Automated Plant Count Using Unsupervised Classification on UAV Acquired Imagery

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DOI: https://doi.org/10.21467/proceedings.1.46

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Abstract

Precision farming is a farm management technique where in observing, measuring and responding is carried out using the latest technology. Its end output is to preserve the resources used in farming while optimizing on the returns. Previously satellites were used for this purpose and it had a lot of drawbacks of weather anomalies, low resolution and lack of real time data. This entire process can be done using an UAV system. In this study we focus on optimizing the time taken and maintain the accuracy of an industrial process of counting plants. Supervised classification is the most preferred method of classification as there is control over the classes and its well-established accuracy. But the main drawback is time taken in training the classifier. As there are more than hundreds of farms plots the same signature file cannot be used as there will be variation in the lighting conditions and shadows patterns. To solve this, we have used iso-cluster unsupervised classification and grouped the classes into plants and non-plant region. The accuracy stood at 95.4% compared to the accuracy of 97.8% obtained from supervised classification. This was within the 5% inaccuracy limit specified by the client. The major gain was the reduction of the time spent on the process. The supervised classification method took about 35 minutes whereas the unsupervised and grouping method took 10 minutes to complete the process for a 1.5 acres farm plot. This is a reduction of 70% of the time taken which is a very significant when plant counting has to be done for hundreds of plots.

Keywords: Unsupervised classification, Plant counting, UAV acquired imagery, Precision farming.

1 INTRODUCTION

Agriculture accounts for about 30 percent of India are GDP [1] and provide employment to 70 per cent of the rural households and 8 per cent of the urban households. As around 70 % of the Indian population live in rural areas [2] majority of them depend on the agricultural sector.

 ISBN: 978-81-936820-0-5

As the population increases every year the load on agricultural sector also increases year by year. In 1952, India had 0.33 ha of available land per capita, which is reduced to 0.15 ha at present. The only way to meet the demand are to increase yield and productivity, as new pastures of land are unavailable to farm. To meet the forthcoming demand and challenge new technologies have to be brought in to revolutionizing our agricultural productivity.

One of the revolutionizing technologies is precision farming [3]. It refers to precise inputs to the farm based on crop requirement, weather and soil to maximize sustainable productivity, quality and profitability. It includes the use of latest technologies such as remote sensing, geographic positioning system and geographical information system with an objective to improve profitability and productivity. Precision Farming gives farmers the ability to use crop inputs more effectively including fertilizers, pesticides, and tillage and irrigation water. More effective use of inputs means greater crop yield without causing much pollution to the environment. The various components of precision farming are soil pH, nutritional status, pest infestation, yield estimation, plant count etc. Plant count is also an important parameter in precision farming [4]. In order to count the plants, the imagery of the farm is required. This can be effectively captured using satellite images or images captured using UAV [5]. Satellite imagery has the disadvantage of having low resolution. Through there are satellites of 1-meter pixel resolution it is not sufficient to differentiate between plants as plants maybe of less than 1 meter in canopy width. Also, satellites cannot be used in cloudy weather conditions and there will be delays in getting necessary government clearances to use the data.

UAV's on the other hand gives data of 2cm pixel resolution. Hence using this we can differentiate between plants. To automate plant counting we must go for classification techniques to differentiate between plants and other quantities. According to literature supervised classification techniques [6] gives the best accuracies but training the classifier takes time. As in the industrial scenario there will be hundreds of plots where plant count is required. The same training samples will not hold good as the lighting conditions differ from plot to plot. Hence the classifier will have to be trained each and every time. This is very time-consuming process. In this paper we discuss an approach to count plants using unsupervised classification techniques [7]. This would potentially save time as no training is required. We also make a comparative study on the accuracies and the time taken from unsupervised and supervised classification and also on principal component analysis [8].

2 STUDY AREA AND DATA

Figure 1: Study area

The study area is chosen for this study is a 1.5acre farm plot. The center of the plot stretch has latitude and longitude of 19.055032 Nand 78.21671 E respectively. It lies in State of Telangana, India. The plants being grown in the farm plot is corn.

Table 1: Data used

Sl no	Data	Purpose
1	UAV Imagery	Unsupervised classification
2	Google earth	Overview
3	Field data	Validation of plant count

3 METHODOLOGY

The farm plot where plant count has to take place is located on Google earth and the UAV flight planning is done. The UAV chosen for this operation is DJI Phantom3. It is a quadcopter type of UAV. The UAV was used to capture ortho photographs. The ortho photographs had a 70% frontal overlap and 70% side overlap[9]. The ortho photographs were captured in the visible spectrum having the bands of Blue, Green and Red. The altitude at which the drone was flown was at 100 meters from the ground level.

Once the UAV completed its mission, all the captured photographs were imported into photogrammetric software for orthomosaic creation. The photogrammetric software used was Agisoft Photoscan. The output was an orthomosaic having true colorwith a spatial resolution of 3cm per pixel and this was imported into ArcGIS for further analysis.

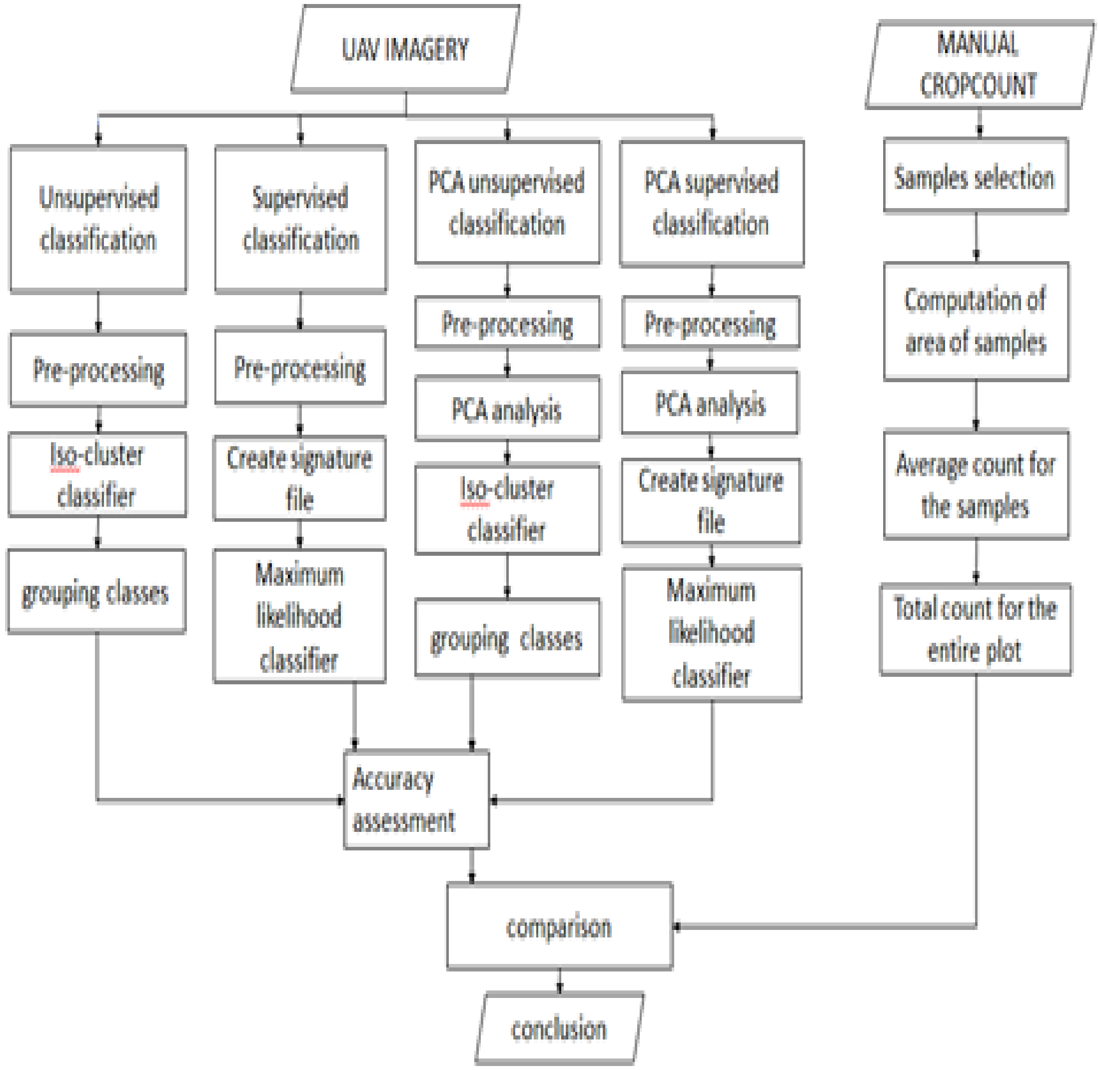

Figure 2: Methodology flow chart

Figure 3: Flight planning

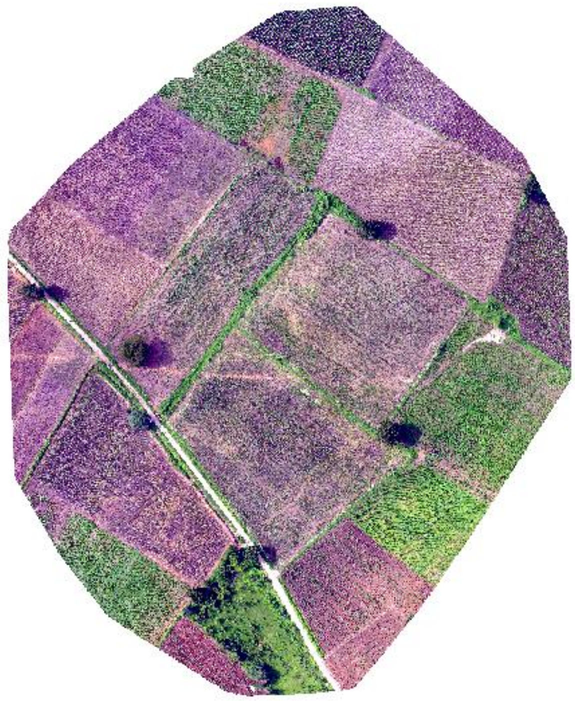

Figure 4: Orthomosaic

A shapefile was created to mark the exact boundary of the farm. This was done using polygon feature by keeping coordinate system as UTM zone 44^{o}N . The shapefile format is the digital vector storage format for storing geometric location and associated attribute information. Using the shape file we clipped the orthomosaic to end up with the exact raster image of the farm plot.

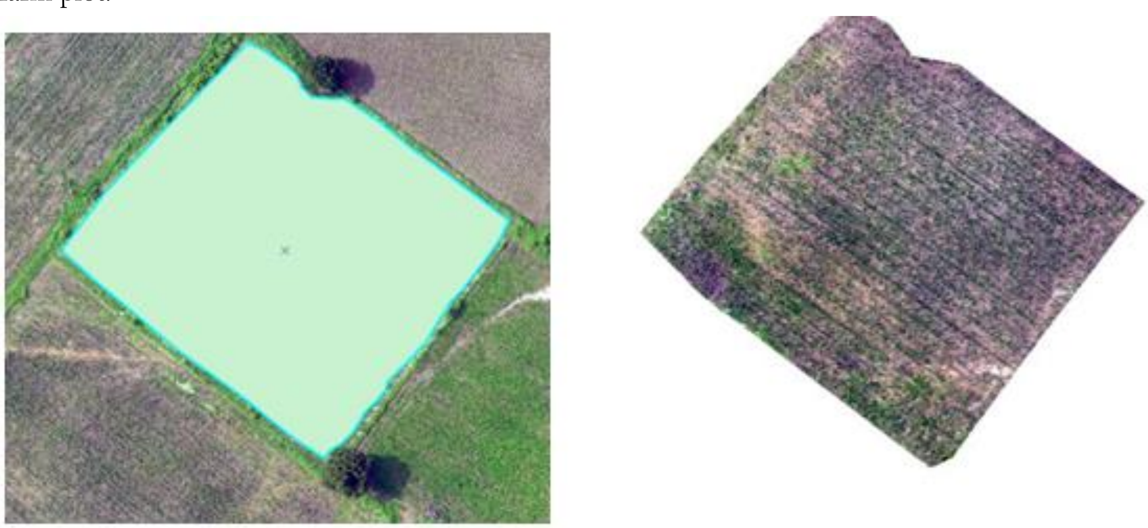

Figure 5: Clipped Orthomosaic

Using the multivariate tool bar unsupervised classification was performed using the iso cluster technique [10]. The parameters used were minimum class size that is the minimum number of cells in a valid class. The number of classes chosen was20 and sample interval as 10 pixels.
After creation of signature file[11], the color bands which represent plants were put into one category as plants and other color bands which are not plants were put into another category as non-plants. The first category consists of only plants and the second category consists of unwanted features like shadow, ground, and shrubs. This categorization is shown in the figure. Where green represents the plants and black represents the non-plant region.

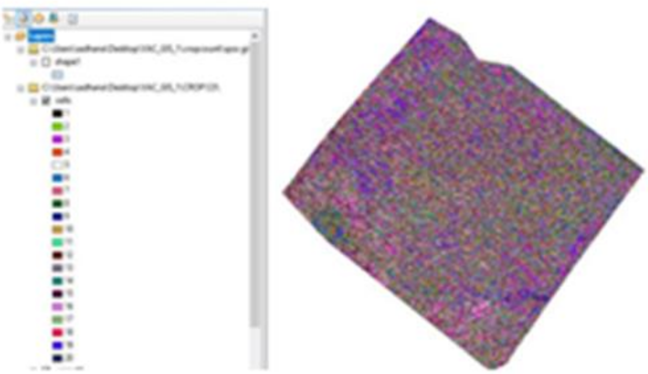

Figure 6: Unsupervised classification

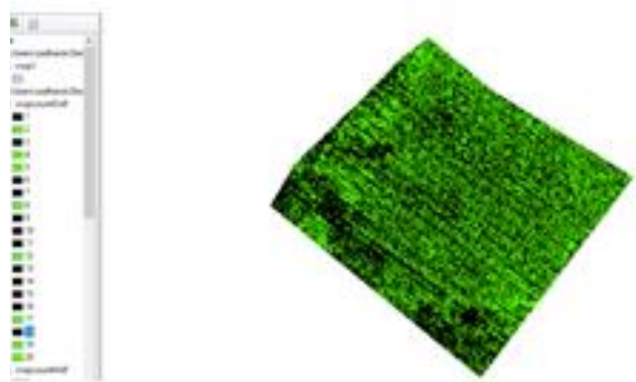

Figure 7: Grouping of clusters

In supervised classification the first step is to create training areas or to create training samples. Under this the multi band raster with three bands are categorised intointo four categories namely ground, plant, shadows and reflecting region. Once the training process is complete signature file was created for these training samples. After creating signature file, using multivariate tool bar supervised classification was performed using maximum likelihood classification technique[12][13]. In this technique the required parameter of signature file obtained by training samples was used.
Principal component analysis was carried out on the farm plot. An input parameter of four components was used. Using this unsupervised and supervised classification was carried out using the same procedure mentioned the above methodology.

ISBN: 978-81-936820-0-5

Proceedings DOI: 10.21467/proceedings.1

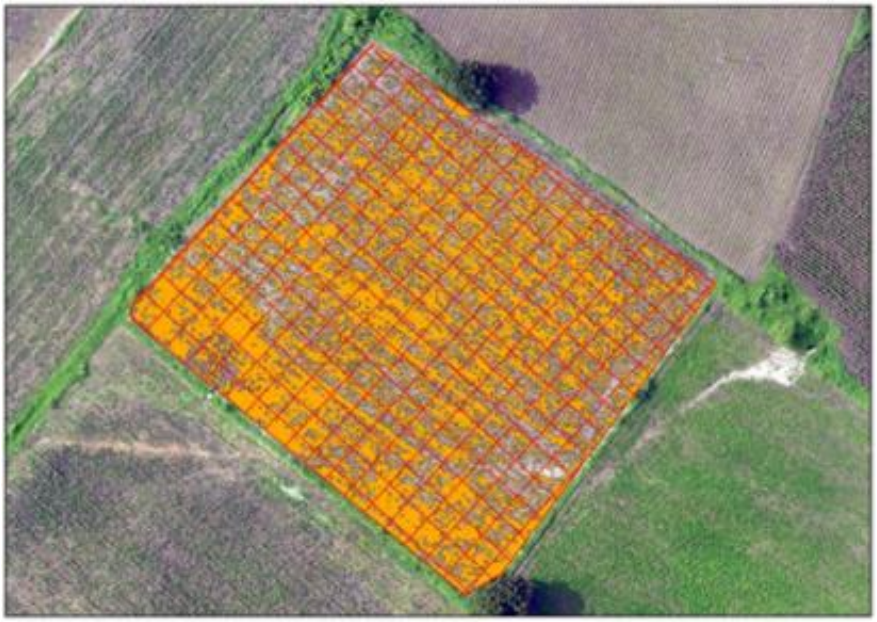

Figure 8: Supervised classification

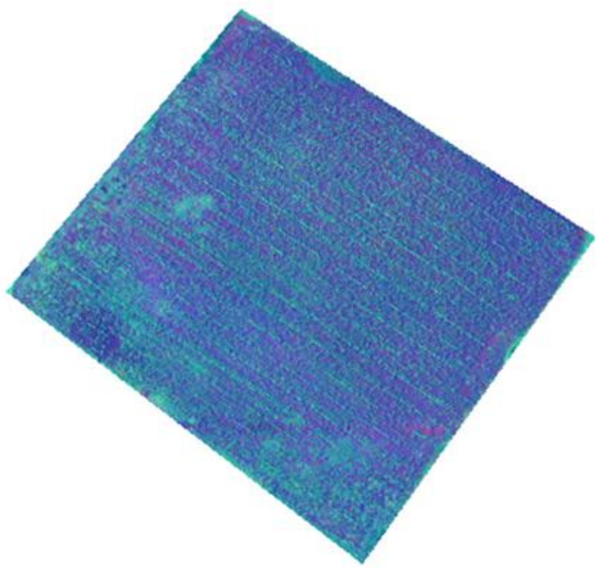

Figure 9: Principal component analysis

4 RESULTS

To compare the accuracies of the results obtained from the four procedures, a manual counting on field was carried out. The farm plot was gridded into subplots as shown in the figure below.

Figure 10: Sub plots

The number of plants in a fairly uniform subplot was counted. The area of plants in each sub plot was calculated by summing up the pixels which belong to plant category in each subplot. The area occupied by a plant was calculated for many subplots by the equation (1).

$$Area\ of\ 1\ plant = \frac{Area\ of\ plants\ in\ a\ subplot + Area\ of\ the\ empty\ rows}{Number\ of\ plants} \quad (1)$$

The average value of area of a plant for all the uniform subplots was calculated. This corresponded to a value of 0.1257 sq meters which is roughly a sqaure of side 35.5 cms. By extensive manual counting the number of plants was obtained for this particular plot was obtained as 25,370plants. Using this the number of plants in the entire plot was found out for the four classification methods adopted. They are listed in the table below.

Table 2: Accuracy assessment

	Classification method	Plant count	Accuracy	Time taken (minutes)
1	Unsupervised	24,202	95.4%	10
2	Supervised	24,811	97.8 %	35
3	PCA Unsupervised	24,136	95.1%	11
4	PCA Supervised	24,725	97.4%	36

5 CONCLUSION

It is evident from the table 2 that the unsupervised classification combined with grouping of classes gives a result within the acceptable standard of 95%. But the main advantage is the reduced time taken by this method which corresponds to 70% saving of time compared to supervised classification technique. Principle component analysis does not significantly

ISBN: 978-81-936820-0-5

Proceedings DOI: 10.21467/proceedings.1

improve the accuracy, or the time taken. Hence this method of unsupervised classification can help reduce time during scaling up of the plant counting exercises in the industries.

6 Acknowledgement

We would like to thank Skylark Drones for sharing the data. We would also acknowledge the technical support provided by Ms Pavithra Raghunathan, GIS Analyst, Skylark Drones.

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