaves using machine learning algorithms like HAAR, HOG and LBP. A set of trained and untrained images are employed in this task. Experiments are conducted using the cascade trainer tool in MATLAB 2016 by varying several parameters and selecting regions-of-interest on the crop for training. Later, the impact of each of the parameters on the above algorithms are recorded and well described in this paper. Furthermore, from the perspective of number of objects detected, it is noticed that LBP has yielded better results than HAAR and HOG.

Key words**:** Computer vision, ICT, leaf identification, HAAR, HOG, LBP, machine learning.

I. INTRODUCTION

1.1 Motivation

India is mainly an agricultural based country with more than 60% of the Indian population deriving their livelihood from the agricultural sector. It is playing a key role as most of the populace contributes fundamentally to the national income. Globally, in the present scenario, introduction of Information and Communication Technology (ICT) enables the dissemination of requisite information to the farmers at the right time with reasonable cost thereby promoting the development and good governance of agricultural sector. The Agri-ICT tasks are classified into five key areas. (i) Inexpensive and ubiquitous network, (ii) flexible and economical tools (iii) advances in data storage and information dissemination (iv) novel business ideas and sharing and (v) the democratization of information including the open access movement and social media [1]. At present many Agri-ICT applications like Management Information System, Water supply and irrigation management, Dairy Farming System, Fruit Tree models, Information Dissemination through sensor networks are playing a major role in supporting the farmers [2, 3, and 4]. Most of the researchers currently are striving for designing a consistent and intelligent decision support system for agriculture sector which proves to be a challenging task. Usually crops are prone to many deficiencies due to the variance in the soil nutrients. Apart from that, change in the colour of the crop leaves can be noticed in those leaves that are infected by pests. The size, colour and shape of leaves keep changing in due course of time until it reaches harvesting stage. So, it is very essential to automatically detect the crop type based upon its colour, shape, texture and establish a real-time crop monitoring system so as to take timely and necessary action. This can reduce manual effort drastically and if properly trained, this can come up with greater accuracy. In this work, machine learning algorithms are applied on the groundnut crop by varying several parameters and observed how the respective algorithms detect and annotate the leaves.

I.I Problem Definition

Machine Learning is a subclass of Artificial Intelligence that enables computers with the capability to learn the things. It does not require explicit programming to define all the steps. Instead, the machine is trained on some large amount of dataset known as training dataset which is huge enough to create a model. Upon perceiving the features extracted from the trained data, the machine takes the decisions on test data based on its learning. In this current work, the training step is performed by selecting the region-of-interest over some groundnut crop images. Later machine learning algorithms for texture are employed over the groundnut crop for experimentation purpose by altering various parameters. Finally, the extracted texture features learnt from the training step are applied over a set of test images to detect the number of objects and annotate them as 'groundnut crop'. MATLAB 2016 is used for this analysis on LBP, HAAR, HOG algorithms.

The rest of the paper is organised as follows. The related works in the area of Groundnut crop, study area in section 2. Feature extraction methods are described in Section 3. Experimentation and results discussion is made in Sections 4. Conclusions and future scope are discussed in section 5.

II. Related Works

The impact of various environmental and climatic conditions resulted in a severe shortage of the food supply during the past three decades. The intensity of the problem was predicted and discussed decades ago by many agricultural and environmental researchers. Especially Cynthia Rosenz et al., expressed that, the global crop production impact is very less. But whereas in the developing countries, farmers will face a severe crisis due to increase in the carbon dioxide gases [5]. Then RK Mall also addressed the same issue with respect to the India's scenario, with special focus on the climate change impact on Indian agriculture [6]. The work states that, the rise of 2°C temperature will reflect a great downfall in the crop production in the northern parts of India. Also that, they expressed, no standard prediction model is sufficient to estimate the crop production in the Indian subcontinent, because of a wide variety of crops and different weather conditions. Whereas N Meera conducted a deep study on the impact of ICT on the Indian agriculture and discussed three major projects, namely Gyandoot, Warana and iKisan projects in detail. They concluded that, the demand and usage of ICT are growing timely. But the specified projects are only implemented for the information and market analysis system [7]. Particularly the concept of precision agriculture evolved two decades ago, but still it has not reached its goals [8]. In the literature of Precision agriculture, many practitioners have worked out on various Internet-of-Things products for the development of precision agriculture (PA) [9, 10, and 11]. Especially, Unmanned Air Vehicles (UAV) usage became wider popular for the monitoring of the PA, D. Gómez-Candón discussed the UAV accuracy for ortho-mosaics aerial images for early site-specific weed management (ESSWM) of wheat crop, with coarse spatial resolutions, [12]. Nengcheng Chen et al.,designed and implemented a novel Cyber-Physical Systems (CPS) for PA using Sensor Observations Service (SOS), Sensor Web Enabled Services (SWE) and integration of many heterogeneous sensors which resulted in the crop monitoring[11]. Ciprian-Radu RAD et al. also went with the crop monitoring system on potato crop using IOT and CPS. But the crop monitoring and management is still a big issue for the past two decades in view of the fact that timely monitoring accuracy, fast dissemination, interoperability and cost effective procedures are yet the major challenges in the area of PA [13, 14]. Recent times, deep learning algorithms of advanced neural networks are getting more crucial for the better precision and high accuracy of CPS [15, 16, and 17]. This in turn improved the parameters like pattern matching and recognition for IOT and big data [18]. In particular the machine learning, pattern recognition algorithms like HAAR feature based on Viola-Jones, Histogram Of Oriented Gradients (HOG) and Local Binary Patterns (LBP) etc., algorithms are a few to mention which are popular for the face detection [19,20,21,22]. Many researchers performed studies and analysis on machine learning methods like SIFT, LSS, HAAR, HOG, LBP and SURF features for the human face and pedestrians detections [23, 24, and 25]. Whereas Xue-Yang Xiao tested the HOG feature extraction on the leaf database [26].To this extensions Arafat, S.Y.conducted analysis on the leaf classification using HOG, Colour Scale Invariant Feature Transform (C-SIFT) and Maximally Stable Extremal Region (MSER) with limited parameters [27]. This work discusses a comparative study on the machine learning algorithms for the detection of crop leaves in the Indian agriculture fields using features like HAAR, HOG and LBP.

II.I Study Area:

The study area, Karakavanipalem which is under Gorapalle panchayat, Pendurthi mandal of Visakhapatnam district, Andhra Pradesh having spatial coordinates of $17^{o}\ 49^{1}\ 40.5^{11}$ N and $83^{o}\ 10^{1}\ 59.3^{11}$ E covers an area of 494 hectares with a population of 3574 (2011). The geographical conditions of the study are more favourable for onion, paddy, millets, and groundnut crops. For the present study the groundnut crop images were collected from the field that cover 0.05 acres. Three types of images were captured from long, average and near distances for the experimentation. The crop images are collected in between 15 February 2016 to 10 April 2016 with a frequency of a week days in Rabi season. The images are collected using 13 Mp with optical zoom camera sensor. In addition soil test was carried out to know the ground favourable conditions for the crop and the soil reports depicts the type of soil as Sandy Clay Loam, pH as 6.6 which is neutral and suitable for all crops, Electrical conductivity is 0.2 mm, organic carbon is H, available phosphorous is 28.86 kg/ acre, and available Potassium is 101.64 kg/acre.

III. FEATURE EXTRACTION METHODS

A brief description of the machine learning algorithms such as HAAR, HOG, and LBP are presented here. These methods are applied on the groundnut crop images and the resultant images are depicted in the following figures 1, 2 and 3.

III.I HAAR feature:

Viola et al. proposed a simple rectangular feature which is similar to Haar wavelet. The values of Haar feature are equal to the difference between the sum of the pixels which lie within the white rectangles and the sum of pixels in the grey rectangles. The template library of Haar feature includes edge template, linear template, center template, and diagonal template etc. The feature template can be set arbitrarily with any size in sub-window.

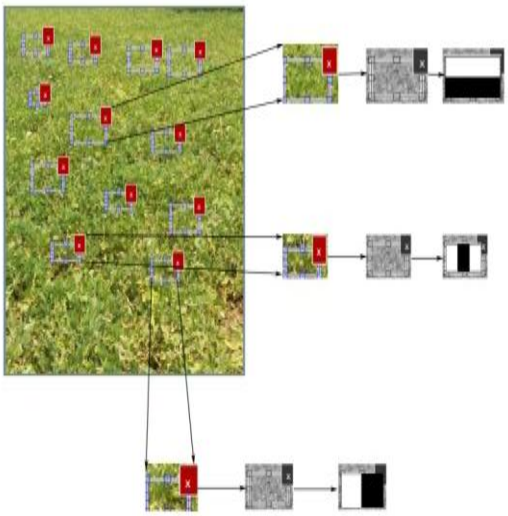

Fig. 1: Applying HAAR Filters on the Groundnut Crop.

III.II HOG feature:

HOG feature descriptors used to compute local intensity gradients or edge directions are similar to histograms of edge orientation features and SIFT features. In practice, the feature extraction process concludes three stages: the first stage applies an optional global image normalization equalization that is designed to reduce the effects of external illumination variations and local shadow, then computes first order image gradients in x and y directions and accumulates weighted votes for gradient orientation over spatial blocks.

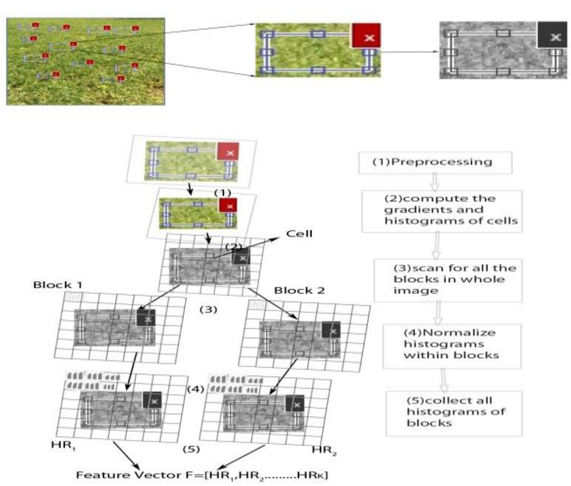

Fig. 2: Applying HOG method on the Groundnut Crop.

III.III LBP feature:

LBP feature is a general texture description operator for measuring and extracting the local texture information of image. The attractive advantages of LBP are its invariance to monotonic gray-scale changes, low computational complexity and convenient multi- scale extension. At each pixel, LBP can be defined as an ordered set of binary comparisons of pixel intensities between the center pixel and its surroundings pixels.

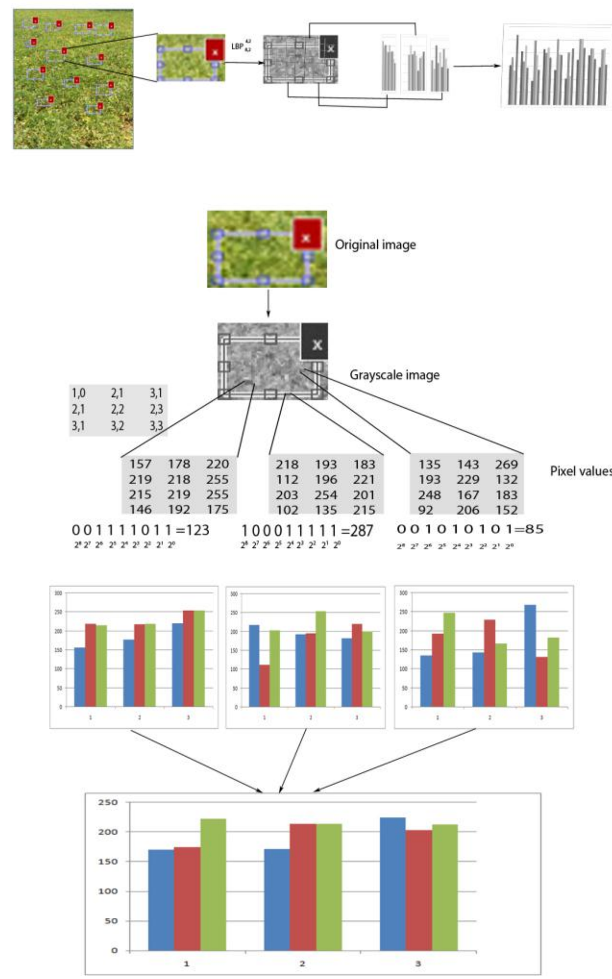

Fig. 3: Applying LBP technique on the Groundnut Crop.

IV. EXPERIMENTATION AND RESULTS DISCUSSION

In this section, notations and assumptions of various parameters considered for the experimentation, its procedure and the impact of these parameters in producing the number of annotated objects with their analysis is discussed.

IV.I Notations and Assumptions:

The experimentation is carried out in MATLAB 2016 with the groundnut crop as the training set. Various parameters considered for the experimentation are false alarm rate per stage (FARS), true positive rate per stage (TPRS), no. of cascade stages (NCS), negative samples factor (NSF), no. of objects detected (NOD), experimented positive samples (EPS), experimented negative samples (ENS) and object training size (OTS). Within cascade trainer there are three different phases. They are: firstly a) select-positive-images based on region-of-interest (ROI), followed by b) negative image selection with object training and finally c) detector phase.

Overall 17 ROI's are selected. The experimentation is carried out with small amount of dataset and it is limited to only texture based classification. In the first phase, selected images are loaded and multiple ROI's are selected in each image. Figure 4 shows the experimental images.

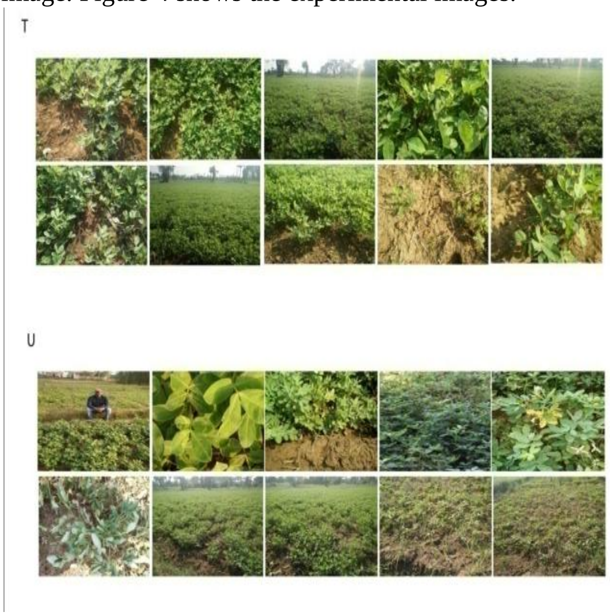

Fig. 4: Trained (T) and Untrained (U) images of the groundnut crop used for this experimental analysis

IV.II Experimentation Procedure

In the second phase, various parameters like FARS, TPRS, NCS, NSF and OTS are considered. The impact of each parameter is discussed in the below sub-sections. All the parameters including the negative masked ROI's are adjusted. Then it is needed to train the Trainer with various feature extraction algorithms like HOG, LBP and HAAR. Training takes place at different stages based on the positive and negative ROI. A maximum of 20 stage training is considered in this experiment. Then the training will be completed within a stipulated time. In the last phase a test image is taken and run with the Detector. Finally, the objects are detected and annotated with the help of xml file which is generated separately during the training process. The object detection depends upon the feature extraction algorithms used and various parameter values.

The number of available positive samples used to train each stage depends on the true positive rate. The rate specifies what percentage of positive samples the function can classify as negative. If a sample is classified as a negative by any stage, it never reaches subsequent stages.

For measuring the performance of retrieval systems, several measures are used that depends on the following four major parameters:

True Positive (TP): True is identified True (correct identification)

True Negative (TN): False is identified False (correct identification)

False Positive (FP): True is identified False (wrong identification)

False Negative (FN): False is identified True (wrong identification)

P = TP + FN (number of correct identification cases)

N = FP + TN (number of wrong identification case)

FAR is the number of false positives that are expected to occur in a given entire image, taken from a given scene. In any case, the FAR is a number of FPs between 0 and infinity --- with 0 being good, and high FAR being bad of course.

FAR = FP/ (FP+TN)…. (1)

NCS: NCS is the number of cascade training stages which have been identified for the training purpose. The number of training stages depends upon the size of the training data set. A small training set is used in this work so as to decrease the number of stages and also sets a lower positive rate for each stage.

TPR= TP/P=TP/ (TP+FN)……. (2)

Experimented Positive Samples (EPS) are derived in the equation, where Total Positive Samples (TPS) is supplied by the user and the values of the True Positive Rate and Number of Cascade Stages parameters.

$$EPS = \text{floor}\left(\frac{TPS}{1+(NCS-1)*(1-TPRS)}\right)\text{……….} \ (3)$$

Fig. 5: Input image for the feature extraction and annotation testing

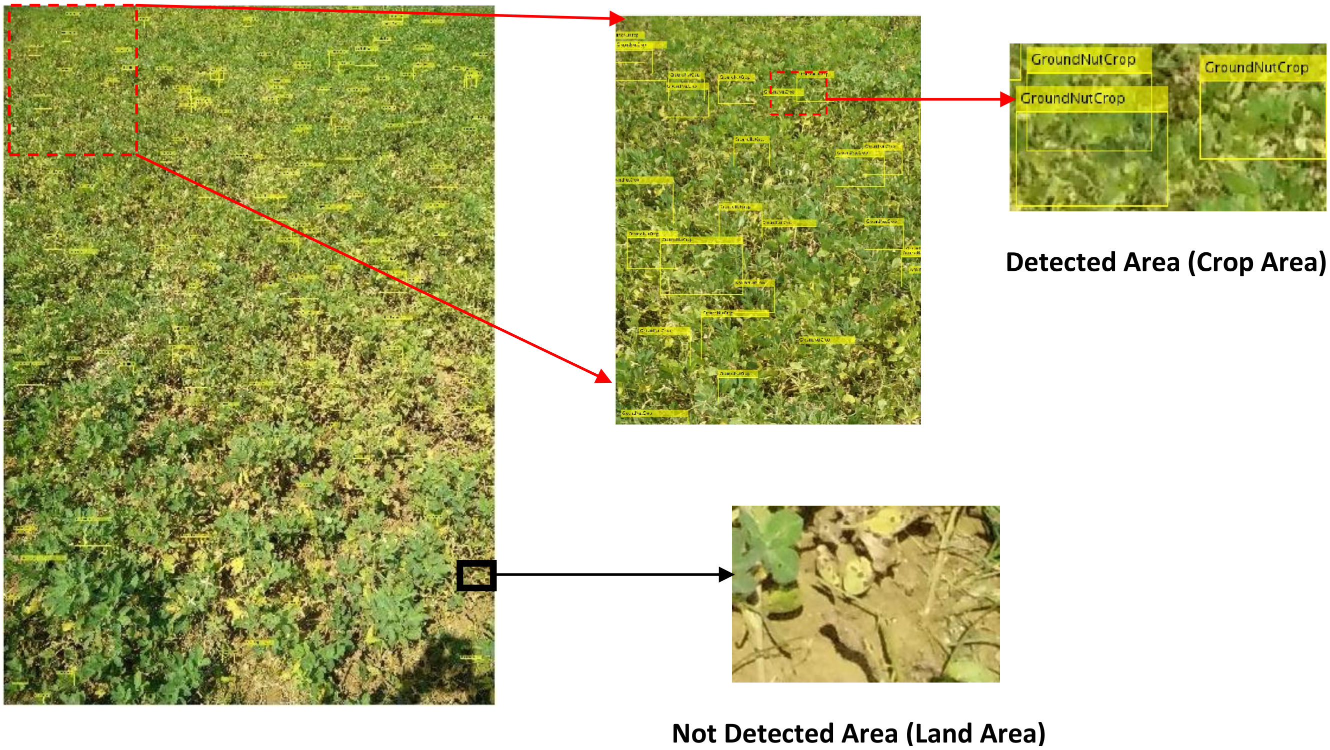

Fig. 6: Simulation results screenshot of the HAAR Feature extraction algorithm with annotation

Figure 7 and 8: Simulation results screenshot of the HOG (Left) and LBP (Right) feature extraction algorithm with annotation

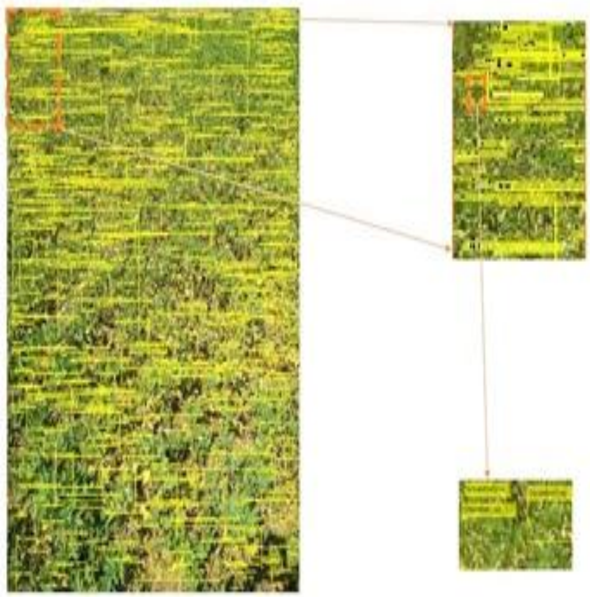

Fig. 9: Simulation results screenshot of the HOG feature extraction algorithm with annotation

Fig. 10: Simulation results screenshot of the LBP feature extraction algorithm with annotation

IV.III Impact of False Alarm Rate per Stage:

After conducting repeated experimental analysis, it is found that TPRS value does not produce any notable changes in detecting the number of objects up to 0.75. So in the table 1, TPRS is considered as 0.8, NSF and OTS with constant values 2 and 32 x 48 respectively and varying the input values of FARS and NSF, the object detection simulation is performed. EPS and ENS depends on the ROI selected on the images and are calculated during the runtime. From the results table, it is observed that there will be a significant improvement. It resulted in various unique object detections in the HAAR, HOG and LBP. Table 1 demonstrates very clearly that the FARS is inversely proportional to the NOD in the case of LBP whereas in HOG it is almost similar to NOD irrespective of FARS increment. On the other hand, HAAR showed different performance compared to HOG and LBP. The detections are unevenly distributed. The stages that are used for the training is maximum 20. But the training of each feature extraction stopped at different stages that depend upon the false positive rate. If the negative image samples equals to the positive samples, the training stages NCS stops. The NCS depends on the EPS and ENS. Fig. 11 is the distribution chart of the average NOD's for each method. On an average LBP exhibited 16% better than HAAR and 99% better than HOG, whereas HAAR performed 97% better NOD than HOG. This performance report is truly based on NOD only.

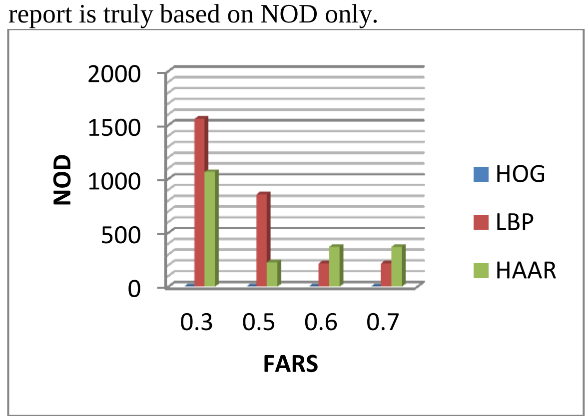

Fig. 11 Depicts the NOD for various values of FARS

IV.IV Impact of False Alarm Rate per Stage Vs Negative Sampling factor:

Considering TPRS as constant with values 0.8, 0.85, 0.995 for tables 2, 3 and 4 respectively, OTS as 32 x 48 and varying the input values of FARS and NSF, the object detection simulation is performed. It resulted in various unique object detections in the HAAR, HOG and LBP. Table 2 demonstrates very clearly that the LBP performed similar object detection except at FARS is 0.6 and NSF is 8. Whereas HOG showed similar performance except at FARS is 0.7 and NSF is 10. Then, HAAR showed typical performance compared with the LBP and HOG. NOD is different detections at FARS is 0.3 and 0.6. Figure 12, 13 and 14 shows the typical performance of NOD of HOG, LBP and HAAR. In Table 3, the impact of FARS and NSF doesn't show any impact on the NOD. In all four cases, it showed similar detections. Table 4 values exhibit similar performance like table 3. It is observed that the TPRS at 0.855 will be best suited for finding the difference between three algorithms without impact of any additional parameters like FARS and NSF. EPS and ENS barely depend upon NOD and NCS. For example, when 3rd and

4th samples are considered in table 2, the number of cascading stages, EPS, ENS is similar for only LBP and HAAR. But it varies in the case of HOG since ENS yields 50 in the 4th sample and it is 17, 25 and 14 for 1st, 2nd and 3rd samples respectively. For minor variations FARS, NSF does not show much impact. It is also observed that, HOG performed detection when there is high ENS and for lower ENS, NOD's are zero. The performance analysis is made on the NOD through each of the machine learning method. It is also observed that, wrong detections like land area recognition are neglected very minimum, it may be neglected.
This observation can be seen clearly in Figure 5.

In Figure 12 distribution chart of HAAR, HOG and LBP is presented based on the average NOD while varying the FARS, TPRS and NSF parameters. Overall, the LBP once again showed its dominance over HAAR and HOG through highest NOD. Comparatively LBP performed 20% better performance than HAAR and 96% better than HOG and HAAR is good than HOG with 95% performance. The comparative results based on the NOD parameter.
Here we are fixing TPRS (0.8), OTS (32*48), and EPS (5) respectively.

Table 1: Impact of FARS on various feature extraction algorithms

S.No	**Feature Extraction algorithm**	**FARS**	**NCS**	**NOD**	**ENS**
1	HOG	0.3	10	0	17
	LBP	0.3	18	1557	25
	HAAR	0.3	4	1065	20-25
2	HOG	0.5	11	0	25-17
	LBP	0.5	20	858	25
	HAAR	0.5	6	226	25
3	HOG	0.6	10	0	17
	LBP	0.6	18	217	25
	HAAR	0.6	4	370	25

Table-2: Impact of FARS on NOD with TPRS as 0.8 for various feature extraction algorithms

S. No	**Feature Extraction algorithm**	**FARS**	**NCS**	**NOD**	**NSF**	**ENS**
1	HOG	0.3	10	0	5	17
	LBP	0.3	17	1557	5	25
	HAAR	0.3	4	1065	5	25
2	HOG	0.5	11	0	2	25-17
	LBP	0.5	20	858	2	25
	HAAR	0.5	6	226	2	25
3	HOG	0.6	8	0	8	14
	LBP	0.6	19	217	8	26
	HAAR	0.6	5	370	8	40
4	HOG	0.7	6	14	10	50
	LBP	0.7	19	217	10	26
	HAAR	0.7	5	370	10	40

Table 3: Impact of FARS on NOD with TPRS as 0.85 for various feature extraction algorithms

S.No	**Feature Extraction algorithm**	**FARS**	**NCS**	**NSF**	**NOD**	**ENS**
1	HOG	0.3	10	5	0	25-17
	LBP	0.3	20	5	217	40-12
	HAAR	0.3	6	5	65	40-6
2	HOG	0.5	9	2	0	48-8
	LBP	0.5	20	2	217	40-12
	HAAR	0.5	6	2	65	40-6
3	HOG	0.6	9	8	0	40-9
	LBP	0.6	20	8	217	40-12
	HAAR	0.6	6	8	65	40-6
4	HOG	0.7	9	10	0	40-9
	LBP	0.7	20	10	217	40-12
	HAAR	0.7	6	10	65	40-6

Table 4: Impact of FARS on NOD with TPRS as 0.995 for various feature extraction algorithms

S.No	**Feature Extraction Algorithm**	**FARS**	**NCS**	**NSF**	**NOD**	**ENS**
1	HOG	0.3	10	2	0	40-9
	LBP	0.3	20	2	217	40-12
	HAAR	0.3	17	2	226	40
2	HOG	0.5	10	5	0	25-17
	LBP	0.5	20	5	217	40-26
	HAAR	0.5	6	5	65	40-06
3	HOG	0.6	9	8	0	40-14
	LBP	0.6	20	8	143	40-12
	HAAR	0.6	6	8	423	40-06
4	HOG	0.7	6	10	14	50
	LBP	0.7	20	10	217	40-12
	HAAR	0.7	6	10	65	40-06

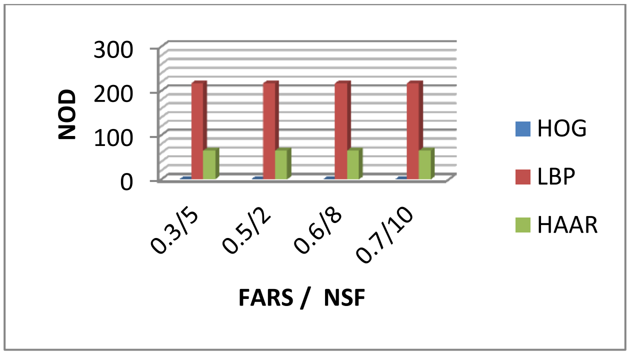

Fig. 12: Comparative analysis based on TPRS with 0.8 and also varying the FARS and NSF using HOG, LBP and HAAR techniques for NOD.

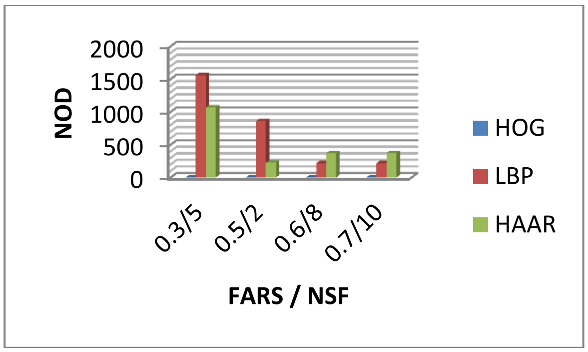

Fig. 13: Comparative analysis based on TPRS with 0.855 and also varying the FARS and NSF using HOG, LBP and HAAR techniques for NOD.

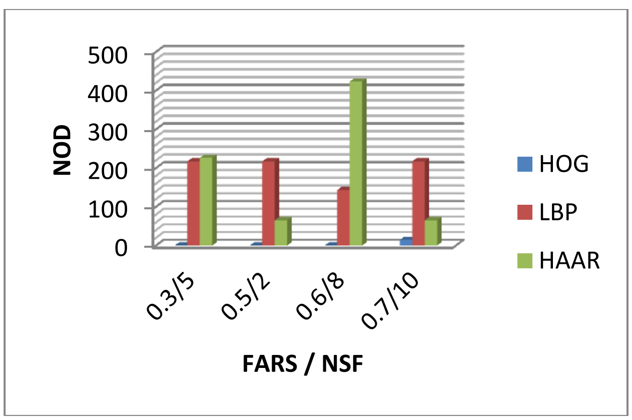

Fig. 14: Comparative analysis based on TPRS with 0.995 and also varying the FARS and NSF using HOG, LBP and HAAR techniques for NOD.

V. CONCLUSIONS AND FUTURE SCOPE

Now-a-days image retrieval is one of the current issues for the researchers and practitioners in the area of computer vision. Especially crop management and agriculture Information system with Internet-of-Things is one of the key areas. The present work discussed here is the comparative study on texture based classification and identification using machine learning algorithms like HAAR, HOG and LBP on the groundnut crop. Various parameters like FARS, TPRS, NCS, NSF, NOD, EPS, ENS, and OTS are considered for this study. Each algorithm showed unique performance in terms of NOD based on the parameters, such as FARS, NCS and NSF. Two types of experimentations are performed on the same crop out of the 17 ROI's selected by choosing the similar ROI for the trained image samples. In the first experiment, the observation was made by assigning NSF with static values and found that LBP performed better detection rather than HAAR whereas HOG showed lower NOD than HAAR. On an average, LBP showed 16% better than HAAR and 99% better than HOG, whereas HAAR showed 97% better NOD than HOG. In the second experiment, parameters like FARS and NSF are varied on the unique data samples of Groundnut crop. Due to the impact of EPS, ENS, NCS and TPRS, distinctive performance at each sample is observed. In general, the LBP once again showed its dominance over HAAR and HOG through highest NOD. Comparatively LBP performed 20% better performance than HAAR and 96% better than HOG and HAAR is enhanced than HOG with 95% performance.

In future, the texture based classification can be applied to the different crop datasets, based on the NOD and it may be possible to identify the crop. It is also possible to combine more image parameters like shape, colour, size, site, association, shadow, and pattern for higher accuracy identifications.

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