Journal of Multidisciplinary Engineering Science and Technology (JMEST)
ISSN: 2458-9403
Vol. 4 Issue 8, August - 2017

Advances of image processing in Precision Agriculture:

Using deep learning convolution neural network for soil nutrient classification

Halimatu Sadiyah. Abdullahi,
Department of Communications Engineering,
School of Engineering & Informatics
University of Bradford,
Bradford, BD7 1DP UK.
H.S.Abdullahi1@bradford.ac.uk

Oba Mustpha Zubair
Department of Communications Engineering,
School of Engineering & Informatics,
University of Bradford,
Bradford, BD7 1DP UK.

***Abstract*— The application of technology to agricultural development can aid/improve agriculture in several ways through pre-planning and post-harvest processes through the use of computer vision technology in image processing to determine the soil nutrient composition, right amount, right time, right place application of farm input resources like fertilizers, herbicides, water, weed detection, early detection of pest and diseases etc. referred to as precision Agriculture. There has been a significant and constant improvement in the area of image processing and data processing which has being a major challenge. A database is developed from images of remote sensing, the images are analyzed and a model is developed to determine the right treatment plans for different crop types and different regions. Features of images from vegetation need to be extracted, classified, segmented and finally fed into the model. Different techniques have been applied to the processes from the use of neural network, support vector machine, fuzzy logic approach and recently, the most effective approach generating excellent results using the deep learning approach of convolution neural network for image classifications. Deep Convolution neural network is used in this research to determine soil nutrients required in a plantation to optimize production. The experimental results on the developed model yielded results with an average accuracy of 99.58 percentage.**

Keywords—Convolution; Feature extraction; Image analysis; Validation and Precision Agriculture:

I. INTRODUCTION

Sustainable agriculture is required to keep up with food production with the pace of population growing exponentially, this can be achieved with the application of emerging technologies in the sector to maximize production across a vegetation. Precision agriculture (PA) is the latest technology that enhances farming techniques by preparing the land before planting, ensuring an equally fertile vegetation across the field, monitoring plantations during in season growth: detection of early onset of pest and diseases, right amount, right time and right application of farm input resources to the right location through harvest and post- harvest processes. [1][2].

Precision agriculture is made up of a set of technologies that make use of sensors, information systems, improved machinery, and informed management to optimize production by accounting for variability and uncertainties in agricultural systems. By adjusting production inputs site-specifically within a field allows better use of resources to preserve the quality of the environment while improving the sustainability of the food supply. [3]. The technology is made mainly due to spatial and temporal variability on the field revealing information as, patterns and spatial relationships. The stages of remote sensing involve energy interaction with the atmosphere and interaction with the target, then the interaction of the energy to the sensor (camera), data transmission and processing, image analysis and finally application of results to treatment areas required[4][5].

Simple applications on the farm involve determining the location of sampling sites, plotting maps for use in the field, examining the distribution of soil types in relation to yields and productivity. Other applications take advantage of the analytical capabilities of GIS and RS software for vegetation classification to predict crop yield, environmental impacts, modelling of surface water drainage patterns, tracking animal migration patterns and other ranges of applications[6].

PA techniques are employed to optimize the use of available resources to increase the profitability and sustainability of agricultural operations. Also, to reduce negative environmental impact and to improve the quality of the environment. With GISs analytical capabilities, variable parameters that affect agricultural production can be analyzed. These parameters are the yield variability, physical parameters of the field, soil chemical and physical properties, crop variability (e.g., density, height, nutrient stress, water stress, chlorophyll content), anomalous factors (e.g., weed, insect, and disease infestation, wind damage), and variations in management practices (e.g., tillage practices, crop seeding rate, fertilizer and pesticide application, irrigation patterns and frequency)[7][8]. Figure 1 shows the process of information flow in crop production.

The process of image collection with remote sensing technology has advanced from the use of expensive resources (aircraft, satellites) where data was only available on demand to obtaining images with Unmanned Aerial Vehicle (UAV), smart phones etc. at more affordable costs and in real or near real times[9]. Analyzing the images provides information that can influence management decision on the farm for immediate treatment on the farm from pre planting to post harvest stages. Features extracted from the vegetation can be derived from its shape, height, texture, color, the rate of growth to develop a pattern to model the farm land.

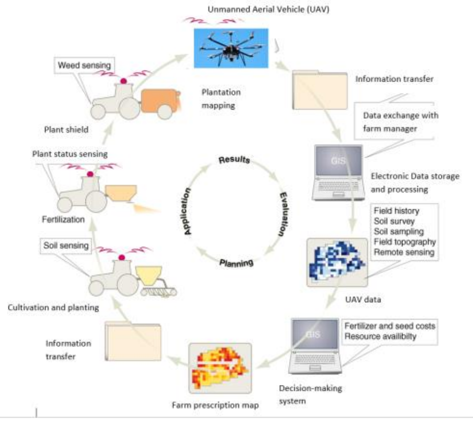

Figure 1: Information process flow of Precision Agriculture.

II. BACKGROUND AND RELATED WORK

A collection of imagery is available from satellites using both active and passive sensors operating from microwave to the ultraviolet regions of the electromagnetic wave spectrum. All of these vary in their spatial, spectral, radiometric and temporal resolution, playing an essential role by identifying which applications the sensors are best suited for. The satellite images are pre-processed and matched together which can provide information about crop identification, crop area determination and the crop health condition. The challenge of satellite image acquisition is the associated cost of obtaining the data, the images are obtained only during visit cycles limiting its availability on demand for real time applications, and also, it's very low resolution considering the long distance to the ground from where the images are taken. The use of smart phones have the ability to produce excellent images, they are equipped with various types of sensors to assist diverse farming tasks. The only set back of this technique is its limitation to cover the entire field within a specific period.

The use of Unmanned Aerial Vehicles (UAVs) is considered an efficient method of data collection on the field. The use of UAVs in agriculture is fast becoming widespread, while the implementation of aerospace engineering and sensor technology are reducing in cost. Drone technology gives the agricultural industry a high-technology remodeling, with planning and strategy based on real-time data gathering and processing [10][11]. UAVs collect images at high spatial resolutions enabling differences in crops to be compared by the centimetre. They also provide immediate visual information about large areas of crops, which help farm managers make fast decisions. UAVs can also transmit live videos from its flight operation to the receiving station on the ground. Depending on the type of camera employed, thermal images can be obtained from the UAV. The images obtained can then be imported into a GIS database for processing. Image processing involves a series of processes which are;

Image enhancement; the process of improving image quality before processing and it entails: noise removal, false color removal or detection, edge detection all done with simple image analysis technique in Matlab with fuzzy logic[12][13][14]. Images segmentation is a pre-processing stage of image analysis involving converting the image into segments based on uniformity. This is an important step necessary for efficient feature extraction. A variety of algorithms is usually developed to generate image objects.

To segment the images, two main domains are used: i) knowledge driven methods and ii) data driven methods (bottom-up) [15]. Feature extraction is the process of parametrizing the farm images for defining efficient descriptors: texture, colour or shape. Several research in the Precision Agriculture focus on this two approaches; feature extraction and classification including anthropometric models, statistical methods, and histograms of gradients. The most successful methods used until now are; artificial neural network and support vector machines. Both methods are combined together to achieve better feature extraction[16].

Artificial neural network in machine learning is an information processing systems that are intelligent programs inspired by the biological neural networks consisting of a computational system of structure, processing method and learning ability. ANN are characterized by a great number of simple processing neuron-like processing elements, a large number of weighted connections between elements, distributed representation of knowledge over the connections of the network. The ANN knowledge acquisition is through the learning process. Different network architectures require different learning algorithms which can be supervised learning where the network is provided with the correct output for every input pattern. The weights are determined to allow the network produce results as closely as possible to the known or set output results. The back propagation belongs to this category for checking errors back in the process[17]. Then the unsupervised learning does not require a known output linked with the input pattern in the training set. It explores the underlying structure of the data set or similarity between patterns and organizes data into categories from these correlations. The other category is the hybrid comprising of both the supervised and unsupervised learning with part of the weights determined through both processes.

There are two main types of ANNs based on architecture; feed-forward and feed-backward for training the network. Feed-forward ANNs are when the output of any layer is not likely to influence the same layer and feedback consists of the signals travel in both directions by involving loops in the neural network[18]. In this paper, a new approach is used in detecting the soil nutrients of a farmland: deep learning approach with using convolution neural network trained to fit the database of the plantation collated for identifying its condition for the required and proper treatment plan. This method was used by (Krizhevsku, 2012) to achieve a top 5 error of 16.4% for image classification with 1000 categories of data classes[19]. The error rate has since reduced significantly with the availability of the large dataset of images (over 10,000) collected by the plant village made freely available.

With precision Agriculture, implementation of management decisions on the farm like the right application of resources like; fertilizer, herbicide, water or nutrients for preparing the soil to make it fertile can be made easily and at the right time, quantity and location would lead to maximizing production the vegetation, informing on crop health and disease detection.

Authors have reviewed, presented and recognized the growing need to develop sensors to suit these purposes while implementing various technologies to increase agricultural production and maintaining the environment at the same time. Neural network model has been developed for estimating soil phosphorus using terrain analysis. They found a significant correlation between soil phosphorous and terrain attributes that can be used to derive the pedo-transfer function for soil p estimation to manage nutrient deficiency. The results showed that P values are accurate with the ANN-based pedo-transfer function with the input topographic variables along with the band 1 justifying 68% variation in the data distribution[20]. (Hulya Yalcin), proposed a CNN architecture to classify the different types of plants from image sequences. The results were compared with others from using SVM classifier with different kernels as well as feature descriptors of LBP and GIST. The performance of CNN achieved an accuracy of 97.47% which outperforms other methods with an accuracy between 74.92 to 89.94% [21].

Hao Li et al developed a series of comprehensive evaluation models used to determine soil nutrient composition using a combination of support vector machine and Artificial Neural Network. The results show that the average accuracy obtained for the general regression neural network was 92.86% indicating that ANN can be used effectively to assess the levels of soil nutrient with suitable dependent variables [22] . Makera M Aziz et al also used artificial neural network to determine the PH levels of soil within 5.5 to 8 and the value of the error recorded was very small. A value estimated by using neural network correlated very well (R2 between 0.8) and had low RMSE values (018), low MAE value (0.8) and low MAPE value 20%.They also suggested that the errors also can be reduced by increasing the numbers of sample data that is used for training to cover more soil color and more ph. Values[23].

This model achieved a precision of between 91 – 98% for separate class tests with an average performance of 96.3%. 13 different types of plant diseases out of healthy leaves with the ability to differentiate the leaves from their surroundings[24]. This was one of the first research implementing this approach.

Support vector machines and spectral vegetation indices were used by T. Rumpf et al to develop a procedure for the early detection and differentiation of sugar beet diseases based. The discrimination between healthy sugar beet leaves resulted in classification accuracy of 97% with the multiple classification between healthy leaves and leaves with symptoms of three diseases achieved an average accuracy of 86%[25]. It was also reported that Y.Lanthier et al did a comparative study between both supervised pixels oriented and the object oriented classification based on image segmentation in precision agriculture using hyperspectral images. Images were acquired with the CASI sensor and a statistical comparison on the mean difference to neighbor objects confirmed that the segments had minimum mixing effects in respect to other segmentation levels and neighboring ground entities[26]. Vyshavi G.K.P et al used neural network and SVM to diagnose plant diseases using image processing producing great results. The image of the plants were converted from RGB to Hue Intensity Saturation or lab color space. The leaf disease segmentation is done by using hierarchical clustering[27].

The relevance of the automatic detection of plant diseases using image analysis was highlighted with a proposed algorithm with SVM classifier that successfully detected and classified plant diseases with an accuracy of 94%. The experiment was performed with a database of 500 plant leaves with 30 different native plant species confirming the robustness of the approach. Application of Texture analysis was used in detecting and classifying the plant diseases[28].

III. METHODOLOGY

Convolution neural network allows a network to be trained from scratch with a large data set or fine tuning an existing model or making use of ‘’off the shelf Convolution neural network features’’. Fine tuning involves transferring weights of the first ‘n’ layers learned from a previous base network onto the new network. The dataset obtained for the new network is then trained with the transferred connections to perform the required tasks. CNN can efficiently learn generic image features and these features can be used with classifiers like the SVM, k-means clustering etc. to solve most computer vision problems. The process involves taking off the last layer of the trained CNN and using the activations of the last connected layer as features; the CNN is used in this stage as a feature extractor instead of a classifier and a classifier is used for the sorting process. Research has shown that this approach is effective for a dataset with small number of images and is also reported to outperform both the fine tuning and training from the scratch approach. CNN has been used for plant disease classification, fruit detection with transfer learning using imagery obtained from two modalities (RGB and NIR) information using late fusion technology to combine both information sources[29]. Deep CNN has also been used for automatic plant identification from image sequences collected from smart agro- stations [21], it has also been used to perform weed detection and classification with UGV applied to the input RGB + NEAR infra-red images[30]. The UGV adjusts the application of the herbicide to its required use. CNN has also been used in the classification of agricultural pest insects by computing a saliency map with the objective of an automated visual system to provide expert- level pest insect recognition with minimal operator training[31].

Despite all the research, this technique has not been exhaustively applied in determining the soil nutrient variation of the plants grown in a region. This is directly related to the production rate of any plantation. It will determine the quantity required and apply the right amount of nutrients where needed for a uniform and maximum germination on the farm.

Early detection of low producing areas on the field can be averted by making available the nutrients or resources required for maximum production during plantation, also early detection of disease is crucial step for the desired production.

Recent work on the soil nutrient determination (soil spectral information) have concentrated on using Artificial neural network and stepwise multiple linear regression analysis, regression analysis, quantitative hyper spectroscopy imaging based approach for assessing soil properties using reflection radiation, least squares support vector machines (LS-SVM) to construct calibration models for soil properties such as nitrogen, phosphorus, potassium [32][33] but none has done the feature extraction or classification with the ConvNets, principal component analysis, grey relational analysis, fuzzy evaluation, index method to analyze SOM quantities and quality in the spectral domain. While it is better to develop models for smaller areas due to non-uniformity of the soil in different regions rather than a larger geographical area. Lack of a global calibration model makes monitoring of the soil parameters quite difficult in the Vis-NIR and mid-IR spectroscopy.

Visible NIR has been developed as a major tool for quantitative determination of SOM and mid-IR for qualitative analysis.

The absorptions by SOM in the Vis-NIR are often not strong or readily apparent to the naked eye, the overall absorption due to SOM in the visible region is broad but clear. Using soil color to estimate SOM produced better results rather than using NIR alone. High spectra quality is desirable for accurate predictions (decrease noise and improve spectral features). Pre- treatment techniques for the spectra is done either by averaging, centering, smoothing, standardization, normalization or transformation. Some of the most frequent pre-treatment techniques are (i) MSC, (ii) SNV, (iii) smoothing and/or conversion to the first or second derivative, (iv) continuum removal, and (v) derivatives[34].

Variables from imagery infer information about soil condition by observing what happens on the surface in the vegetation growth. Factors affecting plant growth are climate conditions, soil properties geomorphological factors[11]. Information such as NDVI serves as an indication of green cover. Other information obtained is the fractional ground cover (FGC), an important factor in wind and water erosion mitigation. These factors that affect agricultural production give an insight into impacts from soil health and highlights areas where production falls short.

In this analysis, the performance of ConvNets is investigated in the quantitative remote sensing of soils with SVM and regression analysis to produce robust results. Soil nutrient analysis influences greatly on the regional distribution of the vegetation, community, biomass, plant size and the species composition. The quality of the soil is its capacity of the soil to function within an eco-system and its ability to sustain healthy plantations. Soil organic matter is the indicator of soil fertility and hence its quality. Understanding the SOM (soil organic matter) concentration helps in the management of soil nutrients present in the soil. SOM (a useful indicator of soil fertility) decreases by climate, texture, soil hydrology, land use, and vegetation. Both mid IR and VIS- NIR spectroscopy has been used to determine soil parameters in different configurations. SOM does not need to be precisely quantified, all that is required is a classification of soil conditions with respect to critical values for the more important properties[35][36].

Presently, with the increasing use of mobile phones, it has proliferated taking advantage of the rapid use of the technology in all parts of the world for a range of applications. Mobile phones approach used with deep learning classification (high-performance processors) can help in the identification process with its high resolution and extensive built in sets of accessories like the high definition camera of the new and improved phones. It allows the use of prompt analysis to be done on a piece of land as soon as possible.

In order to determine the soil composition from plant images, appropriate datasets are required at certain stages of object recognition from training to the evaluation of the performance of the algorithm for recognition. Images were from a primary maize farm site in Nigeria. The images were grouped into a number of classes from the leaf color and pattern. The deep neural network is trained to distinguish the plant leaves from its surrounding.

All the images obtained were resized using the Microsoft picture manager, the dataset needed to be augmented to train the network to learn the features that distinguish one class to another giving the network an opportunity to easily learn the appropriate features. A database of images from a smart phone (Samsung S6 edge +, 16MP, FL 9, auto real time HDR, VDIS, model number: model number; SM-G928F) was generated containing images for training and validation set. The study area used is owned by the Nigerian Government (Lower Niger Basin), used largely for cropping characterized by rain fed production systems. Rainfall data, land privatization, cumulative NDVI data need to be taken over a period of time to be included in the model parameters determining the productivity of the land for the region.

IV. EXPERIMENT

The procedure used for an extensive evaluation of the proposed method for determining the soil composition of a plantation is the use of a pre- trained CNN model for the classification. All images used in the experiments were cropped to a size of 224 x 224 and a data pre- processing step was deployed.

This analysis is used to determine the relationship between spectral radiance and soil parameters from the image reflectance. The correlation coefficients are obtained using the green- red ratio and a vegetation index similar to the NDVI with the red and green bands as represented in table I.

TABLE I. VEGETATION INDEX RESULTS FROM VISIBLE BANDS

Location (Year 2016)	Green band	Red band	Vegetation index	Stepwise regression
Nigeria	0.51	-0.38	0.58	0.75
Nigeria	-0.43	-0.55	0.52	0.78

The effects of vegetation/soil interactions on spectral patterns have reviewed in great detail in numerous papers (Carlson and Ripley 1997; Crist, 1984;Huete et al., 1985; Tucker, 1979)[37][38][39][40]. They all concluded that soil/plant interactions also affect yield. Thus, suggesting that soil variability plays an important part in yield determination and the indices formed are useful in determining plant growth. Plant yield is affected by a number of factors that can be monitored including soil moisture, nutrients, organic matter etc.

The visible RGB spectra cannot tell the difference between the reflectance of plant and soil. But with the use of a constant black background, a pure image can be separated from the soil image. The individual raw images are set to the camera's time and are calibrated with each pixel representing the reflectance value and not the color value. Dark pictures are not a cause for concern during the analysis because of the image reflectance. Orthomosaic of the images is stitched together to contain all individual images taken. The images should be stitched together using location tags as identification before being used to create a map. So, the spectral radiance was converted into vegetative indices such as Vegetation Index (VI). Also, stepwise regression is also performed to select the best band combinations relating to maize plant height. Simple correlations show the extent of topographic features, nutrients and yield behave.

K false Cross validation is used to provide an unbiased estimate of the classification[41]. Validating the model ensures that the quality control process used to determine the SOM complies with the specifications of the development phase. The data set is split into two parts; one set for training and the other for testing and validation. The ten-fold is usually the best with nine sets of the data used for training and 1 set for testing.

V. RESULTS AND DISCUSSION

The production season was at the ample time of June with early season rainfall after temperature rose and diminished during the day time. There was alternating weather with low rainfall at the critical reproductive phase and high temperature during the day contributing to crop stress which translates to low yields. The best correlation was achieved from computed Vegetation Index calculated with an R (correlation of coefficient) value at 0.78 showing a correlation with yield for the maize plantation.

The images from the maize plantation were sliced into patches and analyzed using the visible spectrum of the green and red bands. Values were assigned to each of the slices representing significant cut out areas of the field. The evaluation criterion of soil nutrient content was used to assign variables to the patches. The values represented on each of the patches are the average values of the soil nutrient contents. Table II shows the admitted criterion of the soil nutrient content.

TABLE II. ADMITTED CRITERION OF SOIL NUTRIENT CONTENT

Organic matter/g $\cdot$kg^{-1}	Total nitrogen /g$\cdot$kg^{-1}	Alkali-hydrolysable nitrogen/mg$\cdot$kg^{-1}	Rapidly available phosphorus/mg$\cdot$kg^{-1}
>40	>2.0	>150	>40
30–40	30–40	120–150	20–40
20–30	20–30	90–120	10–20
10–20	10–20	60–90	5–10
6–10	6–10	30–60	3–5

During computation, the results of the soil nutrient contents are saved up in a cell array with the highest number being the most fertile or most productive region on the plantation. The maximum value is then compared with other patches on the field to determine the amount of soil nutrient required for treatment on the areas for an equally fertile plantation. Fig 2 shows the result of the different fertility variations on the land.

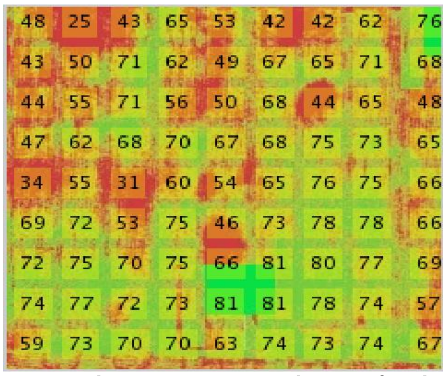

Figure 2: Soil nutrient variation on the maize farm land.

To achieve binary classification, the extracted features were fed into the SVM classifier and the data divided into ten partitions. The results obtained from the ten folds were averaged to get the overall performance of the model or its success rate. With convolution networks, features are learned easily when trained with a much larger datasets. With every iteration, results with great accuracies were obtained even with the 10^{th} iteration. The trained model was tested with the different image classes.

The results obtained are used to train the model of the CNN to accurately identify and specify treatment plans of the different plant areas. An image is used to test the network to produce the values of the individual patch treatment required as shown below. For an image with high soil nutrients, the network was able to predict results at an accuracy of 99.58% while for a badly damaged region, an accuracy of 98.9% were obtained. The results are shown in the graph below drawn with ROC (Receiver Operating Characteristics) in Fig 3.

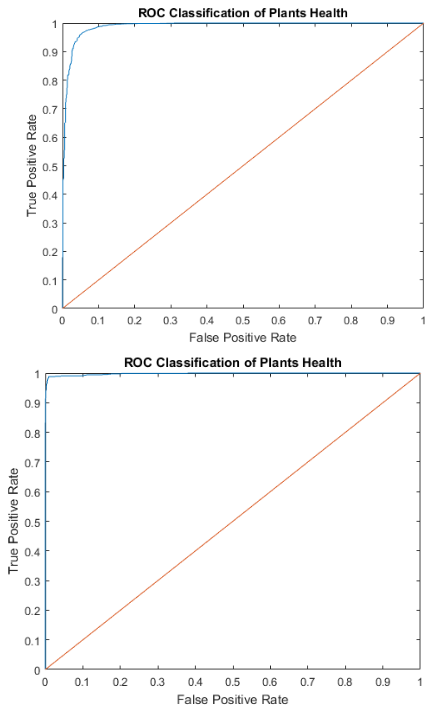

Figure 3 (a) & (b): ROC Results of the analysis using the ConvNets model for both a healthy region and an unhealthy region of a plantation.

The true positive show the image classification as healthy or unhealthy while the confusion matrix show the true negative results from the graphs. The colored graph depicts random guesses, worst case scenario for any predicted model suggesting that the results cannot fall before that level. Also, it depicts that the performance of the algorithm is excellent and further proves the power of the ConvNets and its efficiency especially after conducting the experiments.

VI. CONCLUSION

The use of Support Vector Machine and off- the- shelf ConvNet representations for the problem of estimating soil nutrient content on a maize plantation was used with an average prediction accuracy of 99.8%. This proves the ability of the model to accurately predict the treatment solutions to produce an equally fertile land for optimization of production. This model can be used and developed for different land calibration from one geographical region to another on the country level.

REFERENCES

[1] R. Bongiovanni and J. Lowenberg-Deboer, “Precision agriculture and sustainability,” *Precis. Agric.*, vol. 5, no. 4, pp. 359–387, 2004.

[2] J. V Stafford, “Implementing Precision Agriculture in the 21st Century,” *J. Agric. Eng. Res.*, vol. 76, no. 3, pp. 267–275, 2000.

[3] A. McBratney, B. Whelan, T. Ancev, and J. Bouma, “Future directions of precision agriculture,” *Precis. Agric.*, vol. 6, no. 1, pp. 7–23, 2005.

[4] N. Zhang, M. Wang, and N. Wang, “Precision agriculture - A worldwide overview,” *Comput. Electron. Agric.*, vol. 36, no. 2–3, pp. 113–132, 2002.

[5] H. S. Abdullahi, F. Mahieddine, and R. E. Sheriff, “Wireless and Satellite Systems,” vol. 154, no. January 2016, pp. 388–400, 2015.

[6] E. S. Government of Alberta, Alberta Agriculture and Rural Development, Policy and Environment, “What Is Precision Farming?” Taber, Alberta, Canada, 1997.

[7] C. Brown, “GIS, GPS, and Remote Sensing Technologies in Extension Services Where to Start, What to Know,” pp. 1–6, 2016.

[8] T. Shi, “Ecological agriculture in China: Bridging the gap between rhetoric and practice of sustainability,” *Ecol. Econ.*, vol. 42, no. 3, pp. 359–368, 2002.

[9] C. Zhang and J. M. Kovacs, “The application of small unmanned aerial systems for precision agriculture: A review,” *Precis. Agric.*, vol. 13, no. 6, pp. 693–712, 2012.

[10] “UAVs and Precision Agriculture #15.” [Online]. Available: http://aerialfarmer.blogspot.co.uk/2014/03/uavs-and-precision-agriculture-15.html. [Accessed: 08-Mar-2015].

[11] D. Wright, V. Rasmussen, R. Ramsey, D. Baker, and J. Ellsworth, “Canopy Reflectance Estimation of Wheat Nitrogen Content for Grain Protein Management,” *GIScience Remote Sens.*, vol. 41,

no. 4, pp. 287–300, 2004.

[12] "UAV Cameras and Sensors, Precision Agriculture." [Online]. Available: http://www.thedroneinfo.com/2015/03/13/uav-cameras-sensors-precision-agriculture/. [Accessed: 15-Mar-2015].

[13] J. Barnard, "Small UAV Command, Control and Communication Issues," *with UAVs … with UAVs*, vol. 2010, no. 15 November 2010, pp. 75–85, 2007.

[14] F. G. Costa, J. Ueyama, T. Braun, G. Pessin, F. S. Osorio, and P. A. Vargas, "The use of unmanned aerial vehicles and wireless sensor network in agricultural applications," *2012 IEEE Int. Geosci. Remote Sens. Symp.*, pp. 5045–5048, 2012.

[15] L. Wang, J. Shi, G. Song, and I. Shen, "Object Detection Combining Recognition and Segmentation," *Lecture Notes in Computer Science*, vol. 4843, no. 2. p. 189, 2007.

[16] K. A. Mate G Pooja, Singh R Kavita, "Feature Extraction Algorithm for Estimation of Agriculture Acreage from Remote Sensing Images," pp. 5–9, 2016.

[17] A. K. Jain, J. Mao, and K. M. Mohiuddin, "Artificial neural networks: A tutorial," *IEEE*, vol. 29, no. 3, pp. 31–44, 1996.

[18] S. Sootla, "Artificial neural network for image classification," University of Tartu Artificial, 2015.

[19] K. Alex, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Neural Information Processing Systems (NIPS)*, 2012, pp. 1097–1105.

[20] A. Keshavarzi, F. Sarmadian, E.-S. E. Omran, and M. Iqbal, "A neural network model for estimating soil phosphorus using terrain analysis," *Egypt. J. Remote Sens. Sp. Sci.*, vol. 18, no. 2, pp. 127–135, 2015.

[21] H. Yalcin and S. Razavi, "Plant Classification using Convolutional Neural Networks." 2016.

[22] H. Li, W. Leng, Y. Zhou, F. Chen, Z. Xiu, and D. Yang, "Evaluation Models for Soil Nutrient Based on Support Vector Machine and Artificial Neural Networks," *The Scientific World Journal*, vol. 2014. pp. 1–8, 2014.

[23] M. M. Aziz, D. Rafaa Ahmed, and B. Fareed Ibrahim, "International Journal of Advanced Research in Computer Science and Software Engineering Determine the Ph. of Soil by Using Neural Network Based on Soil's Colour," vol. 6, no. 11, 2016.

[24] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep neural networks based recognition of plant diseases by leaf image classification," vol. 2016. 2017.

[25] T. Rumpf, "Finding spectral features for the early identication of biotic stress in plants." 2012.

[26] Y. Lanthier, A. Bannari, D. Haboudane, J. R. Miller, and N. Tremblay, "Hyperspectral Data Segmentation and Classification in Precision Agriculture : a Multi-Scale Analysis," *Environment*. pp. 4–5.

[27] G. K. P. Vyshnavi, M. R. Sirpa, M. Chandramoorthy, and B. Padmapriya, "Healthy and Unhealthy Plant Leaf Identification and Classification Using Hierarchical Clustering." pp. 448–453, 2016.

[28] S. Arivazhagan, R. N. Shebiah, S. Ananthi, and S. Vishnu Varthini, "Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features," *Agricultural Engineering International: CIGR Journal*, vol. 15, no. 1. pp. 211–217, 2013.

[29] D. S. Srdjan Sladojevic, Marko Arsenovic, Andras Anderla, "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification," *Comput. Intell. Neurosci.*, vol. 2016, 2016.

[30] C. Potena, D. Nardi, and A. Pretto, "Fast and Accurate Crop and Weed Identification with Summarized Train Sets for Precision Agriculture." 2016.

[31] Z. Liu, J. Gao, G. Yang, H. Zhang, and Y. He, "Localization and Classification of Paddy Field Pests using a Saliency Map and Deep Convolutional Neural Network," *Scientific Reports*, vol. 6, no. February. p. 20410, 2016.

[32] E. Ben-Dor, "Quantitative remote sensing of soil properties," *Advances in Agronomy*, vol. 75, no. July. pp. 173–243, 2002.

[33] Y. Qiao and S. Zhang, "Near-infrared spectroscopy technology for soil nutrients detection based on LS-SVM," *IFIP Advances in Information and Communication Technology*, vol. 368 AICT, no. PART 1. pp. 325–335, 2012.

[34] A. Gholizadeh, B. Luboš, M. Saberioon, and R. Vašát, "Visible, near-infrared, and mid-infrared spectroscopy applications for soil assessment with emphasis on soil organic matter content and quality: State-of-the-art and key issues," *Applied Spectroscopy*, vol. 67, no. 12. pp. 1349–1362, 2013.

[35] E. M. Barnes *et al.*, "Remote- and Ground-Based Sensor Techniques to Map Soil Properties," *Photogramm. Eng. Remote Sens.*, vol. 69, no. 6, pp. 619–630, 2003.

[36] C. T. Leon *et al.*, "Utility of Remote Sensing in Predicting Crop and Soil Characteristics," *Precision Agriculture*, vol. 4, no. 4. pp. 359–384, 2003.

[37] T. N. Carlson and D. A. Ripley, "On the relation between NDVI, fractional vegetation cover, and leaf area index," *Remote Sensing of Environment*, vol. 62, no. 3. pp. 241–252, 1997.

[38] A. . Huete, "A review of vegetation indices.pdf," *Remote Sens.*, vol. 13, pp. 95–120, 1995.

[39] R. de Jong, S. de Bruin, A. de Wit, M. E. Schaepman, and D. L. Dent, "Analysis of monotonic greening and browning trends from global NDVI time-series," *Remote Sensing of Environment*, vol. 115, no. 2. pp. 692–702, 2011.

[40] B. Crist, M. Science, D. K. Odense, and M. A. Ratner, "Polymer Fracture - A Simple Model for Chain Scission," *J. Polym. Sci. Polym. Phys. Ed.*, vol. 22, no. 5, pp. 881–897, May 1984.

[41] E.-S. E. Omran, "Improving the Prediction Accuracy of Soil Mapping through Geostatistics," *International Journal of Geosciences*, vol. 03, no. 03. pp. 574–590, 2012.