



Comparative Analysis of Chlorophyll Contents in Herbal Plants Using Regression Model

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Abstract: Hyper-spectral non-imaging data provides the spectral range from 400-2500nm, which has the ability to identify each and every unique material on the surface. Plant leaf identification is a critical task manually and computationally. In the work we have proposed a plant leaf identification system based on non-imaging hyperspectral data and designed our own database for experiments. In this paper we used medical plant (Asparagus, Tulsi, Neem, Panfuti, Tridax, and Justicia) samples and developed hyperspectral signature by using field Spec 4 spectroradiometer. In this study we used the statistical method. We applied regression techniques for comparative analysis for Neem with other plants. As per our results, Neem Chlorophyll and Tulsi and Panfuti Chlorophyll content correlation coefficient is 0.98.

Index Terms – hyperspectral, linear regression, remote sensing, medicinal plants.

I. INTRODUCTION

Neem leaves are obtained from Neem trees that are found throughout India. They are extensively used in making Ayurveda medicine. Neem tree leaves have multiple uses compared to other medicinal plants like Justicia, Asparags, Tridax, Tulsi, and Panfuti. These are all small plants. They have also had medicinal uses, but, as compared to Neem, there are fewer uses. We use a field spec 4 device for spectral signatures. Non-imaging data offers a spectrum range of 350 nm to 2500 nm, allowing Hyperspectral to identify each individual material on the surface. Medical plant identification is a critical task manually and computationally. This paper is related to medical plant identification and classification systems based on non-imaging hyperspectral data to find out the medical content and signature of hyperspectral data. It helps to identify the medical plant and content available in a medical plant.

A hyperspectral image can be thought of as an image cube with hundreds of contiguous spectral bands representing the third dimension. As a result, a hyperspectral pixel is essentially a column vector with the number of spectral bands as its dimensions. Spectral information between narrow bands, for example, is quite helpful and can be utilized for spectral characterization. A hyperspectral imaging sensor combines imaging and spectroscopy in a single system that often includes large datasets and requires new processing methods. Hyperspectral datasets are often made up of around 2150 or more spectral bands with small bandwidths (5-10 nm). Plant leaf identification based on leaf has been carried out by botanists, plant specialists, and many scientists as an essential research task in recent decades. A lot of research has been conducted for the identification of leaf species using non-imaging spectroradiometer hyperspectral data. However, there are a few studies that use hyperspectral data to identify medical plant leaves because hyperspectral data has unique characteristics, such as two thousand one hundred fifty spectral values with high spectral resolution, and so on. The creation of a method for quickly and accurately identifying medical.

Dataset Information:

We are considering Dr.Babasaheb Ambedkar Marathwada university Aurangabad area for sample collection.

- Give the trees

1. Tulsi (Ocimum tenuiflorum)
2. Tridax (Tridax procumbens)
3. Panfuti (Bryophyllum pinnatum)
4. Adulsa (Justicia Adhatoda)
5. Neem (Azadirachta indica)
6. Shatavari (Asparagus racemosus)

In this work we take a six medical plants. Plants identification and physiological status using ASD field spec 4 spectroradiometer. There are much content available in medical plants. In Tulsi contents in oleanolic acid, ursolic acid, eugenol etc. In Bryophyllum (panfuti) contents in triterpenes, phenanthrene, phenolic acid, caffeic acid, malic, oxalic etc. measurement the wavelength of all contents in spectroradiometer. Wavelength range is 350nm to 1100nm per 2 sec.

2. METHODOLOGY

2.1 Spectral Signature Acquisition

In this study, we have collected six plants as a sample which is available in Dr. Babasaheb Ambedkar Marathwada University campus. Collection of Asparagus, Tridax, Justica, Tulsi, Neem, Panfuti, We plucked one samples from each plant and one sample scan the 10 times. We used fresh leaves since it measure of chlorophyll and water which it directly effects on the spectral signature of leaf.[11] The overall dataset of 60 (10*6=60) leaf samples. During the collection process we have also considered and make the geo-tag references of each plant which will be considered as a metadata. The fieldSpec4 instrument was used for give the spectral signatures from leaf samples. The ASD Field Spec 4 spectroradiometer is used to acquire spectral signature of the samples. The wavelength of the instrument is 350-3500nm [1][6][12].White reference panel is used for optimization and calibration before sample recording. The ASD instrument provides halogen lamp with 7w.It is used to record the plant leaf samples by zenith angle of 60 degree from the distance of 45cm above the samples. The field of view is 8 degree and fibre optic cable was set as of nadir where plant samples. Each sample recorded ten times for receiving spectra and the averaged as a pure spectrum. The RS3 (version 6.3) in built software was used for recording the reflectance spectra leaves [6][13]. Finally we obtained (.asd) data file by using fieldSpec4 which possesses ASCII data format [14].

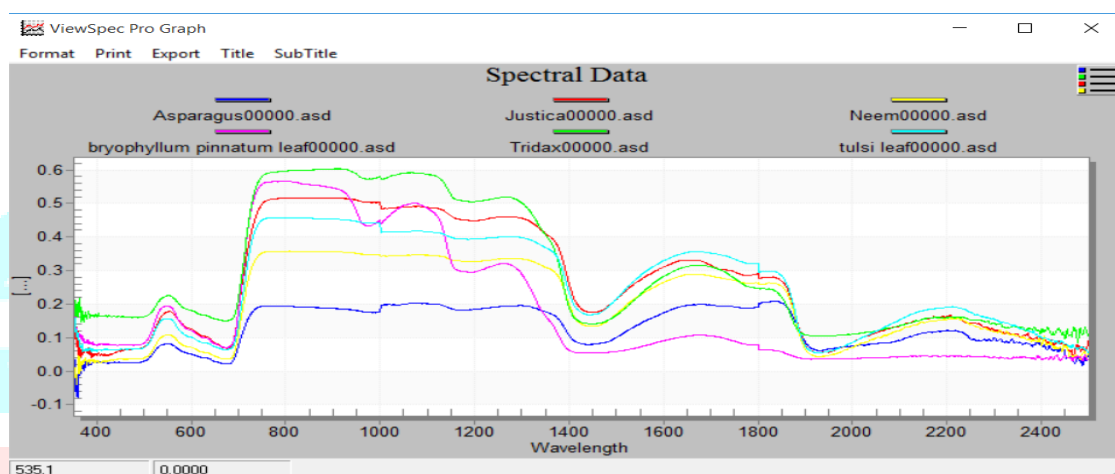


Figure 7.2: Reflectance of All plants

2.2. Data processing

The acquired 10 spectral signatures for each sample are processed by applying mean and generate one spectral signature for each sample. Then convert the spectral signature in numeric format using View spec pro software. Numeric data were opened in Microsoft Excel and process the by applying statistical mean methods for quantitative analysis of soil properties on the respective absorption wavelength range.

3. RESULT

3.1 Statistical Analysis:-

The medical plant calculated in the terms as Tulsi, Tridax, Panfuti, Neem, Asparagus and Justica. Tridax and Tulsi with average values 0.26%, 0.30% and 0.25% respectively. The percentage of Tridax concentrations were highest values than justica and Tulsi. The Tridax varied from 0.61% and 0.11%, Justica was varied from 0.25% and 0.05%, Tulsi is varied from 0.46% to 0.06%. Whereas Neem percentage was 0.20% was varied with 0.36% and 0.03%. Average value of Asparagus and Panfuti were 0.18% and 0.13%.

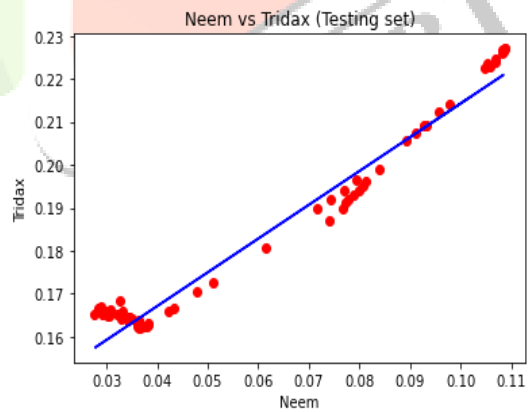
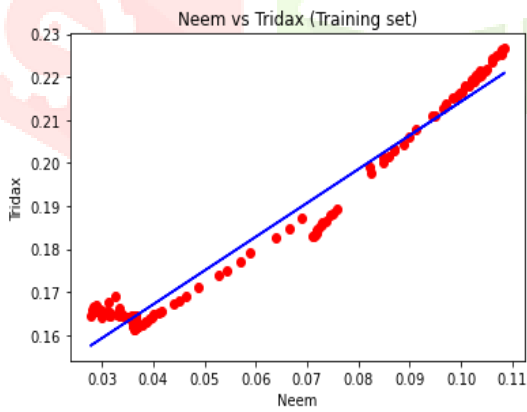
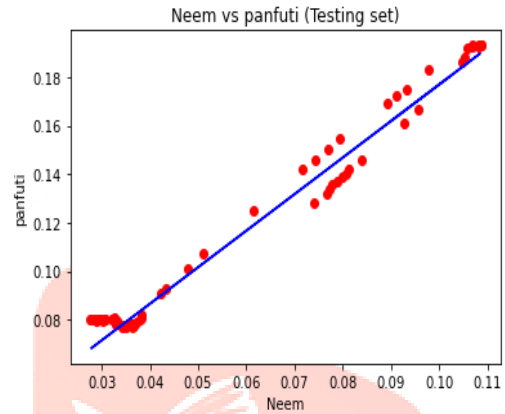
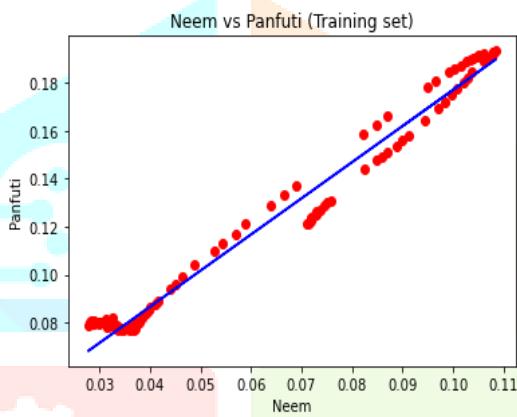
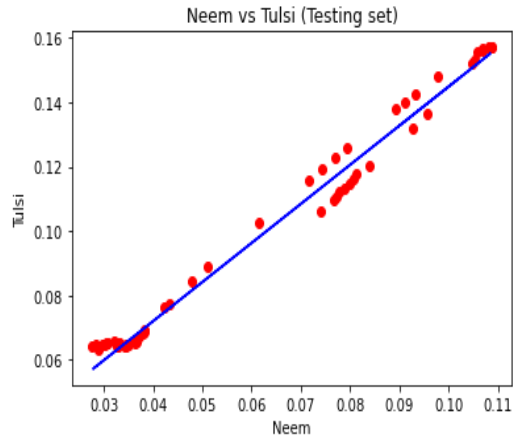
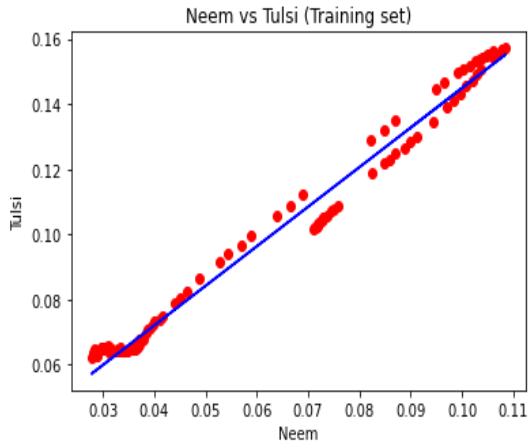
Table 1: Statistical Analysis

Plant	Mean	Max	Min	Median	Variance	Standard derivation
Asparagus	0.13	0.21	0.02	0.12	0.06	0.06
Justica	0.26	0.25	0.05	0.23	0.03	0.16
Neem	0.20	0.36	0.03	0.19	0.01	0.12
Panfuti	0.18	0.5	0.03	0.08	0.03	0.18
Tridax	0.30	0.61	0.11	0.21	0.03	0.18
Tulsi	0.25	0.46	0.06	0.23	0.02	0.14

3.2 Comparative analysis using linear regression model

Regression models describe the relationship between variables by fitting a line to the observed data. Linear regression models use a straight line, while logistic and nonlinear regression models use a curved line. Regression allows you to estimate how a dependent variable changes as the independent variable(s) change. Simple linear regression is used to estimate the relationship between two quantitative variables.

The Neem chlorophyll are independent variable and other plant chlorophyll are dependent variable. The performance of liner regression model the Neem chlorophyll and Tulsi chlorophyll are good co-related and also Tridax and Panfuti are co related to Neem. But justica and asparagus are not co related to Neem chl. Almost Neem chlorophyll and Tulsi chlorophyll are equal



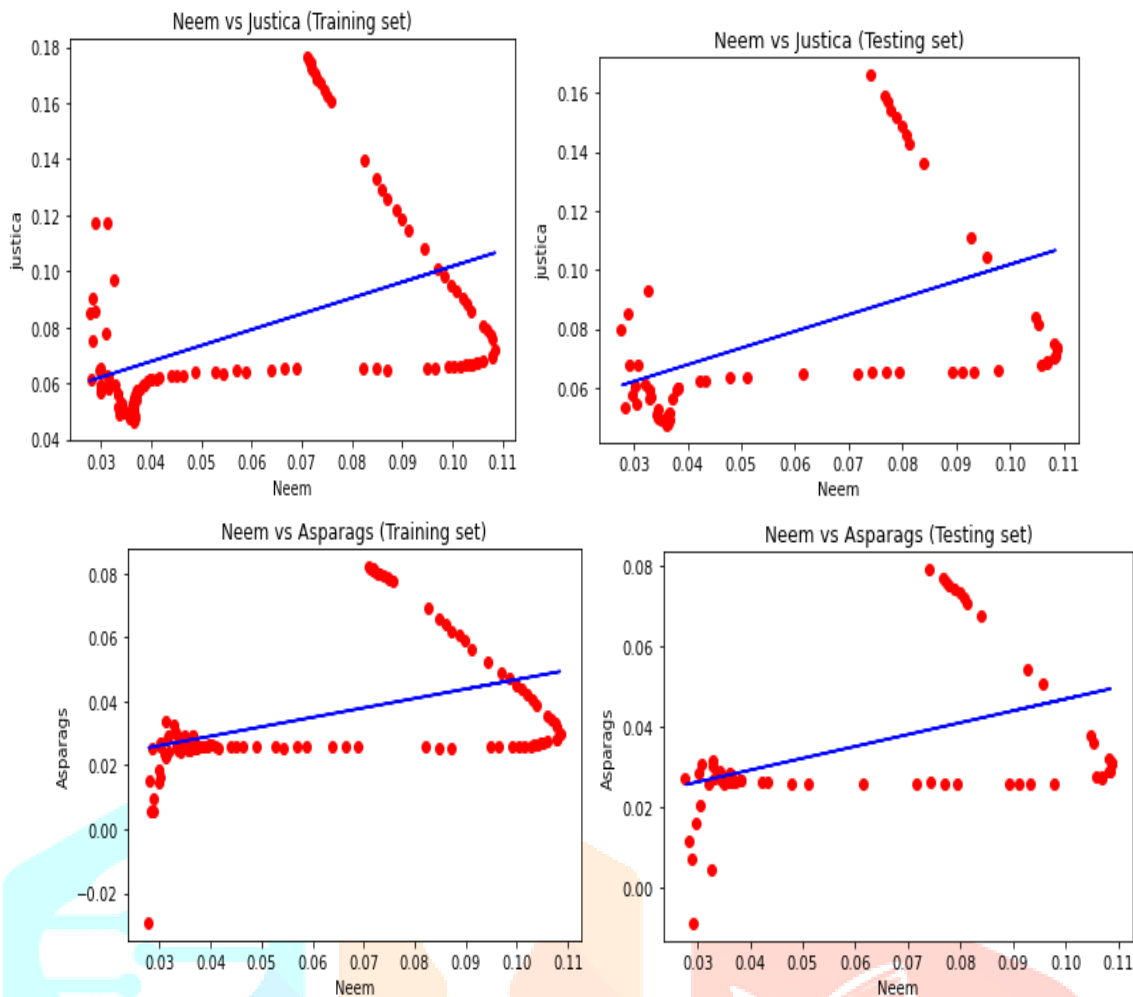


Figure 1: Linear regression of Neem and Tulsi, Panfuti, Tridax, Justica, Asparags.

The linear regression analysis correlation coefficient and goodness of fit model are calculated for finding the correlation and it represent in table 2. In this linear regression for justica and Asparags found minimum value and for Tulsi, Panfuti and Tridax maximum value.

Plant name	Correlation-Coefficient	Goodness of fit
Tulsi	0.9935	0.9871
Panfuti	0.9899	0.9800
Tridax	0.9831	0.9665
Justica	0.4239	0.1797
Asparags	0.419	0.1756

The performance of linear regression model for Neem with others plants are represented in figure 1. On the basis of regression analysis Neem is highly correlated with Tulsi, Panfuti and Tridax

Conclusion

In this research work, the results were produced on non-imaging hyperspectral data which was collected in Geospatial Technology Research Laboratory using FeildSpec4 instrument. Its gives the hyperspectral Signature of medical plant. Chlorophyll is a medicinal content in plant. The present study can be used for plant leaves chlorophyll content within time which has useful applications in agriculture. We apply statically analysis it gives the result is Tridax statistical analysis is very highly reflectance. In this study we have comparison of Neem leaf with other plants using regression analysis with the help of python. As per result Neem tree Chlorophyll content are co- related to Tulsi, Tridax and Panfuti.

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