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Multispectral spectroscopic analysis for classification

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Abstract:* In recent competitive scenarios, multispectral imaging systems are widely used in the area of information retrieval and object classification. This technology has made satellite applications versatile by providing multiband information in specific application sectors like material classification, agriculture industry, and food processing industry. With this experiment, we have made an attempt to address the material classification and access milk purity by acquiring data in Visible and Near Infrared bands between 400 to 1000nm. The experiments were carried out on samples of copper, aluminium, basalt fiber composite and milk. Using machine learning techniques the classification model has been developed. Results are discussed in paper.

***Keywords:* Multispectral signature, photonics , machine learning, spectroscopy.**

1. INTRODUCTION

Multispectral imaging is in great demand due to simplicity in experimenting, cost savvy, flexibility for rapid assessment, consistency in results, non-destructive, super accurate, and has a wide range of applications. The development in unmanned aerial vehicle and ground-based multispectral imaging equipment has been evolved as a major breakthrough in precision agriculture techniques. A crucial aspect of successful agricultural operations will be crop nutrients, humidity level, insect outbreak, contamination with its severity and overall plant fitness. The inspection can been done by visual examination of crops on the ground, traditionally. However these methods have limitations due to the limited perception of the human to identify and discriminate between fit plants and plants suffering various kinds of stress/diseases. In some cases, it is required to know about specific conditions in well before visual indications become evident. Multi-band methodical technology has made possible the valuation of crop stresses and decease, categorisation of soils and crop estimation, in addition to its projecting capabilities. Irrigation levels, pesticide and fertilizer effectiveness, and hard-to-detect diseases can be spotted using multi spectral image sensors. The key is to recognize these signs early and often that is why continuous airborne monitoring allows for trend analysis. Spectrometers are the device using which it is possible to collect spectral response at various spectrums. For a specific target its spectral range would be different and it depends on its material property, its structure etc. Until recently, Earth Observation Satellites carried only broad waveband sensors These sensors have limitations in providing adequate information on terrestrial ecosystem characteristics like accurate estimates of physicochemical and volume characteristics of agricultural crops These limitations result in increasing interest towards narrow-waveband sensors, which are intended to provide more detailed information and enable new applications. The Hyperion and other hyper spectral sensors will generate very large data volumes in 400- to 2500-nanometer spectral range, which make it commanding that novel methods and techniques be developed to handle these data.

Review Of Related Studies

The area of spectrometry covers multiple applications including Pharmaceutical analysis, Biomolecule Characterization, Agriculture application (plants and soil), forensic analysis and many more. Thenkerbal Prasad,et al, [1] collected data from multiple study areas in various ecosystems of Africa, the Middle East, Central Asia, and India . Their major finding was optimal hyper spectral narrow bands (HNBs) between the range of 300-2500nm waveband and hyper spectral vegetation indices (HVIs). In [2] Zhang Chengye has discussed spectral characteristics of copper-stressed vegetation leaves followed by developing the copper stress vegetation index. In this study, the author has analysed Green, Red, Red Shoulder, NIR (Near Infrared) Reflectance Platform, Blue-Edge, Yellow-Edge, and Red-Edge band data to analyse copper stress level along with chlorophyll content at the visible band. In [3] author have used wavelengths of 550 nm, 700 nm, and 850 nm to calculate copper stress vegetation index (CSVI). Author in [4] also discussed crop stresses with copper metal. They have used 46 groups of leaves treated with copper, and obtained reflectance spectra from 400 to 2500 nm. In [5] authors have analysed the connection between leaf reflectance of different seasons and the absorption of metal elements like copper, Cobalt, molybdenum and Nickel. They have developed estimation models within the range of 550 nm to 750 nm. Author in [6] explained about leaf-level solar-induced fluorescence changes under the Cu stress which can be understood as pointer to estimate the level of stress. Authors explained that apparent reflectance is rarely affected by fluorescence emission at 580-650nm and 800-1000nm. In [7] author have discussed that Copper concentrations had negative and strong correlation with chlorophyll absorptions ($r = -0.719$, $p < 0.001$). Author described that wavelet transform based decomposition over 605-720 nm as area parameter was superior to distributed chlorophyll related and wavelet transform based spectral parameters for estimating Copper accumulation in Carex leaves. The authors in [8] have explained that hyper spectral technique provides a economical way to diagnose stresses due to acid rain. Results showed that hyper spectral information could be used to differentiate plant responses under acid rain stress, for the same they have used index in the region of 500–660 nm. The authors in [9] have conducted an experiment on the remote detection of water stress in a citrus orchard. In [10] the authors explore the Raman spectroscopy for analysing the milk including compositions, antibiotic residues in milk. Author in [11] used the excitation wavelength of 532 nm to determine the fat globules (MFGs) components in different liquid milks. Surface-enhanced Raman spectroscopy widely used with a combination of chemo metrics for safety evaluation for the food industry [12, 13, 14]. Many researcher also investigate adulterants in milk powder using the NIR hyper spectral imaging system in [15], Raman Imaging in [16].

Experimental methodology

The experimental setup includes a multispectral sensor positioned at required height by a linear moving stand. The extraction of various multispectral data from the samples has been carried out through PixelSensor™ multispectral sensor. The sensor has exclusive on-chip filtering to pack up to 8 wavelength-selective photodiodes into a compact 9x9mm array format for simpler and smaller optical devices within narrow band VIS-NIR selectivity (400-1000nm). The test specimen has to be placed underneath the sensor by ensuring the distance is 100mm. The sensor is capable of generating the output data in graphical format. The alongside software is required to retrieve quantitative data as per the chosen frame rate and the information can be saved in excel format. The experimental setup is depicted in the figure.1.

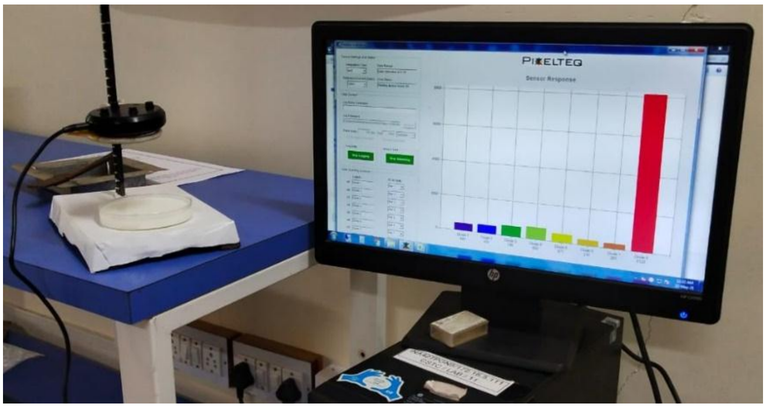

Figure 1 Experiment Setup

To carry out the classification between the metals, four different heavy metals were identified such as Copper. Mild steel, aluminium and basal fiber composite. The surface visibility of a mild steel and basalt fiber composite is similar. In the same context we also had a second experiment to check milk purity. It is true that milk with added water has different reflective index resulting in different spectral response in comparison with pure milk response. This experiment three samples of milk has prepared such as pure milk, milk with 10%of added water and milk with 20% added water. The samples analyzed and the respective spectral radiations were measured and stored into excel file.

In sensor which we have used covers 8 different bands : 425nm, 455nm, 485nm, 515nm, 555nm, 615nm, 660nm, 695nm.

2. EXPERIMENT RESULTS

2.1 **Metal Classification**

First we have prepared the data set using various metals like : Mild Stainless steel, aluminium, copper and Basalt.

Fig 1. shows data distribution for specific features. Here we have 5000 samples for each metal. We have divided data into training and testing with the ratio of 70:30.

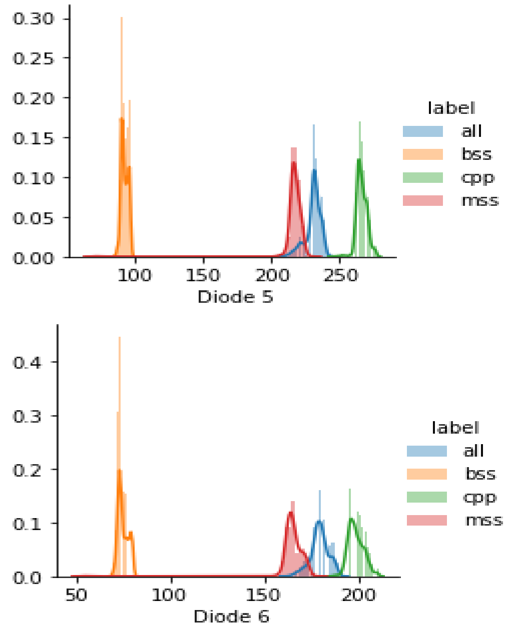

Figure 2 Data distribution for various metals

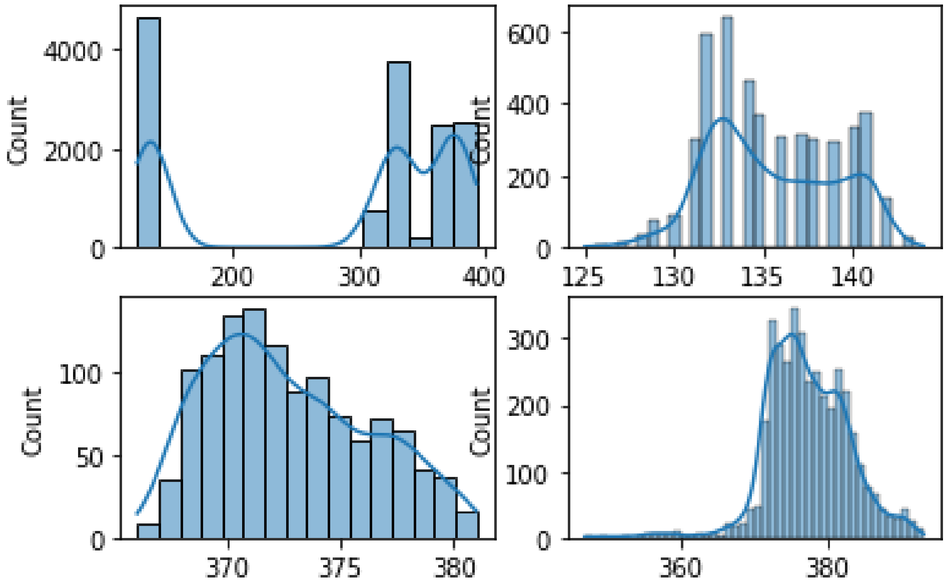

Figure 3 Response of photodiodes of 515 nm for 1. Al, 2. Basalt, 3. Copper, 4. Mild Steel.

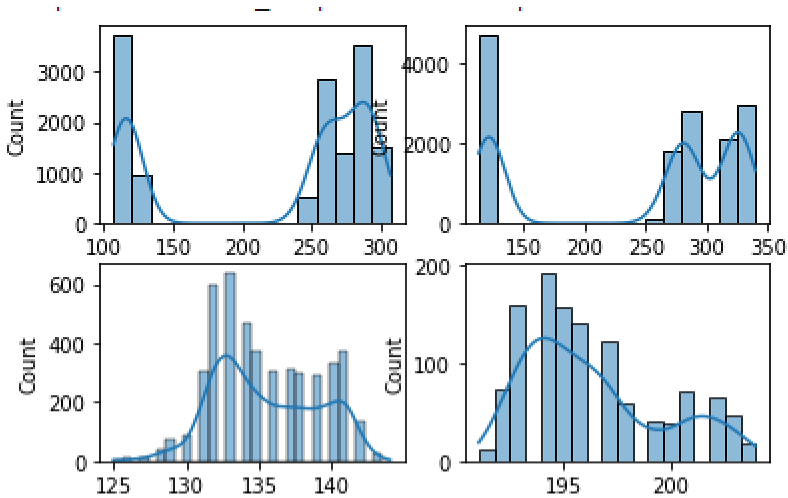

Figure 4 Response of photodiodes of 455 nm, 485 nm, 515 nm, 615 nm for Al.

Results shown in table 1. Here we have used F1 score and accuracy as evaluation parameters.
Accuracy is the ratio of correct prediction to All prediction.
F1 score can be defined as
F1 = 2 * (1/((1/precision) + (1/recall)))
F1 Score will find the balance between precision and recall.
Accuracy and F1 score are for the testing data set which is unseen for the trained model.

Table 1 Results for metal classification

ML model	**Accuracy**	**F1 Score**
KNN	0.9998	1.0
Random Forest	0.9995	1.0
Naive Bayes	0.7786	0.78
SVM	0.9834	0.98

2.2 **Milk Purity Classification**

For the above samples we have 8 features which are responses from 8 bands present in the instrument. For all reading distance and other arrangements are the same. Below fig shows data distribution of various features.
From the graph it can be seen that the distribution overlaps in few cases and hence since it is not linearly separable, complex Machine learning algorithms will be required to classify them. We have tested various machine learning models and results are as below.

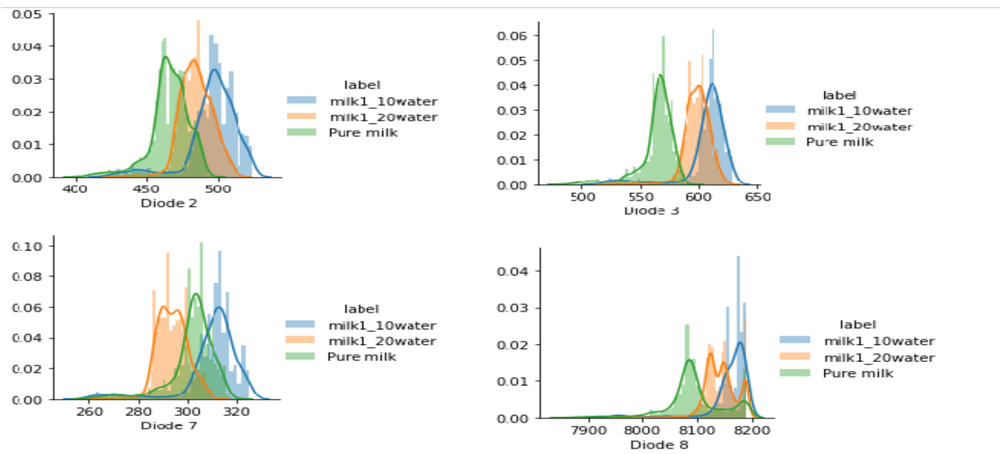

Figure 5 Distribution of various features for given labels

Table 2 Results

ML model	Accuracy in %	F1 Score
KNN	99.16	0.99
Random Forest	99.79	1.0
Naive Bayes	87.31	0.87

3. CONCLUSION

In this paper we have used multispectral bands data to analyze the response of different materials and classify them based on their characteristics. Spectrography is highly used in the field of food processing and agriculture due to its ability to identify specific material based on its properties.

We have generated data using a multi spectral sensing instrument and we have performed data analysis, processing and designed a custom model for classification. Here we have performed two experiments: one with metal identification , second with milk purity checking. In both the experiments for evaluation Accuracy and F1 score is used to check the performance of the designed model and we got both close to 0.99. In future we will use the same setup to classify various diseases in plants for agriculture application.

Compared to spectrography, multispectral imaging systems can give more meaningful data as well as performance, however at low cost spectrography also gives satisfactory level performance and it is used widely by various researchers.

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