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A Combined Color and Texture Features Based Methodology for Recognition of Crop Field Image

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Abstract

This paper presents a methodology to recognize certain crop fields' images using texture, color and combination of both types of features. In this work, we have considered eight varieties of crop images, namely, Brinjal, Cotton, Groundnut, Paddy, Soyabean, Sugarcane and Sunflower. Texture features using GLCM and color features using HSV are deployed. Artificial Neural Network (ANN) is used for recognition. Considering only as feature, classification accuracies of 63.75%, 66.25% and 84.375% are obtained using texture, color and their combination respectively. The work is helpful in the area of agriculture for early detection and prevention of diseases.

Keywords: *Field images, GLCM, HSV, Artificial Neural Network and Pattern recognition.*

1. Introduction

Agriculture is the major source of income for about three-fourths of India's rural population. Technological support to Agriculture is considered important in assessing the development of any country. Poorly trained farmers cannot apply the precision methods and new technologies like use of robots or the use of new irrigation techniques or use of sensors to predict the yield etc. Common technological applications like human computer interaction, virtual environment, robotics and multimedia, include computer vision, image processing and speech processing are possible in the field of Agriculture. Computer vision helps in analyzing the visual input from an image and produces a description to interact with the world. In the proposed work, eight types of fields' images, namely, Cotton, Sugarcane, Paddy, Sunflower, Brinjal, Soyabean, Maize and Groundnut are considered and some sample images are shown in Fig. 1.

Figure 1. Images of Sunflower, Soyabean, Brinjal and Paddy Fields

Two types of features, namely, texture and color are extracted. Texture features are extracted using Gray level co-occurrence matrix (GLCM) and color features from HSV model. These extracted features are used to train and test ANN as recognizer. In order to

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know the state- of-the-art development in automation activities in the fields of agriculture and horticulture, we have carried out a literature survey. The gist of the literature survey is given in this section 2.0.

2. Literature Survey

Hermawan syahputra, et al, (2014) have proposed a plant recognition system of stereo leaf images using gray level co-occurrence matrix. The methodology has used sum of absolute difference (SAD) and 22 features are extracted using GLCM. The accuracy reported is 83.3%. Pallavi P et al, (2014) have proposed leaf recognition based on Zernike moments. This methodology uses shape, vein, color and texture features to identify the leaves. A neural network approach is used to classify the images. Gowri Ariputhiran, et al, (2013) have proposed feature extraction and classification of high resolution satellite images using GLCM and back propagation technique. The performance is analyzed based on its accuracy, error rate and sensitivity. Vishaka Metre et al, (2013) have proposed an overview of the research on texture based plant leaf classification. In this method a leaf is classified based on different morphological features. Manish Maheshwari et al, (2013) have proposed a new feature extraction technique for color image clustering. A color quantization ordering scheme that focuses on color as feature and considers Hue, Saturation and Value space is proposed. To form clusters of images k-means algorithm is applied.

A H kulkarni, et al,(2013) have proposed a framework for recognizing and identifying plants using various features, combined with zernike movements. Classifier used is radial basis probabilistic neural network (RBPNN). Dual stage training algorithm is used to train RBPNN to increase performance of the classifier. Flavia leaf is used for the study. The experimental simulation results show an accuracy rate of 93.82%. Smita Naikwad, et al, (2013) have given an account of advances in image processing for detection of plant diseases using color and texture features. The technique has detected and classified the plant diseases with an accuracy of 83%. S.Abhirami, et al,(2012) have proposed plant species identification based on images of flowers. The features extracted are shape, color and texture. Color based segmentation is carried out using k-means algorithm and active contour model. Texture features are extracted using GLCM. Edge detection is done using Sobel, Robert and Prewitts operators. The classification is done using proximal support vector machine. Abdul Kadir, et al, (2012) have proposed foliage plan identification based on leaves using zerkine moments. Zernike moments are combined with other features like geometric features, color moments and gray level co-occurrence matrix. For identification, probabilistic neural network is used. The experiment show that combined features yield good result.

Ashutosh Kumar Bhatt et al, (2012) have proposed an artificial neural network based apple classifier. Input is collected from software and web camera, ANN is used to classify apple according to quality. Experimental data show better results compared to predicted values. Dr J Abdul Jakeel et al, (2012) have proposed an artificial neural network based detection of skin cancer. The methodology for feature extraction used is 2D wavelet transform. ANN is used as a classifier. Norasyikin Fadilah et al,(2012) have proposed oil palm fresh fruit bunch ripeness classification using ANN. This method is used to automate the decision of grading oil palm FFBs (fresh fruit bunches), which replaces manual human grading method. Results show that ANN is able to generalize four ripeness categories of oil palm FFB. R Venkta Ramana Chary, et al, (2012) have proposed feature extraction method for color image similarity. Color projection and different mathematical approaches like mean, median, standard deviation are applied to retreive images within a large collection of images. For retreival of images, RGB color combinations are considered. Results are observed to be efficient.

Haipeng Yu, et al,(2009) have proposed image retrieval method which includes color, textural and special features of wood species. A total of 9 features are extracted to retrieve wood species. The results show that combined effect of these features yield good results. LiyingZheng, et al,(2008) have proposed a method to separate green vegetation in color images using mean shift procedure for segmentation. Multiple color features are extracted like hue, saturation in HSI color space and red, green, blue in RGB space. With mean shift segmentation algorithm, extracted features and BPNN, images are classified as green and non-green. R Pyadipati, et al,(2006) have proposed a color co-occurrence method (CCM) and discriminant analysis method to recognize citrus plant diseases. The method used texture based Hue, Saturation and Intensity (HSI) color features extracted using CCM and statistical classification algorithm to identify diseased and normal citrus leaves. H Fu and Z Chi, (2006) have proposed a combined approach of using artificial neural network and threshold to recognize plants based on images. Leaf veins are extracted to define features for plant species recognition. The results show that combined approach is good.

From the literature survey, it is observed that certain work on recognition of plants based on leaf characteristics has already been carried out. Several feature extraction methods like vein, Zernike moments etc. are being deployed. However, no considerable work is carried out on recognition of field images of varieties of crops. Human beings rarely view one or two leaves in a field. Instead, the entire field image is considered for recognition. This is the motivation for the proposed work.

The remaining part of the paper is organized into four sections. Section two gives the literature survey, section three deals with methodology, which further explain about image acquisition, preprocessing, feature extraction and classification, section four gives with results and discussion and finally section five deals with conclusion.

3. Methodology

The proposed methodology on combined color and texture features based methodology for classification of crop field images is divided into four steps, namely, Image acquisition, Preprocessing, Feature extraction and Classification as shown in Fig. 2.

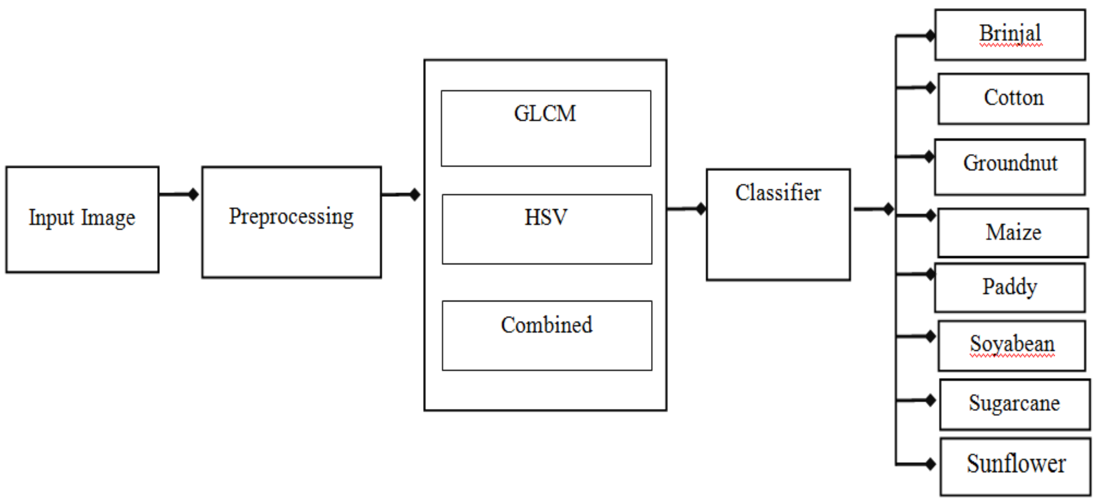

Figure 2. Block Diagram of the Proposed Work

3.1 Image Acquisition

The field's images are captured using Sony digital camera of 16.1 Mega Pixels. The images are captured under fixed focal length under standard illumination conditions. The field images of Paddy, Sugarcane, Sunflower, Groundnut, Cotton, Maize, Soya Bean, and

Brinjal are used in the present work. The data set consists of 20 images of each field crop. A total of 180 images are considered for experimental study. Some of the sample images are as shown in the Fig. 3.

Figure 3. Field images of Groundnut, Maize, Sugarcane and Cotton

3.2 Preprocessing

The fields' images captured are of 3456 X 4608 pixels. We have filtered and resized the images. Median filter is found to be suitable for the proposed work. The images are resized to 512 X 512 pixels. A sample image of paddy field before and after filtering is shown in Fig. 4.

Figure 4. Sample Image before and After Filtering

3.3 Feature Extraction

From literature survey, we found that feature extraction techniques used are color, texture, shape etc. In the proposed methodology, an exhaustive experimentation is carried out considering color and texture features.

3.3.1 Gray Level Co-occurrence Matrix (GLCM): Visual system of human beings use second order distribution of gray levels as discriminator in identifying textures. Some of the characteristics of texture are homogeneity, entropy, contrast and others. GLCM is very useful to obtain valuable information about the relative position of the neighboring pixels in an image. The co-occurrence matrix GLCM (i,j) counts the co-occurrence of pixels with gray value i and j at given distance d. The matrix element P(i,j) is separated from its neighborhood by a pixel distance ($(\Delta x, \Delta y)$, one with intensity I and the other with intensity j. Number of gray levels is denoted by G. μ is the mean value of P. μ_x and μ_y are the means and standard deviations of Px and Py. The direction of neighboring pixels to represents the distance can be selected, for example 135o, 90o, 45o, or 0o, as illustrated in Figure 5.

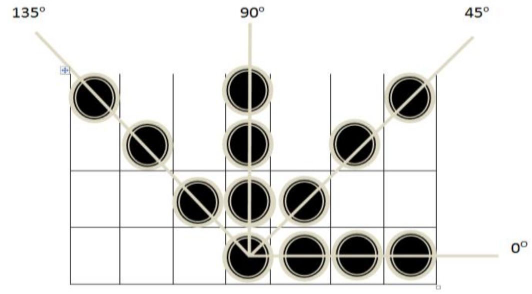

Figure 5. Directions in Calculating GLCM

Autocorrelation= $\sum_i \sum_j (ij).P(i,j)$ … (1)

Table 1. Autocorrelation Feature Values for Different Field Images

Brinjal	Cotton	Groundnut	Maize	Paddy	Soyabean	Sugarcane	Sunflower
24.1119	22.0856	22.5134	23.2861	21.1201	20.7113	24.7828	19.7109
23.6060	29.6321	20.9259	21.8625	20.6094	21.7553	25.3469	20.7545
24.3305	23.5454	19.3553	19.5751	19.5246	20.1003	23.2533	21.0163
24.2179	20.8160	24.8980	24.2241	20.6673	19.8544	24.1300	21.8298
22.3906	21.0447	21.5332	24.3650	21.3370	20.5203	21.2734	20.9112
20.1065	21.5781	20.7822	22.8061	19.5573	21.8742	26.8223	28.1540
22.8760	19.7231	19.1834	12.8416	19.2251	19.9482	22.5949	24.0996
21.4424	24.5872	22.6780	13.6716	19.9423	22.2696	26.0679	24.5178
24.5491	27.5046	21.5045	26.0302	22.4673	21.9306	26.7388	22.6717
25.3675	22.4095	21.7652	23.6258	22.1956	22.6315	25.1625	22.2957
23.8400	23.0675	20.6994	24.5443	23.1584	19.6667	24.3797	22.3222
24.4419	21.4232	21.9096	21.1245	22.1867	23.0422	24.5458	22.0486
25.1366	23.6985	22.7019	22.9797	21.4486	21.8950	25.1323	24.1313
24.2559	20.4671	23.4563	24.4630	21.7487	23.2932	22.1501	23.7007
23.3021	23.9773	22.9697	25.1126	21.1201	20.5436	21.8302	21.5769
24.1588	25.1650	21.1602	17.0398	20.6094	23.1840	21.8271	20.7545
22.2288	24.9027	22.6895	22.7387	19.5246	21.1492	25.5935	19.7109
22.1743	22.1374	22.5410	21.4434	20.6673	22.4197	26.1134	21.6968
22.9865	24.6083	23.7960	19.8601	22.1956	23.0956	27.7082	28.1540
22.2812	24.1615	23.7960	24.6506	23.1584	25.1228	24.4146	24.0996

In the proposed work, we have considered all the 22 features, initially. The five prominent texture features, namely, autocorrelation, cluster prominence, sum of squares of variance, sum of variance and sum of average are utilized in the work. The reduction in the number of features Autocorrelation refers to repeating patterns like presence of periodic signal obscured by noise and is given by equation (1). The autocorrelation values for the different varieties of field images are given in Table 1. Considering the tabular values the classification accuracy of the extracted feature autocorrelation is as shown in the Fig.6.

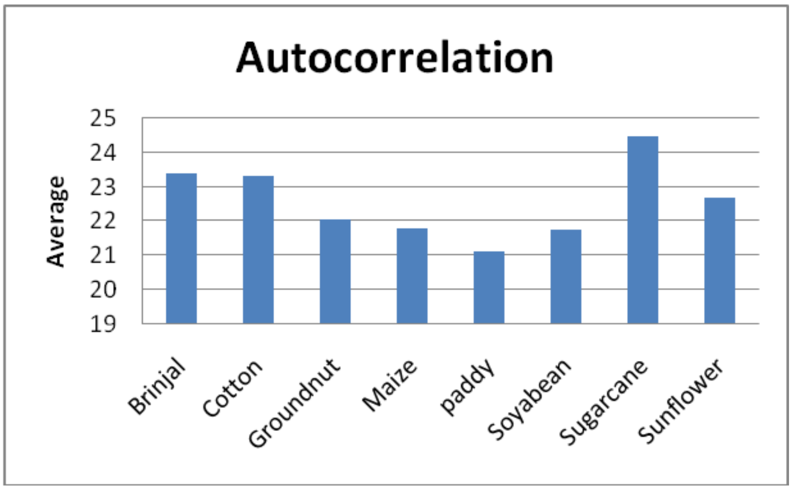

Figure 6. Autocorrelation Classification Accuracy

Cluster prominence is the measure of the skew in of the matrix, in other words the lack of symmetry and is given by the equation (2). The extracted feature values from the algorithm are given in the Table2. The classification accuracy of cluster prominence is given in the Fig.7.

$$\text{Cluster Prominence}=\sum_i \sum_j P(i,j).(i-\mu x+j-\mu y)_4 \quad \ldots (2)$$

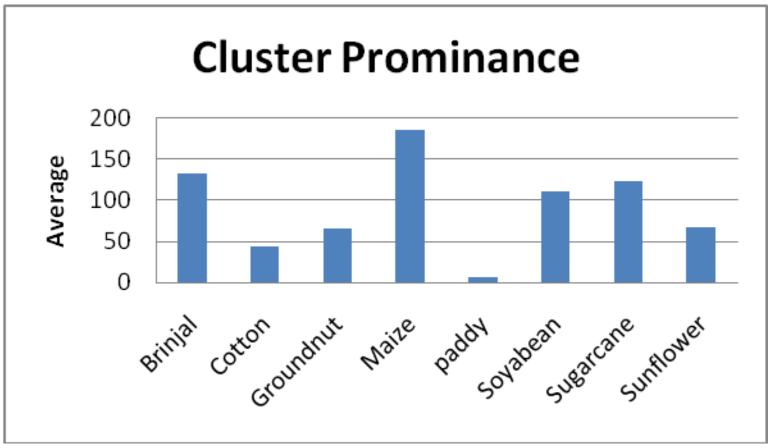

Fig.7. Cluster Prominence Classification Accuracy

Table 2. Cluster Prominence Values of all Field Images

Brinjal	Cotton	Groundnut	Maize	Paddy	Soyabean	Sugarcane	Sunflower
130.2619	18.0145	54.3874	264.3967	9.5720	112.4264	56.0695	66.7312
168.6870	52.2004	44.8960	199.3252	1.6932	121.6650	197.6057	31.1979
157.7387	63.6262	45.5494	158.2652	5.5684	144.1989	49.0297	62.9901
236.3847	15.2933	23.5871	253.9035	2.6715	176.8790	28.6825	49.9067
281.9142	36.8663	32.4154	147.1910	15.5241	44.4060	20.7930	64.4407
33.2573	31.0668	26.1112	241.0088	31.4437	60.7674	285.6442	153.4413

37.5427	24.2235	30.7968	88.6757	2.9750	61.2150	32.4268	46.6054
34.2149	11.1889	18.4072	86.2144	3.4638	40.6355	255.7799	200.0652
71.0562	21.3162	71.3125	405.0479	5.5096	82.0314	337.7018	67.1831
61.2947	30.9508	37.2266	193.2681	3.6783	51.7179	230.6312	30.2503
84.9212	106.6059	50.1306	121.6926	4.3150	201.5391	435.1584	43.5750
117.6614	12.9524	66.1265	126.7949	2.9960	109.7506	104.3095	38.9869
78.5932	9.6271	129.2786	198.1362	12.0614	109.3417	44.4894	95.4558
235.9950	10.0365	97.0550	241.5461	4.4007	121.0959	40.6179	38.1755
219.7504	86.3774	86.5048	177.9869	9.5720	87.1005	37.0213	46.7128
162.7342	73.5733	23.6529	250.2582	1.6932	129.6857	72.1816	31.1979
175.3604	56.0388	126.2489	149.7133	5.5684	78.8703	27.9132	66.7312
164.5568	27.8576	146.5334	28.9316	2.6715	91.0222	25.8416	22.2182
102.3618	62.1862	94.8570	188.3717	3.6783	183.6837	138.8371	153.4413
94.4015	131.5426	94.8570	187.5685	4.3150	225.3045	37.5815	46.6054

Sum of squares of variance is the sum of squared differences from the mean and is given by equation (3).

$$\text{Sum of squares of variance} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(i-\mu)^2 \cdot P(i,j) \qquad \dots (3)$$

The values of the sum of squares of variances (sosvh) are given in Table 3. The classification accuracy for sum of squares of variance feature is as shown in the Fig. 8.

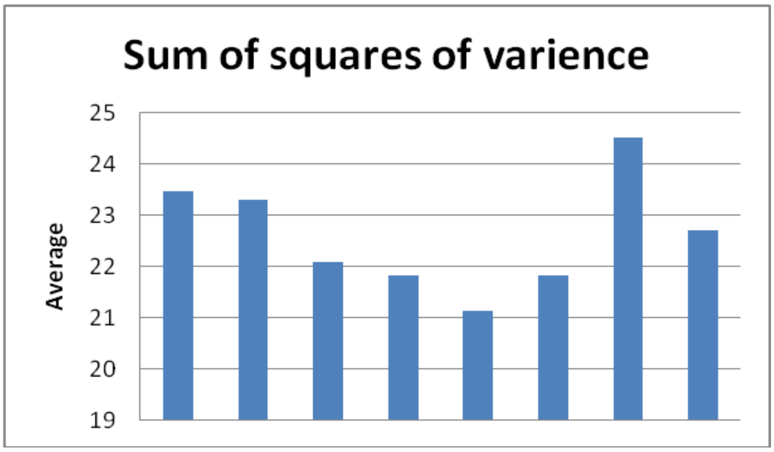

Fig 8 Sum of Squares of Variance Classification Accuracy

Table 3. Sum of Squares of Variance Values of all Field Images

Brinjal	Cotton	Groundnut	Maize	Paddy	Soyabean	Sugarcane	Sunflower
24.1566	22.0228	22.6526	23.3798	21.1373	20.7586	24.7548	19.6587
23.7573	29.6282	20.9673	21.8541	20.6254	21.7740	25.3031	20.7065
24.4243	23.5094	19.3631	19.5800	19.5839	20.1669	23.2380	21.0450
24.3550	20.7342	24.8057	24.2419	20.7086	19.9869	24.1338	21.8592
22.5699	20.9620	21.4894	24.3159	21.3518	20.6390	21.2715	21.0124
20.0308	21.5441	20.7263	22.8279	19.6264	22.0325	26.7849	28.0967
22.8105	19.6722	19.1731	12.8579	19.1862	20.0615	22.5508	24.0397
21.3863	24.6177	22.5945	13.6609	19.9331	22.3584	26.0171	24.6117
24.6366	27.4719	21.7420	26.0013	22.4216	22.0703	26.8215	22.7137
25.4699	22.3491	21.8990	23.6476	22.2014	22.7237	25.1151	22.3411
23.9552	23.0657	20.7959	24.5192	23.1431	19.8833	24.4746	22.3181
24.5059	21.4551	21.9804	21.2582	22.1690	23.1827	24.4983	22.1988
25.1807	23.7255	22.7222	22.9989	21.4747	21.9486	25.3698	24.1548
24.4059	20.4899	23.4881	24.4410	21.7382	23.2888	22.1174	23.7482
23.4594	23.9571	23.0488	25.0653	21.1373	20.5028	21.8106	21.5856
24.2877	25.1389	21.1517	17.0443	20.6254	23.2347	21.8212	20.7065
22.4083	24.8271	22.6780	22.7078	19.5839	21.1409	25.7321	19.6587
22.3608	22.1216	22.5560	21.4120	20.7086	22.4908	26.2482	21.5961
23.0799	24.5620	23.8240	20.0217	22.2014	23.1592	27.8217	28.0967
22.3022	24.1143	23.8240	24.6351	23.1431	25.1316	24.6156	24.0397

Variance is a measure of the dispersion of the values around the mean and combinations of reference and neighbor pixels. The extracted feature Sum of variance is given by equation (4).

$$\text{Sum of variance}=\sum_{i=1}^{2G}(1-\mu)^2 \,.\, P(i,j) \qquad \ldots \quad (4)$$

The values of sum of variance feature (svarh) are given in Table 4.

Table 4. Sum of Variance Values of all Field Images

Brinjal	Cotton	Groundnut	Maize	Paddy	Soyabean	Sugarcane	Sunflower
61.5071	61.0611	55.7271	56.9893	58.3234	49.3826	66.2892	50.7963
58.3437	80.3930	52.0006	53.0085	61.8918	52.8026	67.1609	56.3565
61.2019	63.1366	47.5872	47.3914	54.4222	46.8611	59.3473	53.3639
59.4160	58.1708	70.8356	59.9239	60.6515	45.7124	63.6148	56.0812

52.8150	59.9018	56.3524	61.2630	57.0448	50.6348	55.6125	51.1937
55.4595	56.8757	57.5992	55.4469	49.0071	53.4473	71.5249	74.2299
61.6839	52.1498	49.0793	29.3502	56.7187	47.7280	59.5911	65.6907
56.8136	68.4345	64.1541	31.6332	58.0660	56.3497	70.1662	61.0937
62.1173	79.7163	51.5087	66.2641	69.0747	53.0418	68.7146	57.8827
65.1970	60.5256	54.9923	57.8917	66.5957	56.2368	66.6322	59.2300
59.1702	58.8455	50.9031	62.3729	70.2538	44.9776	61.5559	59.4742
60.6539	58.0381	54.2515	50.4392	67.0080	56.1474	65.6986	55.8162
63.5955	66.1316	56.3702	57.2550	59.2134	53.5573	65.1201	62.0724
59.1868	56.2105	61.1277	61.1419	64.6484	58.2847	58.1461	63.8025
55.9458	64.2813	56.9338	63.1232	58.3234	51.0583	56.0741	56.5042
61.1356	69.1056	55.9701	39.8998	61.8918	57.6098	54.3368	56.3565
52.6087	71.0402	56.9390	59.3872	54.4222	53.2897	68.1268	50.7963
52.6290	59.4655	55.8722	57.2754	60.6515	54.7261	70.1771	63.5427
56.3020	67.7406	61.0470	46.1985	66.5957	55.5514	71.1651	74.2299
55.4269	62.6439	61.0470	61.3892	70.2538	62.5564	62.6972	65.6907

The classification accuracy for sum of variance feature is given in Fig. 9.

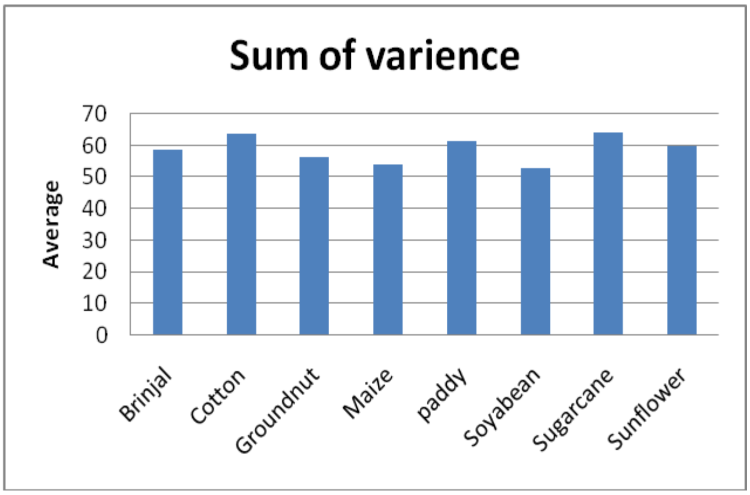

Figure 9. Sum of Variance Classification Accuracy

Sum of average is the sum of all values and divided by the total number of values and is given by the equation (5).

$$\text{Sum of average(Mean)} = \sum_{k=2}^{2G} k \sum_{ij} P(i,j) \qquad \dots (5)$$

The texture features extracted out of the above mentioned feature is given in Table 5. The classification accuracy for the sum of average feature is given Fig.10.

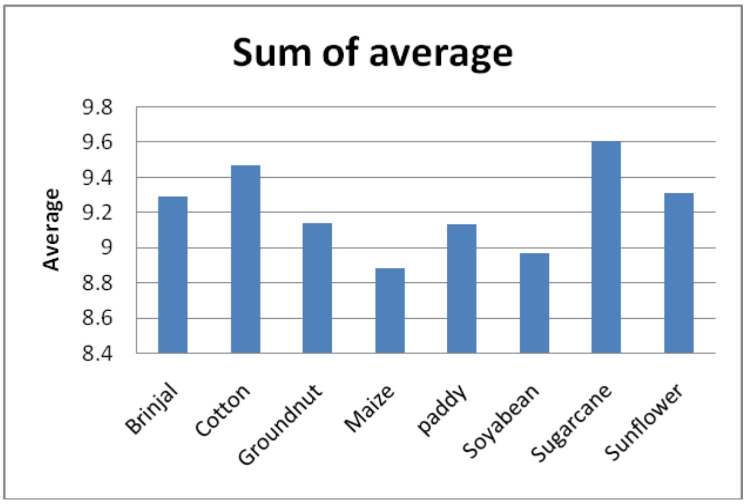

Figure 10. Sum of Average Classification Accuracy

Table 5. Sum of Average Values of all Field Images

Brinjal	Cotton	Groundnut	Maize	Paddy	Soyabean	Sugarcane	Sunflower
9.4608	9.2669	9.2660	9.1161	9.1142	8.7629	9.7759	8.6273
9.2564	10.6692	8.9258	8.9156	9.0502	8.9662	9.6955	8.9612
9.4658	9.4784	8.5723	8.4805	8.7848	8.5633	9.4030	8.9623
9.2511	9.0024	9.8378	9.3062	9.0597	8.4843	9.6760	9.1472
8.8063	9.0416	9.0994	9.4945	9.1273	8.8666	9.0824	8.8760
8.7888	9.1222	8.9754	9.0134	8.6839	9.1204	9.8525	10.2754
9.3653	8.7187	8.5738	6.8589	8.7180	8.6639	9.3375	9.6517
9.0722	9.8355	9.3989	7.0576	8.8817	9.2594	9.7571	9.5347
9.6551	10.3755	9.0204	9.5221	9.4383	9.0964	9.7593	9.3032
9.8609	9.2932	9.1657	9.2769	9.3861	9.2927	9.6139	9.3143
9.4690	9.2582	8.8820	9.5890	9.5869	8.3334	9.1917	9.2822
9.5250	9.1710	9.1081	8.8248	9.3831	9.2271	9.6724	9.2276
9.7472	9.6609	9.1034	9.1625	9.1791	8.9598	9.8693	9.5740
9.2979	8.9740	9.3833	9.4269	9.2831	9.2522	9.2431	9.5938
9.1285	9.5111	9.3253	9.5670	9.1142	8.7088	9.1505	9.1247
9.4326	9.8013	9.0591	7.7011	9.0502	9.2006	9.0796	8.9612
8.9608	9.7750	9.1015	9.2320	8.7848	8.9070	9.9889	8.6273
8.9780	9.2675	9.0337	9.1091	9.0597	9.1331	10.1008	9.1982
9.2288	9.6921	9.4624	8.4695	9.3861	9.1138	10.2461	10.2754
9.0843	9.4656	9.4624	9.4849	9.5869	9.4440	9.7178	9.6517

3.3.2 Color Features: There are different color spaces such as HSV, CMY, and LUV etc. Color intensity is represented independently in HSV (Hue, Saturation and Intensity) space, whereas it is not possible in RGB space.

3.3.2.1 HSV: Humans perceive colors as a combination of 3 colors: Red, Green and blue. The representation of HSV space is derived from the RGB space cube with the main diagonal of the RGB model as the vertical axis in HSV as shown in Fig. 11. The colors vary from unsaturated (gray) to saturated (no white component) as saturation varies from 0.0 to 1.0. Hue ranges from 0 to 360 degrees with variation from red, going through yellow, green, cyan, blue and magenta and back to red. The color space intuitively corresponds to the RGB model from which the other color models are derived through linear or nonlinear transformations.

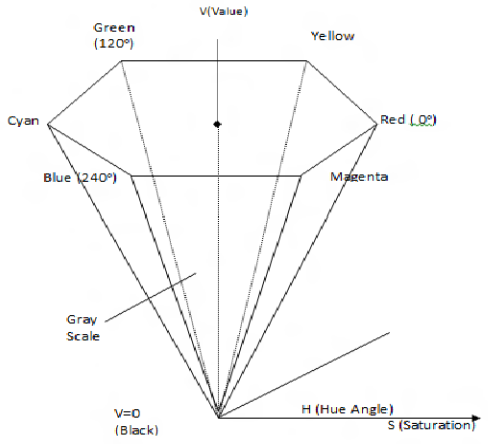

Figure 11. HSV Color Model

Based on Hue, Saturation and Intensity (HSV) color model mean and standard deviation are extracted. Mean provides average color value in the image and is given by the equation (6).

$$\text{Mean} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} Pij \qquad \dots (6)$$

The hue, saturation and intensity mean generated for all kinds of field images is as shown in the Table 6. The classification accuracy for the color feature mean is as shown in the Fig.12.

Table 6 HSV Mean Values of Different Field Images

Mean	Brinjal	Cotton	Groundnut	Maize	Paddy	Soyabean	Sugarcane	Sunflower
Hue	0.3183	0.3159	0.3004	0.2790	0.2630	0.2936	0.3257	0.2897
Saturation	0.2940	0.2800	0.3740	0.4720	0.6249	0.4108	0.2914	0.3153
Value	0.5745	0.5906	0.5803	0.5609	0.6130	0.5757	0.6005	0.5795

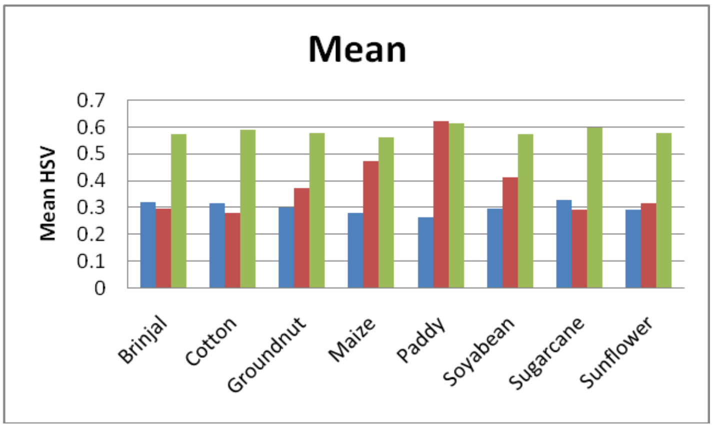

Figure 12. HSV Mean Histogram Plot

Standard deviation is defined as the square root of variance and is given by the equation (7)

$$\text{Standard Deviation} = \sqrt{\left[\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(Pij - \mu)\right.} \quad 2] \quad \ldots \quad (7)$$

The hue, saturation and intensity standard deviation generated for all kinds of field images and the classification accuracy is given in Table 7. Classification accuracy for the feature standard deviation is as shown in Fig.13.

Table 7 HSV Standard Deviation Values of All Field Images

STD	Brinjal	Cotton	Groundnut	Maize	Paddy	Soyabean	Sugarcane	Sunflower
Hue	0.0684	0.0890	0.0786	0.0811	0.0246	0.0728	0.0721	0.0700
Saturation	0.1265	0.0927	0.1254	0.2470	0.1198	0.1715	0.1302	0.1079
Value	0.1995	0.1366	0.1668	0.1934	0.0808	0.1991	0.1629	0.1545

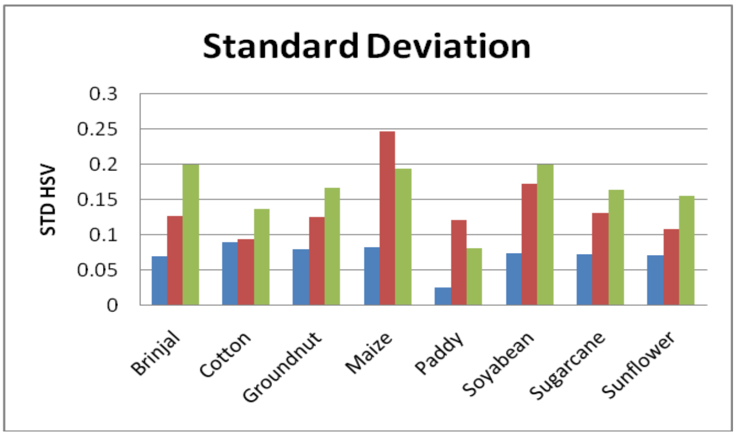

Figure 13. HSV Standard Deviation

3.3.3 Combined features: Considering individual features, the results obtained were not satisfactory. We experimented with combination of texture and color features. The results are quite encouraging. A total of seven features are finally deployed in the present work. The classification accuracy for the combined features is as shown in Fig. 14.

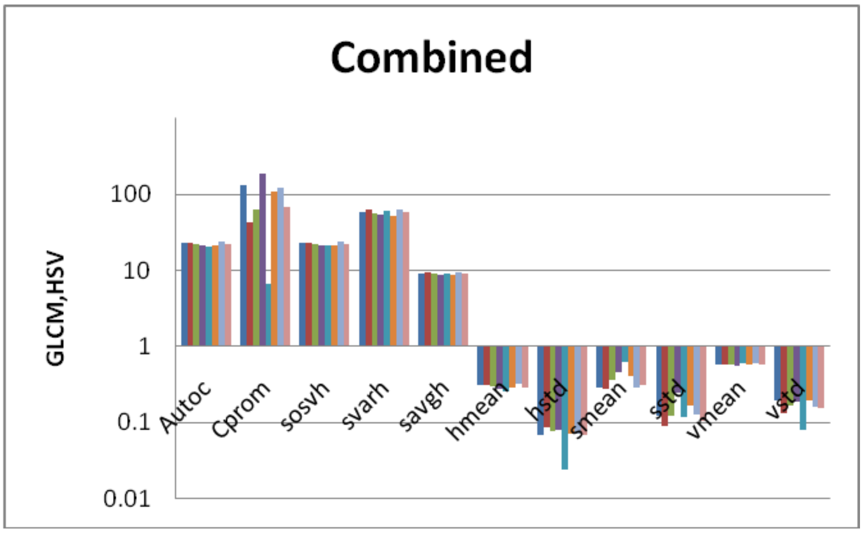

Figure 14. Classification Accuracy for Combined Texture and HSV Features

3.4 Classification:

Based on the computational simplicity Artificial Neural Network is used as a classifier. Feed forward multilayer network is used for the proposed work and back propagation algorithm is used for training the classifier. Classification is attempted in 3 stages, firstly, only with the texture features; secondly, with the color features and lastly with combination of both texture and color features. Input layer has seven nodes and output layer has eight nodes. The hidden layer is one. The termination error is set to 0.001.

4. Results and Discussion

We have used a total of 160 images. The average classification accuracy for GLCM features is given in Fig.15. The average classification accuracy for color features is given in Fig.16. The maximum accuracy is obtained for paddy field images. The minimum accuracy is obtained for groundnut field images. This is observed for both types of features.

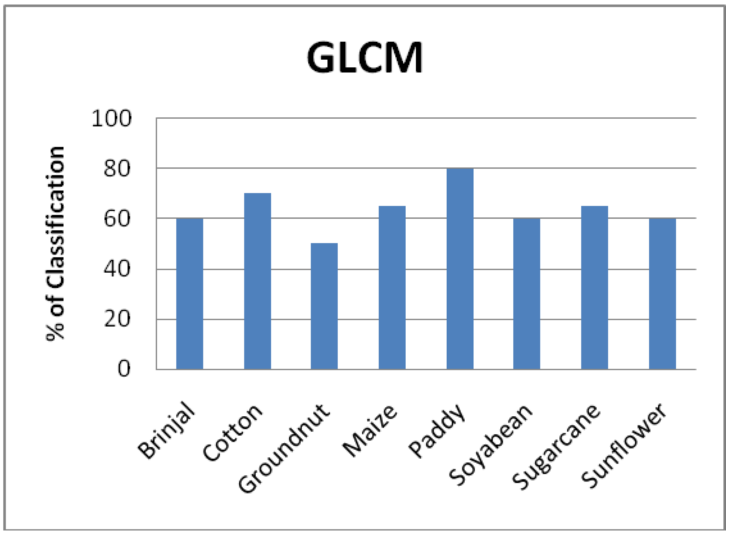

Figure 15. Classification Accuracy for GLCM Features

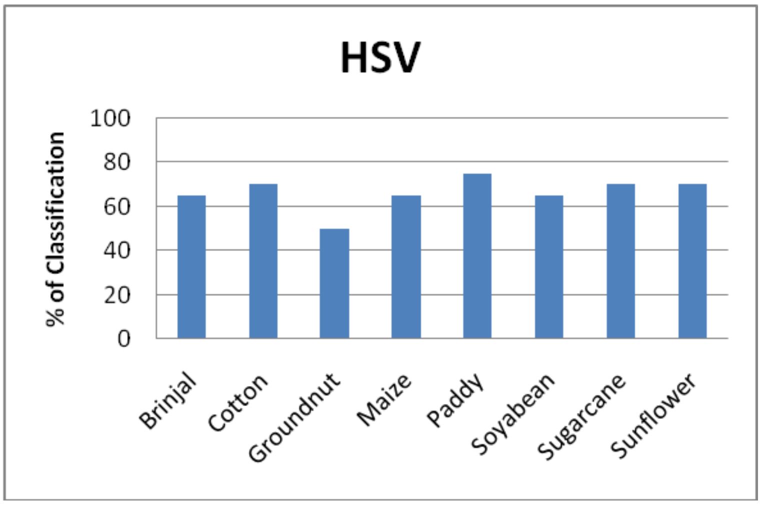

Figure 16. Classification Accuracy for HSV Features

Combination of texture and color (GLCM and HSV) features has resulted in classification accuracy of 84.375% and is given Fig.17. Accuracies are improved for all the field images.

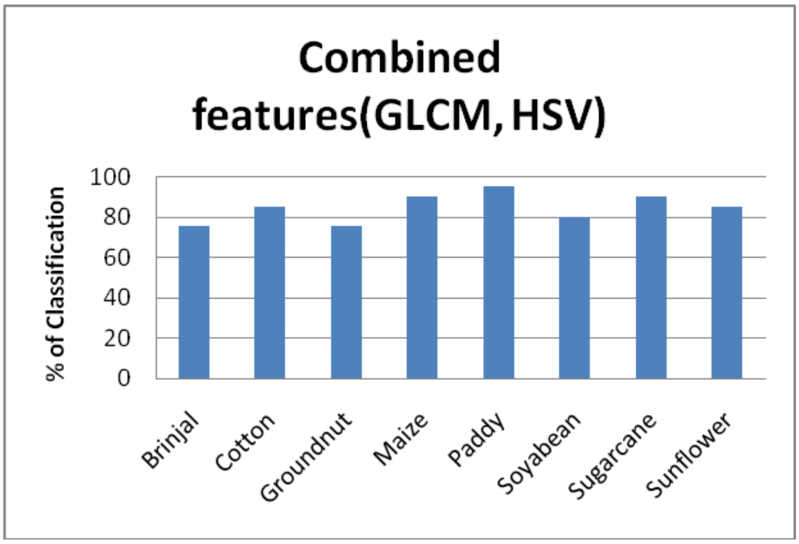

Figure 17: Classification Accuracy for Combination of Features

5. Conclusion

The work has reported the accuracies of classification of field images of 8 different types of crops. The color and texture features are deployed. An artificial neural network is used to classsify different types of crops. The combination of features has given good results compared to individual features. We have obtained an average accuracy of 84.375% for combination of features. The work finds application in technology deployment in Agriculture.

References

[1] H. Syahputra,, A. Harjoko, R. Wardoyo and R.Pulungan, "Plant recognition using stereo leaf image using gray-level co-occurrence matrix", *Journal of Computer Science* 10, no. 4, **(2013)**, p. 697.

[2] P. Pallavi and V. S. Veena Devi "Leaf regognition based on feature extraction and zernike moments", International journal of innovative research in computer and communication engineering", vol. 2, no. 2, **(2014)**.

[3] G. Ariputhiran and S. Gandhimathi, "Feature Extraction and Classification of High Resolution Satellite Images using GLCM and Back Propagation Technique", International Journal Of Engineering And Computer Science, vol. 2, no. 2, **(2013)**, pp. 525-528.

[4] V. Metre and J. Ghorpade, "An Overview of the Research on Texture Based Plant Leaf Classification", International Journal of Computer Science and Network, vol. 2, no. 3, **(2013)**.

[5] M. Maheshwari, M. Motwani and S. Silakari, "New Feature Extraction Technique for Color Image Clustering", International Journal of Computer Science and Electronics Engineering, vol. 1, no. 1 , **(2013)**.

[6] A.H. Kulkarni, H.M. Rai, K.A. Jahagirdar and P.S. Upparamani, "A Leaf Recognition Technique for Plant Classification Using RBPNN and Zernike Moments", International Journal of Advanced Research in Computer and Communication Engineering, vol. 2, no. 1, **(2013)**, pp. 984-988.

[7] S. Naikwadi, N. Amoda, "Advances in image processing for detection of plant diseases", International Journal of Application or Innovation in Engineering & Management, vol. 2, no. 11, **(2013)**.

[8] S. Abirami, V. Ramalingam, and S. Palanivel, "Species Classification of Aquatic Plants Using PSVM and ANFIS", Pattern Recognition and Image Analysis, vol. 23, no. 2, **(2013)**, pp. 278–286.

[9] A. Kadir, L. E. Nugroho, A. Susanto and P. I. Santosa, "Leaf Classification Using Shape, Color, and Texture Features", International Journal of Computer Trends and Technology, **(2011)**, pp. 225-230.

[10] Bhatt, Ashutosh Kumar, Durgesh Pant, and Richa Singh. "An analysis of the performance of Artificial Neural Network technique for apple classification", AI & society, vol. 29, **(2014)**, pp. 103-1111.

[11] J. A. Jaleel, S. Salim, R.B. Aswin, "Artificial Neural Network Based Detection of Skin Cancer", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, vol. 1, no. 3, **(2012)**.

[12] N. Fadilah,, J. M. Saleh, H. Ibrahim, and Z. A. Halim, "Oil palm fresh fruit bunch ripeness classification using artificial neural network", In Intelligent and Advanced Systems (ICIAS), 2012 4th International Conference, **(2012)**.

[13] R. Venkata Ramana Chary, D.Rajya Lakshmi and K.V.N Sunitha, "Feature extraction method for color image similarity", Advanced Computing: An International Journal , vol.3, no.2, **(2012)**.

[14] H. Yu, J. Cao, W. Luo and Y. Liu, "Image Retrieval of Wood Species by Color, Texture, and Spatial", International Conference on Information and Automation, **(2009)**.

[15] L. Zheng, J. Zhang, and Q. Wang, "Mean-shift-based color segmentation of images containing green vegetation", Computers and Electronics in Agriculture, vol. 65, no. 1, **(2009)**, pp. 93-98.

[16] Pydipati, R., T. F. Burks and W. S. Lee, "Identification of citrus disease using color texture features and discriminant analysis", Computers and electronics in agriculture, vol.52, no. 1, **(2006)**, pp.49-59.

[17] Fu, H., and Z. Chi. "Combined thresholding and neural network approach for vein pattern extraction from leaf images", IEE Proceedings-Vision, Image and Signal Processing, vol. 153, no. 6, **(2006)**, pp. 881-892.

