Crop Health Analysis with the Help of Soil Parameters by Using ASDFieldspec4 Spectroradiometer

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Abstract. Crop health information represented through hyperspectral data is of great importance for precision agriculture. Because of the similarity in the spectral signatures of crops, discrimination of crop health using non-imaging spectral signatures is still a very challenging task for researchers. In this research work, spectral signatures are developed for soil, cotton, and maize crops from study area. Crop health is analyzed by considering of soil parameters and discriminated against Cotton and Maize crops. These all objectives prove to be essential in precision agriculture. ASD Field Spec4 for spectral signature collection has used, which has the capacity to discriminate objects in the range of 350-2500 nm. The study has carried out on various wavelength ranges or values. We have applied NDVI and CRI2 spectral vegetation indices for the analysis of spectral signature crops. Soil spectral signatures have been created and observed the N(Nitrogen), P(Phosphorus), K(potassium) and pH value of soil. Effects of various indices are studied and developed threshold values for health analysis of crops and found the relationship between soil health and crop health. Through the investigational study of results we found that NDVI and CRI2 performs well for crop health analysis. Finally Supervised machine learning algorithms SVM and KNN applied for classification of healthy and unhealthy crops in which SVM gives the result for health analysis of Maize is 90% and 87.5 for Cotton. KNN gives the accuracy of 85% for Maize and 92.5 for Cotton.

Keywords: Precision Agriculture · Crop Health Analysis · Spectral signature · Vegetation Indices · NPK · pH value · ASD FieldSpec4 Spectroradiometer · Supervised Machine Learning

1 Introduction

Given that it generates over 17% of the country's GDP and employs more than 60% of the workforce, agriculture is a significant sector of the Indian economy [1]. But growing global population is employing burden on natural resources to fulfil the enlarged human needs. We have to focus on how to increase the crop yield and for that an effective exploitation of the natural resources has become more significant than ever

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to meet these enlarged demands. Precision agriculture plays an important role to solve this problem. Precision agriculture is a management of farming which includes observation, measurement and attending to the plant needs. Through the use of cutting-edge, environmentally friendly technologies, such as remote sensing, sensors, GPS, and data analytics, precision agriculture attempts to improve the effectiveness of resource utilization. To increase the crop yield we have to pay attention on crop health which is basically depend on soil health, environmental changes, rain condition, etc. Monitoring the health of the soil is crucial since it might affect the crop's quality if the water and nutrient levels are out of balance [40]. Crop health promotes food availability and food security. So that it is required to take precaution and early treatment of the crop illness. By visually we cannot identify the diseased plant earlier than a sensor. We have used a Hyperspectral sensor ASDFieldSpec4 device to create the spectral signature of crop which gives the emphasize information about every objects. A spectral signature is a term used to describe how an object reflects light at different wave lengths of the electromagnetic spectrum. Various materials have very variable spectral reflectance signatures. The reflectance of snow is very high in the visible region (blue, green, red), resulting in its "white" appearance (i.e., colour theory tells us that high and equal amounts of blue, green, and red result in the colour white). With poor reflection in the visible, great reflection in the NIR, and lower reflection in the SWIR section of the spectrum, vegetation display displays distinctive spectral reflectance characteristics. Plant stress, senescence, chlorophyll concentration, leaf type and morphology, as well as other factors, alter the spectral reflectance fingerprints of vegetation.

1.1 ASD FieldSpec4 Sensor

Hyperspectral data with Nano-level reflectance details are provided by ASD Field Spec 4 with the wavelength limit of 350–2500 nm. Due to its 3 nm VNIR and 8 nm SWIR spectral resolution, the ASD FieldSpec4 provides improved spectral achievement over the whole solar irradiance spectrum. The SWIR region (range: 1000 nm - 2500 nm) is especially beneficial for the detection and the identification of combinations with limited spectral features in the longer wavelengths, such as alteration minerals and gases for atmospheric investigation. Because of its resolution, which matches the spectral resolution of the ASD FieldSpec4 sensor, it is also a perfect choice for validation and calibration of a sensor, ground truthing, and creating spectral libraries (Fig. 1).

1.2 Electromagnetic Spectrum

Gamma rays which have the shortest wavelength in the electromagnetic spectrum, are followed by lengthy wavelengths employed in communications (microwaves). These are a number of names that are frequently used to characterize the different spectral regions for remote sensing [6].The blue (0.4 tomicro m), green (0.5 to 0.6 micro m), and red (0.6 to 0.7 micro m) are spectral intervals of the visible (VIS) region (0.4 to 0.7 micro m). NIR or near-infrared (range 0.7 to 1.2 micro m) is particularly interesting because of its ability to discriminate green vegetation. From 1.2 to 3 micro m - shortwave infrared (SWIR).

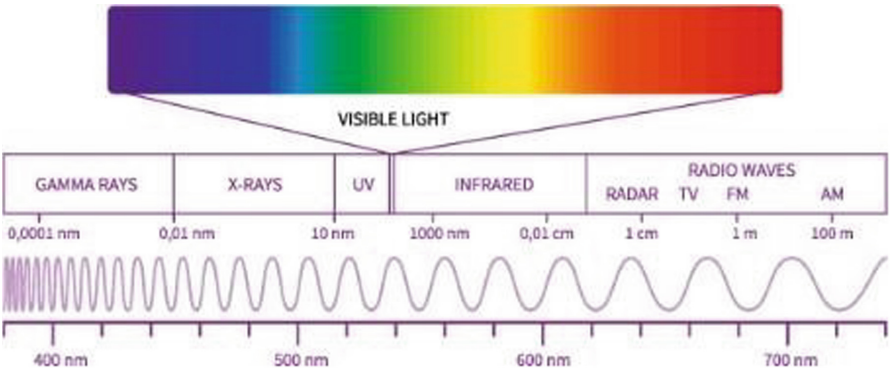

Fig.1. Electromagnetic Spectrum [8].

2 Literature Survey

We have studied various recent research works in the field and some of them are listed below such as Surase R. R., et al., developed a system with the combination of ASD Field spec and Hyperion sensor. Which discloses crop parameters based on spectral vegetation indices. Selected crops were Cotton, Maize, Vigna Radiata, and Bajara. A total of 400 spectral signatures were measured using a spectroradiometer within the wavelength range 350 nm to 2500 nm along with the EO-1 Hyperion dataset. An acceptable parameter for the range of -1 to + 1 was determined to be the Normalized Difference Vegetation Index. They also outlined the fundamental requirements for collecting a standard hyperspectral database utilizing the 0.35–2.5 μm ASD Field Spec 4 Spectroradiometer. Additionally, the ASD device offers database gathering in the field and laboratories employing targets with a 1 degree, 8 degrees, and 25 degrees Field Of View [32].Vlachopoulos, O., et al., has assessed the crop health status for barley and oat crop through green area index and vegetation indices and achieved the accuracy of 94% by using random forests algorithms. They have collected the database through the unmaned aircraft system (UAS) with the payload of multispectral optical sensor of Red Edge. The camera is having 5 bands (blue, green, red, red-edge, and NIR). They have classified the crops in two classes as stressed and vigorus [33]. AbdelRahman, M. A., et al., has created soil type map for study area in Karnataka. In that they have tested the EC, pH, BD, OM, and some micronutrients by using remotely sensed data of (LISS III and LISS IV) and ancillary data [34]. Moghadam, P., et al., have used visible, NIR and SWIR region of hyperspectral image and machine learning techniques for plant disease detection. They have used various vegetation indices for health assessment. In that they have concluded that, NDVI and SR are related to stress and biomass, PSSR response to chlorophyll concentration and WBI (water Band Index) is relate to the leaf moisture. They have SVM on vegetation indices which gives 93.6% accuracy in VNIR region [35]. Gholizadeh, A., et al., they have used ASDFieldSpec4, ASDFieldSpec3, and FOSS XDS Rapid Content Analyzer for soil testing they have used 143 soil samples from various places. All three devices gives almost same results but there is only variation in the visible region. FOSS XDS spectrometer gives the better result than other two [36].

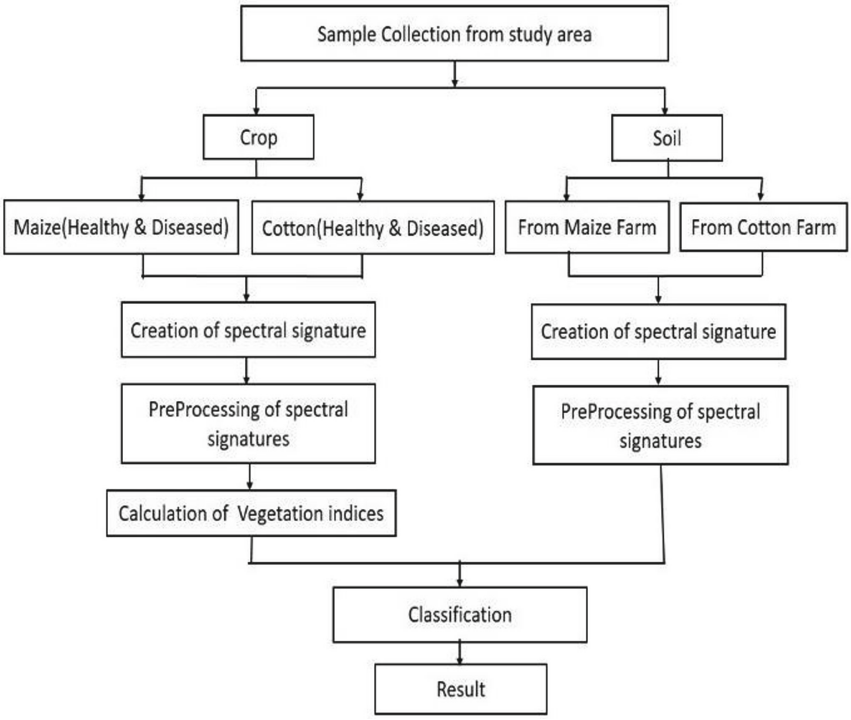

Fig. 2. Methodology for research work.

Panwar, A., et al., have gone through an experiment held in a greenhouse to check the plant stress because of soil health by using image processing and machine learning techniques. The have captured all the images of every stage of selected plants, preprocessed it and applied random forest based algorithms for detecting the changes in plant leaves by their color[37]. Teke, M., et.al, collected the survey about the hyperspectral remote sensing for precision agriculture. In that they have stated that hyperspectral technology can be used for health analysis of crops and soil very effectively [38] [39]. Hyperspectral technology can be used in precision agriculture for crop and soil health monitoring [40], crop yield estimation [41], crop health assessment [42], and for various applications in precision agriculture. Various paper have been observed about plant growth and soil health. But very less amount of papers have been observed about how soil health affects the crop health or plant. Through the relevant study, machine learning algorithms and hyperspectral technology can be used for plant health assessment (Fig. 2).

3 Methodology and Materials

3.1 Data Collection and Study Area

In ruby season total 80 samples in which 20 samples of each healthy and unhealthy selected crop (Cotton and Maize) were randomly selected from the field of the selected

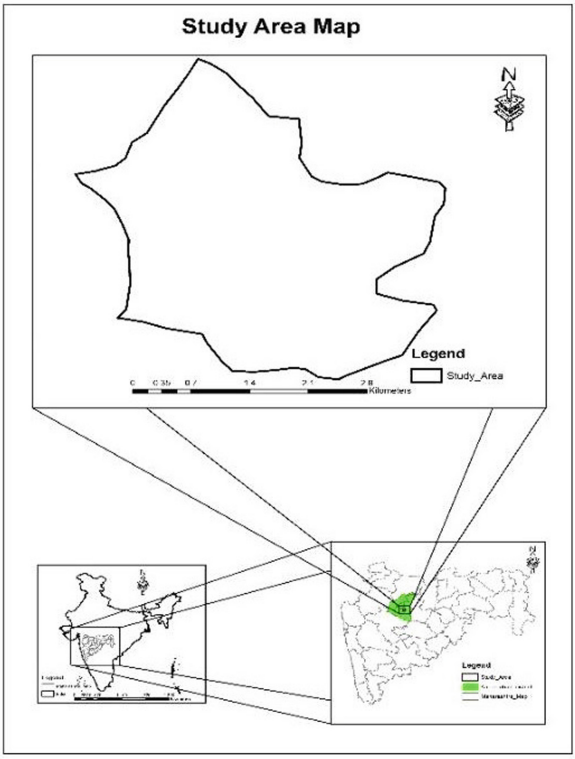

Fig. 3. Study Area at Sawangi in Aurangabad District. (Created by using QGIS)

study area, and same number of the soil samples were taken. The study area is the region of Aurangabad district located at the position 19056 '12.75" N, 75022'.8.47" E. The database was collected in Nov 2021 with the temperature in the range of an average high of 29.20c°C (84.60F) and an average low of 18.80 °C (65.80F), and the average humidity was 50%. The annual rainfall was 777 mm. Soil texture was black soil (Fig. 3). At the time of sample collection the crop age was about 90 days, because after the 90 days age, the cotton recommended to spray fertilizers. And the maize starts to create its food (Table 1).

3.2 Collection of Spectral Signatures

Utilizing an ASD Field Spec4 device that is properly situated in a dark room. The device is first warmed up for 20 min. The white reflectance panel used to calibrate the accuracy and detector response, improve the signal, and optimize the signal using the RS3 software. After successfully obtaining White Reference spectra that displayed 100% reflectance, we successfully collected each sample's spectral signature by placing each sample in front of the spectral gun at a height of 5 cm and with a FOV of 8o. Less than two hours were spent keeping the leaves fresh in the plastic bag before the spectral reflectance was assessed. Samples of leaves taken with a Fieldspec4 and measured for

Table1. Size of the dataset.

Name of Crop/Sample	Healthy	Unhealthy	Total
Cotton	20	20	40
Maize	20	20	40
Total Leaf Samples	40	40	80
Soil of cotton	20	20	40
Soil of maize	20	20	40
Total soil samples	40	40	80

spectral reflectance between 350 and 2500 nm. To brighten the samples, 50W quartz halogen lamp is utilized as the light source. The lamp's height from the source was held at 42 cm. Then taken 10 utterances of each sample by each angle by rotating sample in clockwise direction (total 800 utterances for Crop and Same for the Soil samples) and taken mean spectral signature of these 10 spectral signatures for analysis.

3.3 Pre-processing

The wavelength range of the Spectroradiometer is 350 nm to 2500 nm. It has three detectors: a visible detector, a shortwave infrared detector 1, and a shortwave infrared detector 2. After calibration, each sample has a shifting sensor error. With the aid of the software ViewSpecPro, the specified sensor noise was eliminated from each sample. Selected important band wavelengths and converted reflectance spectra into ASCII values for further procedure.

3.4 Spectral Vegetation Indices

NDVI is mostly used vegetation index which generates the value from -1 to + 1. There is a good chance that you have healthy green leaves if the value is close to + 1 and unhealthy if it is close to 0 or -1. But each form of land cover requires a clear border. The difference between near-infrared and red reflectance divided by their sum is used to calculate the NDVI.

$$\mathrm{NDVI} = (\mathrm{R800} - \mathrm{R670})/(\mathrm{R800} + \mathrm{R670}) \tag{1}$$

The normalized difference for carotenoids represents about the infected level of crops. In places where the concentration of carotenoids is high, the CRI2 index yields better results. Greater carotenoid concentration relative to chlorophyll is indicated by higher CRI2 readings. This index has a value between 0 and greater than 15. Greater value indicates unhealthy vegetation [27] (Table 2).

$$\mathrm{CRI2} = (1/\mathrm{R510}) - (1/\mathrm{R700}) \tag{2}$$

Table 2. Calculated vegetation indices for crop

NDVI				CRI2			
Cotton		Maize		Cotton		Maize	
Un healthy	Healthy	Un healthy	Healthy	Un Healthy	Healthy	Un Healthy	Healthy
0.414	0.772	0.234	0.647	5.111	4.751	4.411	1.487
0.518	0.794	0.171	0.599	6.390	4.482	3.975	1.811
0.319	0.812	0.277	0.596	4.601	4.355	3.052	1.123
0.547	0.813	0.277	0.661	5.305	4.869	2.736	1.311
0.458	0.827	0.435	0.708	6.961	4.686	2.736	1.611

Table 3. Threshold values for crop health analysis [23] & [24].

Crop Name	NDVI	CRI2
Cotton Healthy	> 0.75	< 5.0
Cotton Unhealthy	< 0.75	> 5.0
Maize Healthy	> 0.6	< 2.0
Maize Unhealthy	< 0.6	> 2.0

In the above-calculated vegetation indices, the values of NDVI for diseased cotton and maize are smaller than the values of healthy cotton and maize, because chlorophyll content is higher in healthy plants. CRI2 values are greater in diseased plants than in healthy ones as they represent diseased plants (Table 3).

From the research study we get some empirical threshold values which classify the healthy and unhealthy crops and will help to further study. Each and every crop has its own range of reflectance. In which we developed a vegetation index value which will classify the healthy and unhealthy crop leaf. Above table shows the threshold values of the vegetation indices for health analysis of the crop leaf.

4 Analysis and Discussion

It is feasible to analyze the impact of electromagnetic radiation on the visible region of electromagnetic spectrum on cell structure by observing Near Infrared (780–1400 nm) and Short Wave Infrared (1400 - 3000 nm) area impacts caused by the moisture available in leaves. Absorption by photosynthetic pigments of leaf is the most important mechanism, which focuses largely on the reflectance and transmittance values. About 65% of all pigments are composed of chlorophyll a and b. Chl a is the pigment that all kinds of mature plants require. In the 410–430 nm and 600–690 nm ranges, Chl a exhibits very strong light absorption, whereas Chl b exhibits very high absorption in the 450 nm–470 nm region. High reflectance value is obtained in the green region at about 550 nm

in these absorption bands [29]. Carotenoid exhibits light absorption between 440 and 480 nm. [30]. Water have a significant impact on the spectral characteristics of leaves in the short wave infrared region. The primary water absorption bands are at 1450 nm, 1940 nm, and 2700 nm.

After taking spectral signatures of all the samples and pre- processing we calculated its mean spectra. And found the following results.

In Fig. 4, the reflection of healthy Maize (Fig. 5 a) and healthy Cotton (Fig. 5 b) is higher at green band (range 550 nm) and absorption at the red and blue (450 and 650) band because of Photosynthetic pigments (Chlorophyll a and b). Healthy plants require to absorb red and blue light for photosynthesis and produce chlorophyll. A healthy plant with more chlorophyll will reflect more in near-infrared (NIR) energy than a unhealthy plant. As in above figure, both the unhealthy reflectance is less than healthy reflectance. Thus, we can assess the health of a plant by observing its reflectance spectra [32]. At the wavelength 1450, 1950, and 2500 nm there is absorption because of moisture in leaf.

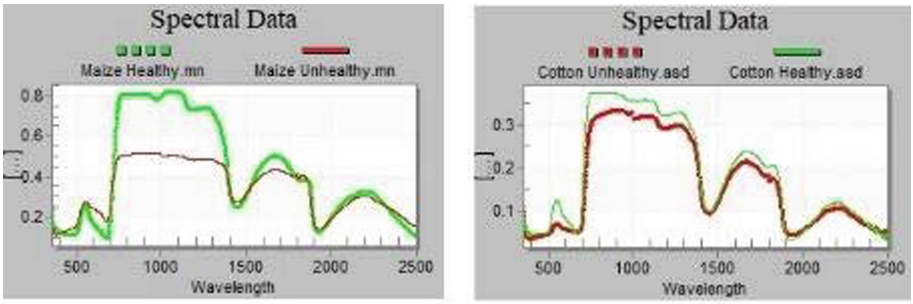

Fig. 4. Healthy-unhealthy signatures of Cotton and Maize.

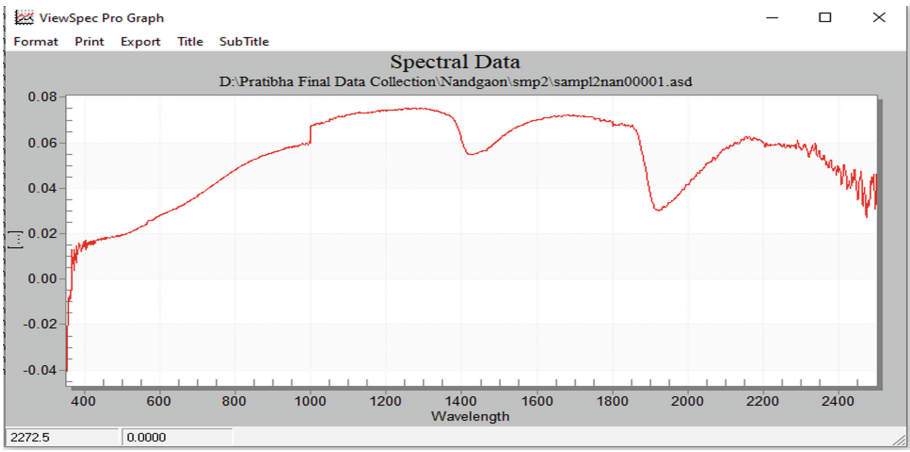

Fig. 5. Mean Spectral signature of soil samples taken from study area.

Table 4. Relation of crop yield and soil ph. [19] & [20].

pH value:	4.7	5	5.7	6.8	7.5	8.5
Maize(yield)	34%	73%	83%	100%	85%	75%
Cotton	40%	75%	90%	100%	95%	75%

4.1 Soil Spectral Signature

ASD FieldSpec4 Spectroradiometer is used to forecast soil's physical and chemical properties, such as soil pH (1477 nm, 1932 nm, and 2200 nm), Nitrogen (1702, 1870, 2052 nm and 1376 nm) [25], carbon (2040–2260 nm), Phosphorus (2021- 2025 nm, 2240-2400 nm) [26]. For which RS3 software is used for the purpose of data collection and the ViewSpecPro software is used for processing of the data.

In the visible spectrum soil will obtain red which means that is reflecting the red wavelength which will around the 700 nm the most. Green wavelength is still being reflected but not is much as red. In the Near-Infrared electromagnetic spectrum (750-1400 nm), we see that reflectance of soil continuous to rise and enters the level of Shortwave-Infrared (1400-3000nm). We can see that soil reflectance much more energy in Shortwave Infrared wavelengths and it doesn't in the Near-Infrared or visible for electromagnetic spectrum.

4.2 Soil Properties that Effects on Crop Health

Nitrogen is mostly important for the growth of plants leaves. Phosphorus is responsible for growth of roots and flower and development of fruits. Potassium helps to the overall functions of plant. The N:P:K (Nitrogen, Phosphorus, and Potassium) in soil should be in sufficient range. If it is too much less, it is harmful for crop and crop yield. While too high presence of one or more nutrients will lead to disturbed plant growth. Moreover, the N:P:K should be present in balanced [22]. Soil pH is a main variable in the soil because it controls almost all the chemical and biochemical processes within the soil. It shows the measurement of the acidity or It is important to study the soil pH in precision agriculture because it regulates plant nutrients availability by controlling the chemical forms of the various nutrients and influence their chemical reactions. So that, soil and crop qualities are coupled with soil pH value. Generally, the range of soil pH is from 1 to 14, the finest range for most agricultural crops is between 5.5 and 7.5. [28].

Table 4 shows the ideal pH value for crop is 6–7. When pH value is very less and very high it is harmful for the crops. As pH is less(4.7) the crop yield is also less i.e. 34% only, as pH increases (pH = 5) then crop yield = 73% that means crop yield increases, when pH = 5.7 it is good for crop as crop yield is 83% and the best pH is 6.8. But more than this limit it is harmful for crops. We have observed the soil sample's pH value 7.5 to 8.5 and it is moderate alkaline. And crop yield is 75 -85%.

Table 5. Relation of the soil parameters with the health of crop and soil [3].

Soil Sample	N (%)	P (%)	K (%)	pH	Soil Health	Crop Health
Sample 1	47.66	90.99	83.45	7.5	Normal	Unhealthy
Sample 2	50.99	89.10	85.01	7.3	Normal	Healthy
Sample 3	61.85	91.02	80.24	6.9	Best	Healthy
Sample 4	49.50	88.33	82.00	6.6	Normal	Unhealthy
Sample 5	53.36	87.63	79.99	8.03	Normal	Healthy

Table 6. Classification results

Crop	**SVM**	**KNN**
Cotton Maize discrimination	97.5%	97.5%
Maize Health analysis	90%	85%
Cotton Health analysis	87.5%	92.5%

Table 5 shows the results of some randomly selected soil sample's parameter values and average health of the soil with related the health of related crop. The values are calculated with the help of soil chemical testing values and reflectance values. For sample 1 in above table, overall soil health is good but the crop is unhealthy because in the parameters of the soil, nitrogen value is low (i.e. 47.66) which is directly proportional to the chlorophyll content of the leaves. For sample 2, nitrogen is better than previous (i.e. 50.99), phosphorus and potassium is also good and pH is also good so the related crop is also good or healthy. Sometimes it may happen soil condition is perfect for crop but the weather is not good that time also crop will unhealthy and sometimes soil condition is not good but the fertilizers used perfectly that time also crop will healthy. It means the crop health is not only depend the weather or fertilizers or soil condition it should have all the parameters suitable for it.

5 Classification

For the classification purpose we have used supervised SVM and KNN machine learning algorithms. Following are the results of applied algorithms: (Table 6)

5.1 Supervised Machine Learning (SVM)

On unknown data, the support vector machine classification model performs well. The most straightforward illustration of this technique is the greatest margin classification model. The most basic classification problem is resolved by this classification model. Binary classification with linear separable training data is the problem at hand. This categorization approach identifies the hyper plane with the greatest margin.

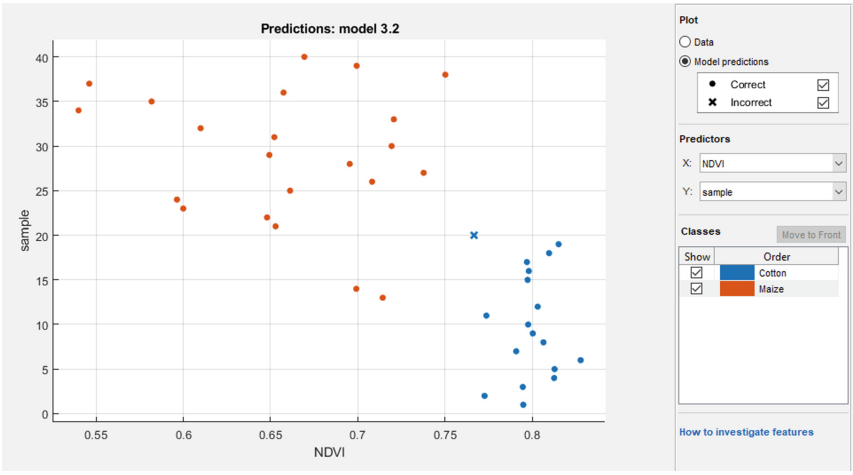

Fig. 6. SVM for Cotton and Maize discrimination

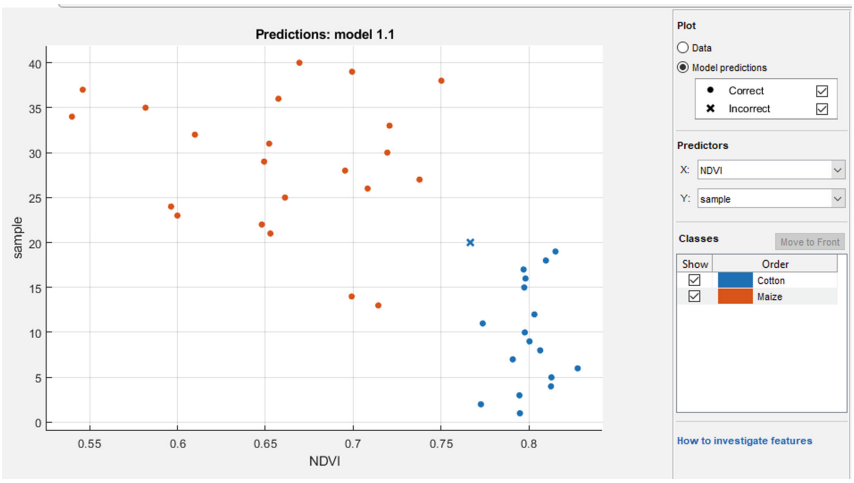

Fig. 7. KNN for Cotton and Maize discrimination

This supervised machine learning is a model which appoint classification techniques to solve linear classification problems. After giving the labelled training data set, SVM can classify any data for each category of training set. SVM and KNN both gives the same accuracy of crop classification as 97.5%. The SVM for cotton crop gives the accuracy of 87.5% and gives the accuracy of 95.0% for Maize crop (Fig. 6)

5.2 K- Nearest Neighbor (KNN)

KNN is a supervised learning technique which assumes the similarity between the new data point and available data point and keep that new point into a group which is most

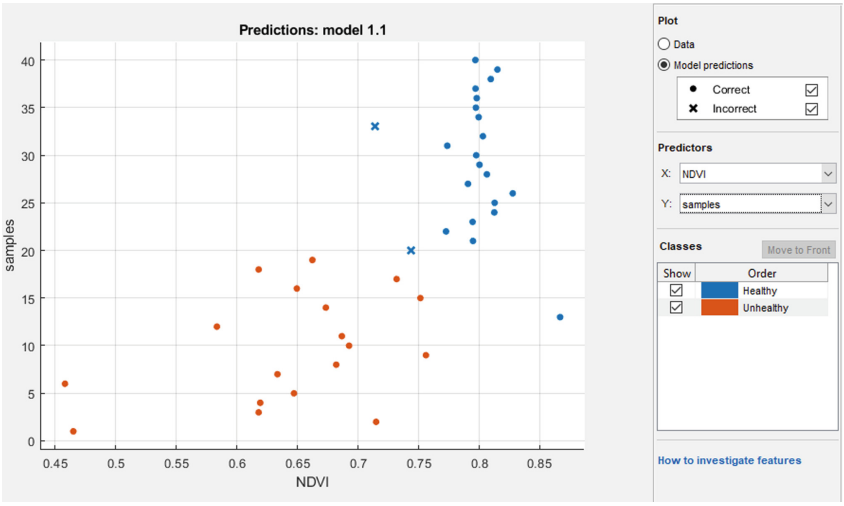

Fig. 8. SVM for Cotton Health analysis

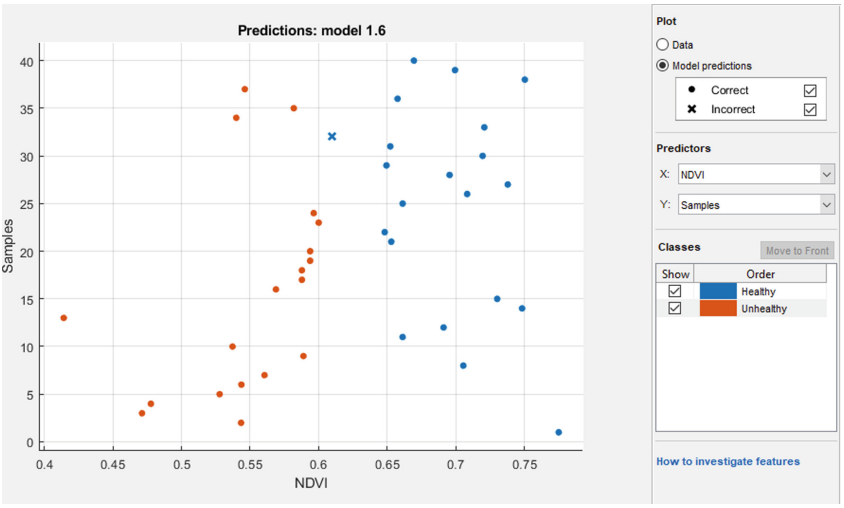

Fig. 9. SVM for Maize Health Analysis

nearest to that point (Fig. 7). This method relies on analogous learning. For classification purposes, this classifier is frequently employed (Fig. 8). Unlike other classifiers, this one waits until the very last moment to build a model on a given tuple. In the event of an indefinite variable, this classification model searches for the K trained variables that are closest to the indefinite sample. The sample is then allocate to the closest class by this classifier (Fig. 9). The KNN for cotton crop gives the accuracy of 92.5% and gives the accuracy of 97.5% for Maize crop (Fig. 10).

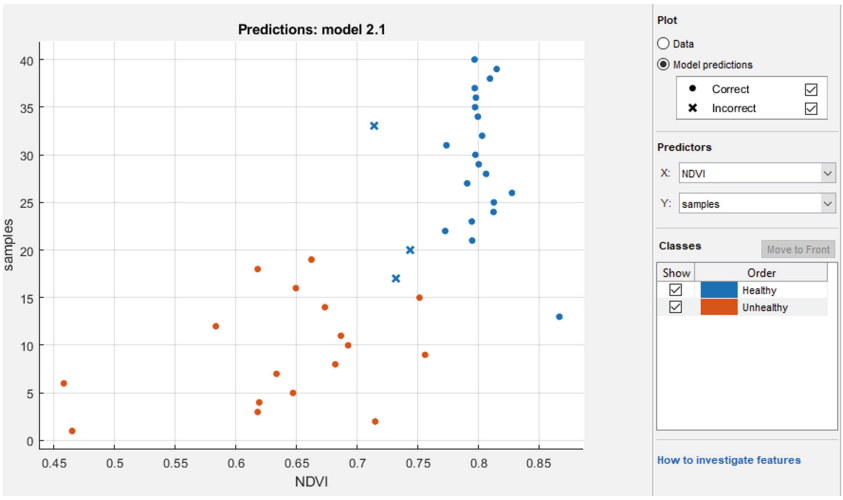

Fig. 10. KNN for Cotton Health Analysis

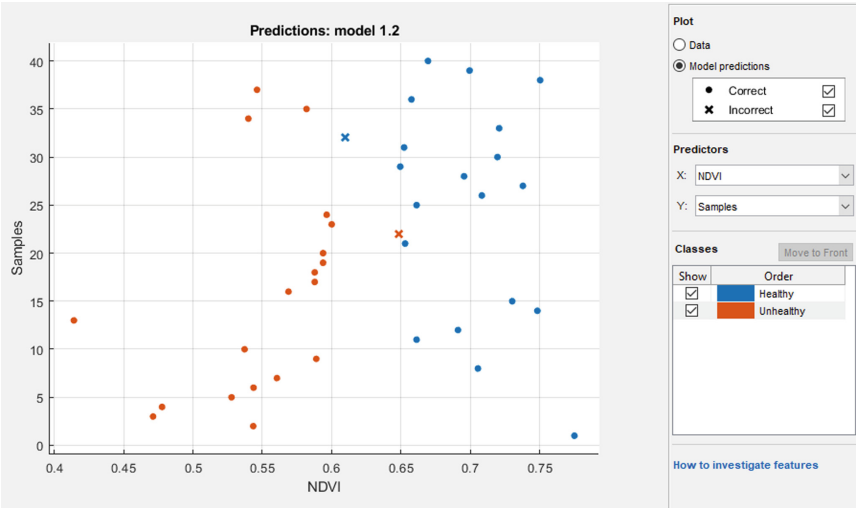

Fig. 11. KNN for Maize Health Analysis

6 Conclusion

The current study investigates Spectroradiometer- based health analysis and the impact of the soil content on the crop health (Fig. 11). The complete investigational investigation was implemented using ViewSpecPro software, and Python. Crop spectral responses were examined in both healthy and sick stages. Various vegetation indices were applied for health assessment in which NDVI and CRI2 shows better result for health analysis. Research shows the impact of the soil nutritional content on the crop health in that

some specific parameters are focused like nitrogen, potassium, phosphorus, and pH value. Nitrogen is mostly related to chlorophyll content. For the classification purpose supervised learning is used. SVM gives the better result for Maize health analysis than the KNN algorithm and for Cotton crop KNN gives the better accuracy than SVM. And for crop type discrimination both the classifiers SVM and KNN gives good accuracy.

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