Detection of Weeds In Unstructured Wheat Field Using Image Processing And Machine Learning

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***Abstract*— Weed distribution levels range between low and excessive densities. Two computer vision-based algorithms are presented in this paper to identify widespread weeds in wheat fields under natural field conditions. First algorithm explores weeds by image processing rules. Algorithm used color to differentiate flowers from soil. While texture analysis strategies are used to distinguish weeds from crops than in the second step multi class linear kernel SVM used for classification of the images whether it is a wheat field or weed based on the weed thicknesses which is shown in images. Back propagation and RBF kernel SVM used for comparison between results. On the basis of execution time and accuracy back propagation neural network outperform rather than multi-class linear kernel SVM shows better result.**

Index Terms—Weeds, Image Processing, Morphological operations, Computer Vision.

INTRODUCTION

Agriculture plays an important part in the economic development of nations, directly and indirectly. It is consequently very critical that charges are reduced and the quality and amount of crops improved. Approach to precision farming (PA) is a crucial one. Precision Farming Agriculture aiming to distinguish remedy fields so that it will optimize earnings and ecological component mitigation in neighborhood conditions.

Weeds and bugs are the most dangerous competitors for wheat production. Weeds are undesirable plants. They not most effective affect production, but also reduce the high-quality of plants and make it risky for human consumption. A standardized volume of herbicide is spread in the field in the conventional plant control methods. Such approaches are labor-intensive, time-consuming and expensive. Therefore, much work has been done to support computer vision and robotics for site-specific weed management.

Automated approaches to weed detection essentially fall into three categories; shape-based classification, texture-based classification based on spectral signature. Environment evaluation of plant leaf in shape-based analysis is whether it is crop or weed. [1] Suggested two methods of discriminating against ryegrass carrot plants and Fat Hen (weeds). In the first method, the shape of the leaf is used as the only feature with precision ranging from 52 to 74%.. For maize fields, weeds are identified through a network of neural returned propagation [2].Considering the particular shape of the corn leaves and the configuration of the vein, a system is proposed [3] for the use of frequency filter and edge density filter.

Testing this approach demonstrated 92 per cent accuracy when weed plants were detected.

[4] Explored the potential for classification of weeds using both spatial and spectral texture features. The Gabor Low-Level Wavelet extracts capabilities at the same time as the faraway neuro-internet is used to classify patterns with 3 feed layers with eight hidden nodes. They simulated the visual system of humans to differentiate broadleaf and grass like weeds and obtained 100 percent precision. [5] Two texture-based methods for weed detection have been suggested. Their methods are based on the supposition that leaves of grass have more edges than weeds. First method used local mean and variance as the classification features and filter for Bayes.

The morphological operators are based on the second form. For the first method the correct weed detection rate is estimated from 77.70 to 82.60 per cent and for the second method 89.83 to 91.11 per cent. When electromagnetic energy hits three items in the crop plant; the energy will absorb, transmit and reflect.

The satellite spectral imaging changed into studied with the intention to detect significant weeds in sugar beet fields [6]. The Normalized Vegetation Difference Index (NDVI) is determined from reflected red and near infrared wavelengths. Calculating NDVI of weed patches in the training area is achieved by supervised classification of the entire sugar beet region. [7] Its used ground-level images with spectral and spatial resolutions for the identity of grasses and huge leaf weeds. A fractional assessment of the insurance is carried out on each picture to differentiate it into 4 classes: wheat, soil, grass weed and wide leaf weed.

This method provided an overall 85 per cent accuracy. Another strategy for recognizing weeds is to use trends between crops and weed rows. In these methods vertical lines are used for crops and then weeds are identified by measuring field row edges. A system which consists of two processes is proposed [8]. Images are cut up into cells that in the first cycle are delimited by crop row. Area-based attributes of each cell are used to quantify the crop-weed relation.

In second process, the support vector machine is used which decides for each cell, it should be sprayed or not. They reported that 85 percent of weeds were detected correctly, and [9] Proposed a fuzzy weed management system specific to the site. SVM for detecting 4 species of corn weed at an early boom stage [10]. They used Gray Level Co-occurrence Matrix (GLCM) and histogram distribution to extract weed and texture features from the field snap shots in grey level. Analysis of the elements of the Principle become used to choose the best aggregate of functions.

The consequences showed that SVM classifiers with particular feature alternatives can precisely be diagnosed from 92.31 to 100%.Evaluated that [11] to detect weed and nitrogen tension, SVM needs to identify hyper spectral images of corn fields. Based on the above-mentioned study, we may say that computer vision algorithms in Precision Agriculture help farmers manage weeds specifically for location. Weed detection function must be conducted with conditions of outdoor illumination.

Weed identification should not be influenced by various weather conditions, such as rainy and sunny conditions. [11] Aside from unregulated lighting, imaginative and precious systems regularly face another challenge, due to the shadow of the nearby crops, with unparalleled light. Some objects are darker in these images which makes it difficult to differentiate them from the soil. The algorithms proposed are designed for identification of large leaf weeds in scattered areas of wheat where weeds and crops can overlap and have the same color. That is how the remainder of the paper is structured. Section 1 outlines the proposed algorithm for the identification of weeds based on shape and texture. Section 2 describes classification of weed density using linear multi-class SVM kernels. Section 3 discusses results. Finally section 4 concludes the paper with future work.

1- ***SHAPE AND TEXTURE BASED WEED DETECTION***

This algorithm is based on features of leaves in shape and texture. Color knowledge is used for extracting soil from the field of vegetation. Shape and texture characteristics are used to differentiate weeds and crop. This algorithm consists of two steps:

1. Segmentation of soil and plant
2. Discrimination of Weed and wheat

Proposed Shape and Texture dependent Weed Detection method is shown in Figure 1.

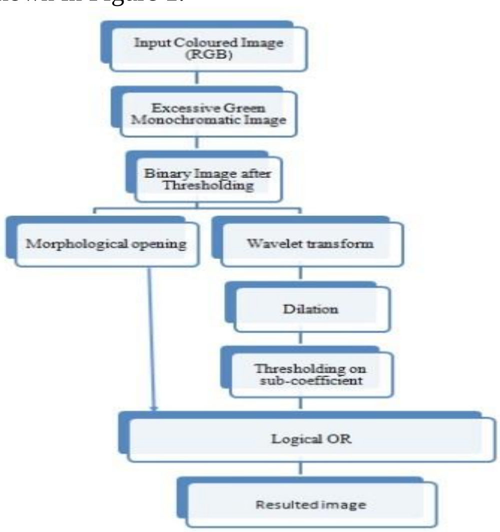

Fig. 1. Texture and Shape Based Weed Detection Algorithm

A. Segmentation of Soil and Plant

The initial step within the algorithms for weed detection is normally a segmentation of flowers from the ground (weed and wheat). This step is a pre-processing phase. This flow not best reduces facts processing in destiny stages, it also simplifies the detection of weeds via the renovation of flora simplest. Because the greener colorings of flowers pixels are than the soil, this step is specifically taken into account in color flora indicators (red, blue and green pixels). Many studies papers talk the most well-known strategies of excessive green method proposed in 1992. Two measures are inspired via the proposed method of segmentation of the soil [17].

- The first step is transform the colored input picture into a gray-level single dimension photograph as in keeping with Eq (1) below. After applying this step on a test image with coefficient a=-1, b=2, c=-1, Figure 2 shows resulting monochrome gray level image.

$$P(i, j) = a \times R(i, j) + b \times G(i, j) + c \times B(i, j) \qquad (1)$$

Here R (i, j), G (i, j) and B (i, j) are the coefficients at each of the pixels P(i, j) and a, b and b.

- The grey level photo is then converted right into a binary picture the use of a thresholding technique to symbolize a place of vegetation as white and a relaxation as black consistent with Eq 4. The thresholding result is proven in Fig.3, with a limit cost set at 195

$$Binary_{(i,j)} = \begin{cases} 255 & \text{if } P_{(i,j)} > Threshold, \\ 0 & \text{if } P_{(i,j)} \leq Threshold, \end{cases} \qquad (2)$$

During experiments different combinations of coefficients (a, b, c) and threshold values were checked to find optimum a=-1, b=2, c=-1 and threshold=195 vales.

B. Discrimination of Weed and Wheat

The following step is to extract a portion of a white seed. This stage's output will be the images containing only broad-leaf weeds.

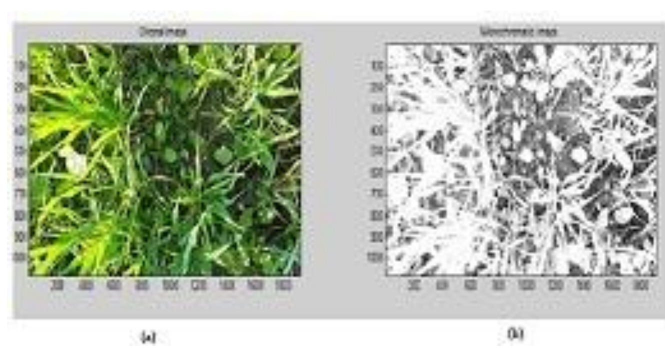

Fig. 2. Effect of the first soil segmentation phase (a) Original image (b) Monochrome image with a = -1, b=2, c=-1

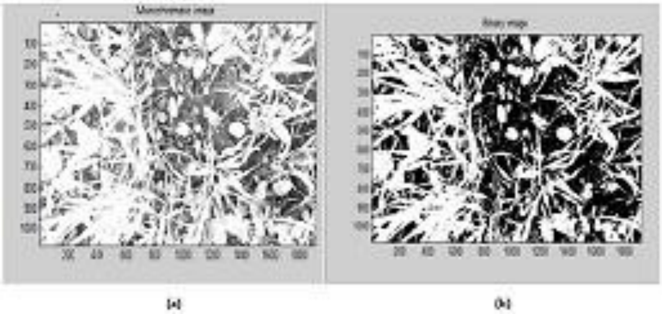

Fig. 3. Thresholding results (a) Monochrome image (b) Binary image with threshold=195. The vegetation area is depicted in white and the soil in black type.

This is the most difficult, since weeds and wheat are the same color and the grain is distributed. [13]The following steps in the system proposed are further divided into two sections:

- Shape based analysis
- Analysis based on texture

These two stages use weed detection techniques for image processing. The results of the stages above are fair OR in finishing the final product.

➢ ***Shape Based Analysis:***

This stage is rely on the leaf form used in image processing to be weed detected. Wheat leaves are thin, narrow and blade shaped whereas broad-leaf weeds have oval leaves, eclipse leaves, small and thick. [14] Considering the features of weeds and wheat on the leaf, this phase detects weeds based on area and distance.

To this end morphological operations were used. Morphology is a systematic set of image processing operations manipulating images based on their form. Morphological operations add a structuring characteristic to an image input to generate an image output of the same size. The value of each pixel in the output image is determined in the input image by applying a rule to the respective pixel and its neighborhood.

We used a morphologic operator of Matlab with a flat structure to classify certain white areas in the image with a related region and radius above the threshold. Figure 4 shows weed detected image with following structuring factor parameters after application of morphological operator.

Shape = disk
R (radius) = 35
N = 4 (N is used for approximation)

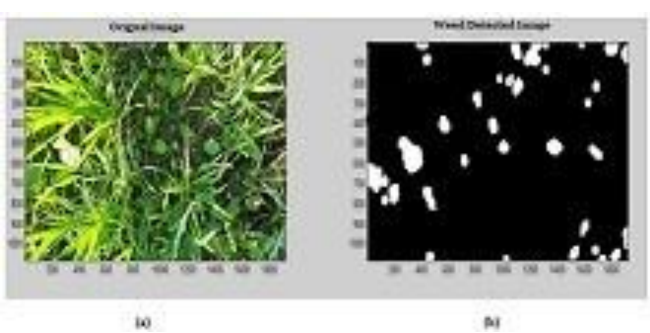

Fig. 4. Shape-based weed detection result (a) Original image (b) After applying radius=35 to binary image morphological operation.

➢ ***Texture based Analysis:***

The blade of wheat is long and strong, the edges rugged. The amount of energy activity is higher than in weeds in the wheat portion. Wavelets are therefore used for weed detection to regulate this feature. [12] Fourier may also be used to detect higher operating areas, but we must assess the increasing frequency not given by Fourier. In signal and picture processing, the transformation wavelet has come to be a effective method. Wavelets are a sequence of localized basic functions with clear orthonormality, frequency and time-domain requirements, quick deployment and possibly compact aids. For image processing there is a two-dimensional wavelet transform.

The DWT transformation is a linear process. The DWT transformation. It operates on a data vector with a two-inch integer power that converts it into a numerical vector of the same length. This is a technique that divides data into different components of frequencies and studies each component at a resolution suitable for its scale [18].

In the proposed process, discrete two-dimensional wavelet transformation is applied to the binary image was manufactured after preprocessing step. An appropriate sub-band is extracted which is rich in details.

In our case, we have extracted mainly diagonal subband coefficients with a strong strength of wheat. The result after discrete wavelet transformation of the sub band extraction is shown in Fig 5.

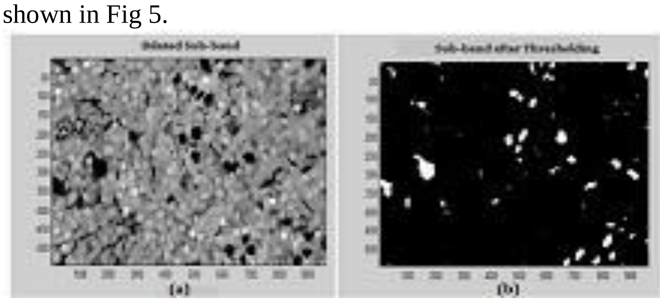

Fig. 5. Figure shows sub-band after (a) Dilation (b) Thresholding.

During the extraction "dilation" followed by thresholding by the morphological operator as shown in Figure 6. A conceptual OR on the resulting shape analysis and texture analysis images is used to achieve the final result.

FIG. 6. Final result of Weed Detection based on shape and texture (a) Original weed image marked (b) logical shape and texture based evaluation results.

The output image may contain small white areas that are not weeds but noise. As a post processing step a closing operator followed by thresholding is used. In dilation and erosion a flat square shaped structuring factor is used. [19] Areas greater than threshold found are then removed. Figure 7 shows the final output picture of the detection of weeds based on form and texture after noise deletion. Green circled areas are the weeds found in the texture analysis, and not in the form analysis. Likewise blue circled areas are those weeds found in shape analysis and not texture analysis.

2- *WEED DETECTION USING MULTI-CLASS LINEAR SVM*

In this area, an additional arrangement of rules is characterized which decides the nearness of weeds in wheat crops essentially dependent on weed thickness. This methodology utilizes a multiclass direct SVM bit to association field pix into 3 classes;

1. Having not weed.
2. Having less weeds.
3. Having more weeds.

Various highlights, for example, nearby ternary example (LTP), SURF, SIFT, and factual surface highlights are utilized to choose the list of capabilities for the preparation classifiers. Of correlation purposes, the back-propagation neural system and non-linear Gaussian RBF SVM were utilized.

A. Multi-class Linear SVM:

Yang, Jianchao, et al are proposing a multi-class SVM based linear SPM kernel. During preparation, it has linear time complexity and needs constant test time. This classifier tires to learn linear functions on a given training data, so that it can predict test data labels using one against all strategy when test data is presented. [15]

Limited memory Broyden Fletcher Goldfarb Shanno (LBFGS) is utilized in preparing. All SVMs are prepared by tackling unconstrained raised improvement issue. This multi-scale direct SVM has a straight multifaceted nature, since it examines the preparation information straightly. Following apps are considered to find best selection of features.

1) Local Ternary Pattern (LTP):

Nearby ternary example (LTP) is an expansion of Local Binary Pattern. The key drawback for LBP is that the nearness of commotion impacts its productivity. [16]

LTP defeats that shortcoming, and is vigorous against clamor. As opposed to LBP thresholding three qualities are utilized (1, 0, - 1).This measures values of neighboring pixels using the following equation.

$$f(x) = \begin{cases} 1 & \text{if } p > c + k, \\ 0 & \text{if } p > c - kandp < c + k, \\ -1 & \text{if } p < c - k, \end{cases} \quad (3)$$

In this equation k is threshold, constant C is the center pixel value and p is the opposing pixel value.

2) Speeded Up Robust Features (SURF):

The function SURF is a scheme for detecting images. The second derivative masks are based on Gaussian and a feature descriptor entirely based on the local Haar Wavelet response .SURF consists basically of stages. Interest points in the images are recognized in the primary step and descriptors are created for each step within the 2nd step. Hobby point in photographs is first-class perfect for blob-like structure. [20] Has an inclination to blob light on dark and dark backgrounds. In complex, cluttered and partially hidden gadgets, it can detect gadgets because they can be invariant in terms of conditions, scale, rotation, distortion and changes in lighting fixtures.

3) Scale-Invariant Feature Transform (SIFT) :

D.Lowe had suggested it in 2004. This extracts the keypoint and computes the descriptors thereof. The interpretation, scaling, and turn are invariant. It changes over the picture to an expansive arrangement of vectors of the nearby capacity. Filter calculation is made out of 4 stages:

1. Outrageous extraction at a scale-space
2. Localization Key point
3. Priority assignment
4. The Descriptor Key point

Sparse codes have been used in experiments followed by maximum spatial pooling of SIFT descriptors.

4) Surface Component:

Surface component details is commonly used for classifying objects. Samples of weed and wheat leaving have been taken in various conditions for textural analysis, including the (in sunlight, covered, dark) area, the local mean (min and max value), entropy, strength, correlation, contrast, local range and weed-crop homogenity.

Analyzed. Analyzed. Contrast, correlation, entropy, homogeneity and energy were found to be used as an excellent indicator for weed and wheat classification.

3- *EXPERIMENT RESULTS AND DISCUSSION*

Colored photographs were taken from a field of wheat near Lahore in April 2014. Camera had a 1920 by 1080 pixel resolution. Photos were taken at a height of 1-1.3 m in sunny days with clear conditions. Images were captured every two weeks during the growing season of wheat crops.In Shape and Texture Based Weed Detection 35 colored images have been used.

Informational collection images for the grouping of weed thicknesses were classified into three weed thickness classes and 33 images were included in each class. Experimentation was conducted on a Matlab 14 program framework with Intel Core i3 microchip, 2.00 GB RAM, and 2.53 GHz.

B. Weed Detection Based on Shape and Texture

To evaluate the exactness of the weeds and the phase of wheat separation, ground-truth pictures were taken by physically denoting the weed territories in each picture of the dataset. If comparing the quality of the output image with the corresponding ground-truth image, the white pixel count is then used. [21] Table I shows the accuracy of the proposed

Algorithm has been tested on 35 images and then taken on average.

Shape-based investigation accurately identifies weeds more than surface based examination however fit as a fiddle based examination the pace of off base weed discovery (vegetation zone is distinguished as weed) is higher than the surface based examination.

TABLE I
WEED DETECTION RESULTS OF SHAPE AND TEXTURE BASED WEED DETECTION

Detection rate	Shape based analysis	Texture based analysis	Shape and Texture Based Weed Detection
Correct weed%	72%	69%	74%
False positive%	15%	12%	100%

Results showed that there is potential to use both features; shape and texture to increase the accuracy of weed detection. The processing time efficiency of the algorithm was estimated on a 2.53 GHz processor with 2.00 GB RAM. Table II shows the processing time for each step of our Weed Detection Algorithm based on Shape and Texture. That shape can be noticed the baseline measurement is a significant contributor to the processing time. Detection and soil segmentation based on texture takes less time compared to detection based on shape.

TABLE II
AVERAGE AND ST.DEV OF EXECUTION TIME ON 35 IMAGES

Stages	Average(sec)	St.dev(sec)
Soil segmentation	0.38793	0.007912
Shape based detection	1.100188	0.043881
Texture based detection	0.426933	0.008498
Complete method	1.978167	0.054903

C. Weed Density Classification:

Performance is assessed by well-known techniques of cross validation. Experimental process is replicated 5 times, and randomly selected for accurate results in each iteration training and testing data. In every iterations average accuracy is reported for each class. Mean accuracy is measured at the top, and standard deviation. [22] It also tracks the run time for function selection, training and testing. In multi-class straight SVM and non-direct RBF piece SVM, 20 percent of pictures for each class are utilized for testing, and 80 percent for approval. Neural network back-propagation uses 50 percent of images per class for preparation, and the remaining 50 percent for validation.

The results of 3 classifiers trained in SURF descriptors are shown in Figure 7. The mean precision is shown along the y-axis and the sum of focus is shown on the x-axis. In nonlinear RBF portion SVM and the neural back-propagation system of Multiclass, direct SVMs prepared in SURF descriptors, execution is superior to execution.

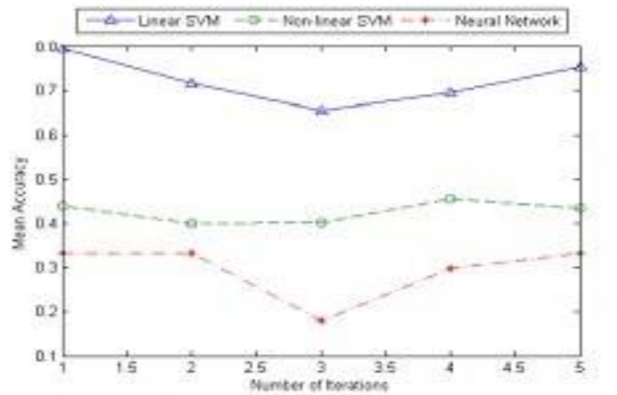

Fig. 7. Figure shows Mean Accuracy of Three Classifiers Trained on SURF Descriptors

Whenever prepared on SIFT meager codes, multi-class straight SVM appropriately arranges weeds with more than 0.84 Mean accuracy. Graph 8 shows a comparison of linear SVM with two other SIFT-trained classifiers with sparse codes.

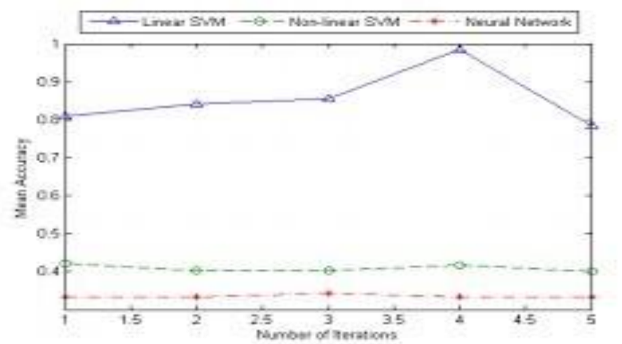

Fig. 8. Figure shows Mean Accuracy of Three Classifiers Trained on SIFT Sparse Codes

Figure 9 shows three classifiers, prepared in their grouping precision on five surface attributes (entropy, power, relationship, and complexity). In these analyses it is demonstrated that the surface highlights increment the precision of each of the three classes.

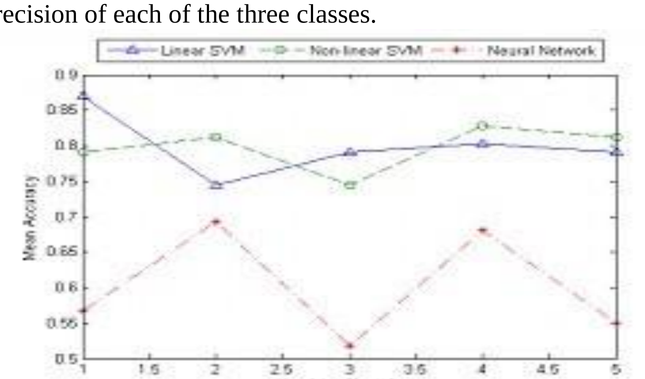

Fig. 9. Figure shows Mean Accuracy of Three Classifiers Trained on Texture Features

The non-linear texturally trained SVM has the same average precision as multiclass linear SVM.

In Figure 10, the diagram shows the yield of the consolidated list of capabilities of three classifiers prepared on LTP and surface capacity. It very well may be discovered that the exhibition of multiclass SVM prepared on consolidated list of capabilities is better than that of nonlinear RBF and back-propagation of neural network.

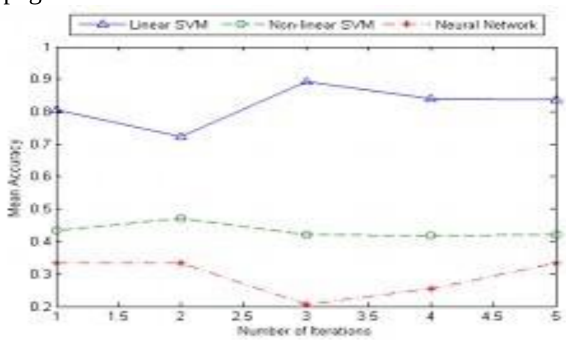

Fig. 10. Classification Results of Three Classifiers Trained on LTP and Texture Features

Table III displays mean accuracy of three classificatory using specific feature sets. Multi-class of SVM mean accuracy which is trained on any set of features is better than two other classification.

TABLE III
MEAN ACCURACY OF THREE CLASSIFIERS USING DIFFERENT FEATURE SETS

Feature Set	Linear SVM	Non-linear SVM	Neural Network
SURF	0.72	0.43	0.30
SIFT Sparse codes	0.85	0.40	0.34
LTP	0.78	0.43	0.35
Texture Feature	0.80	0.79	0.60
LTP+Texture Feature	0.82	0.43	0.29

The results were also noted, be that as it may, execution time is longer while the LTP alongside five surface highlights gives mean accuracy of 0.82 and less execution time. [23] The multi class SVM prepared on meager SIFT code gives a superior middle precision of about 0.75 for all highlights. The processing time and medium precision are interchanged. The execution time of five separate function sets is shown in Table IV for each classifier.

TABLE IV
EXECUTION TIME OF THREE CLASSIFIERS (THE VALUES ARE IN SECONDS

Feature Set	Linear SVM	Non-linear SVM	Neural Network
SURF	0.48	0.63	0.49
SIFT Sparse codes	4.37	4.50	4.37
LTP	0.19	0.29	0.21
Texture Feature	0.35	0.38	0.36
LTP+Texture Feature	0.77	0.87	0.78

Runtime per picture includes time for extraction and testing of features. It takes much less time for evaluating multi-class linear SVM and back propagation neural network.

We have concluded following four details about weed density classification after conducting various experiments.

1) Numerous class direct SVM arranges more precisely the weed thickness than the non- straight SVM part RBF and the back- propagation of the neural system. Testing process takes less time than non-linear SVM
2) Filter Sparse codes prepared in multi class direct SVM orders weed thickness as the most exact mean of 0.85 however it takes
   4.37 seconds to open a solitary picture for meager SIFT codes
3) SMV and the neural back-propagation organize gave the best mean precision to non-straight RBF pieces when preparing in five Texture capacities (entropy, quality, difference, relationship, and consistency). Non-direct SVM and straight SVM, prepared in surface qualities gave around a similar normal precision yet non-straight SVM takes more time to test than straight SVM.
4) The mix of LTP highlights and surface is the subsequent best list of capabilities after inadequate SIFT codes. Multi-class Linear SVM has conveyed a mean accuracy of around 0.82. It takes 0.77 seconds to extricate capacities from a solitary picture, which is not exactly the time required to remove inadequate using SIFT.

4. CONCLUSION AND FUTURE WORK

Selective applications of herbicides and local weed detection are extremely important in precise agriculture. Two Algorithms in this paper. This is suggested for weed identification in scattered wheat fields. First calculation depends on picture preparing methods and second is utilizing Straightforward SVM multi-class handling procedures. Regardless of the likenesses among weed and harvest leaves and profoundly factor lighting conditions, the Texture and Shape analysis for Weed Detection calculation performs proficiently with 74 percent discovery rate. After selection experiments with feature set, it has been discovered that multi-class SVM prepared on LTP and five other surface attributes will acknowledge field images with an exact mean of 0.82. Similar research has demonstrated that multi-class linear SVM performs better on mean accuracy and execution time rather than non-linear RBF kernel SVM and back-propagation. Multi-class linear SVM detects more precisely weed in less time compared to an algorithm based on image processing. This incorrect and miss identification was due to many factors, including crop shadow, occlusion and light exposure. Algorithms suggested have substantial performance, but changes need to be made in order to achieve greater precision. Our ways of detecting narrow-leaf and grassy weeds in wheat

Crops need to be extended. Hyper-spectral field images will be available in future used to improve its accuracy.

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