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REPORT

ON

HYPERSPECTRAL IMAGING IN PRECISION AGRICULTURE

TECHNICAL SEMINAR ON SUSTAINABILITY

(19EC6SRTSR)

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ABSTRACT:

Agriculture-the primary sector is facing a lot of challenges in the world of globalization. Increased stress on the environment, degradation of natural resources, and expanding populations are the major concerns. The paradigm shift in the philosophy of agriculture from the conventional irrational usage of natural resources to a judicious, precise and rational use of the available resources has been a guiding light in the last few decades. This is called precision agriculture which has received a lot of attention in the global research community. The data regarding the soil properties like soil moisture, weeds distribution, nutrient contents of the soil are of utmost importance for carrying forward precision agriculture. In this paper,it has been explained that a revolutionary imaging technique known as the hyperspectral imaging technique can be used to obtain the data required to carry out precision agriculture. The hyperspectral imaging technique has been discussed in detail with a greater emphasis on analysis of the datasets obtained using machine learning algorithms and pre-processing techniques.The machine learning algorithms have been implemented using python.A special class of algorithms called pan-sharpening algorithms are also explored.

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1.INTRODUCTION

Remote sensing techniques like Ultrasound, LiDAR, Active cameras, Structured Light cameras, thermal imaging cameras, multispectral cameras have all been used over the last few decades for obtaining images of agricultural fields. Figure 1 shows the evolution of the sensing methodologies. It is very much clear from the figure1 that the latest innovation in the field of sensing techniques is Hyperspectral Imaging. All the other conventional methods of sensing have a major limitation with respect to the resolution of the images obtained, whereas HSI has a very high resolution which would facilitate the users to obtain a greater and much clearer amount of information about the farmlands.

Figure1: Evolution in the use of range and artificial vision sensors for morphological characterization and fruit/plant detection. The years report the first use of these sensing systems for agricultural purposes

Courtesy: IEEE/ASME TRANSACTIONS ON MECHATRONICS

2.FUNDAMENTALS OF HYPERSPECTRAL IMAGING

In any imaging technique, the basic idea is to shine light on an object ,receive the light reflected by the object and try to construct the object with the photonic information received. Every material has its own characteristic emission, absorption and reflection spectrum. Imaging is a kind of inverse mapping where we try to recognize a given material by analyzing its spectral characteristics. In case of commercial digital cameras, mainly 3 bands of wavelength Red, Green and Blue are used. Hence, the information gathered about the object is very much limited. In case of multispectral imaging, a few bands of wavelengths are used. So, the information gathered is relatively better qualitatively and quantitatively. But the resolution of the images is not very good. This limitation is overcome by adopting hyperspectral imaging technique in which hundreds of bands of wavelengths are used to capture the information about an object under observation. Hence, a lot of very fine spectral details of the object which are otherwise unavailable if other techniques are employed can be obtained.

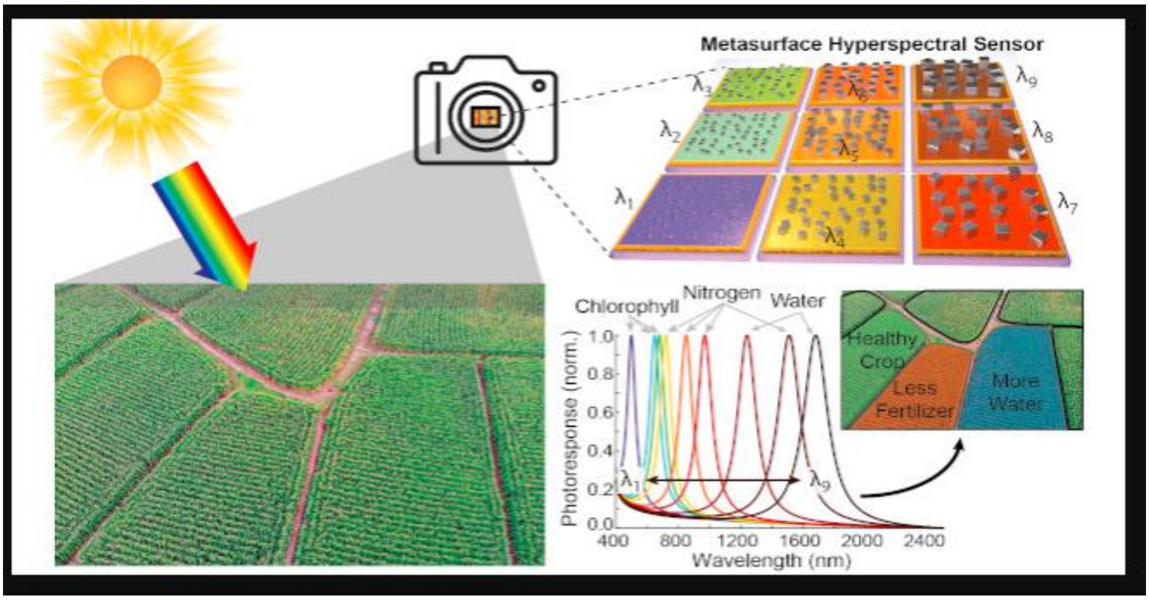

Figure 2. Employment of Hyperspectral imaging in agriculture

Courtesy: Maiken Mikkelsen and Jon Stewart, Duke University

3. PREPROCESSING OF HYPERSPECTRAL IMAGING

Images contain qualitative and quantitative information as they consist of being large datasets and visually interpretable entities. One of the challenging problems in processing high dimensional data is the computational complexity resulting from processing the vast amount of data volume.A hyper-spectral image is a wide collection of data, stored in pixels, each of them usually highly correlated to their neighbours and they are composed by thousands or, sometimes, millions of data points. Thus Data pre-processing or data cleansing is a crucial step and most of the ML engineers spend a good amount of time in data preprocessing before building the model. Hyper-spectral Image preprocessing is the term for operations on images at the lowest level of abstraction.The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis tasks. Preprocessing of hyper-spectral imagery includes geometric correction, orthorectification, radiometric correction, and atmospheric correction Soil reflectance in the visible near-infrared and mid-infrared regions has been widely used in many studies. These hyper-spectral images taken under laboratory conditions have minimal source of noise. On the other hand, Images taken by remotely sensed airborne or space-borne data or sensors are influenced by atmospheric interference and the occurrence of spectral noises. Preprocessing of hyper spectral imaging for satellite- and airplane-based hyper-spectral images, the geometric and orthorectification correction are generally performed on images and the radiometric and atmospheric corrections are done on standard image processing.In UAV a digital elevation model (DEM) and ground control points (GCPs) are usually needed for performing the orthorectification and geometric correction, accurate sensor orientation information recorded by an IMU will be needed for these corrections. Some of the preprocessing techniques are as follows

1. ***Calibration***

The calibration of image captured in reflectance, absorbance or transmittance mode allows us to generate a corrected image using a black and a white reference image: the black image can be obtained by placing the cap on the lens of the camera, instead the white image is carried out of a high reflectance material placed inside the framing area.

2. ***Radiometric correction***

Radiometric correction is conducted to convert image digital numbers to radiance using calibration coefficients that are provided by the sensor manufacturer. The radiance is measured by any given system over a given object when influenced by factors such as changes in scene illumination, atmospheric conditions, viewing geometry, and instrument response characteristics. For generating mosaics of satellite images taken in visible light, it is usually necessary to apply a sun elevation correction and earth-sun-distance correction. The sun elevation correction accounts for the seasonal position of the sun relative to the earth. It normalises the image data acquired under different solar illumination angles by calculating pixel brightness values assuming the sun was at the zenith on each date of sensing. The earth-sun distance correction is applied to normalise for the seasonal changes in the distance between the earth and the sun.Radiometric data processing used in quantitative applications is conversion of DNs to absolute radiance values. Such conversions are necessary when changes in the absolute reflectance of objects are to be measured over time using different sensors. Normally, detectors and data systems are designed to produce a linear response to incident spectral radiance. The absolute spectral radiance output of the calibration sources is known from pre launch calibration and is assumed to be stable over the life of the sensor. Thus the onboard calibration sources form the basis for constructing the radiometric response function by relating known radiance values incident on the detectors to the resulting DNs.[4]

3. *Atmospheric Correction:-*

Atmospheric constituents such as gases and aerosols have two types of effects on the radiance observed by a hyper-spectral sensor. When images captured by the UAV flown at low altitudes, the images acquired are influenced by various atmospheric absorptions and scatterings, such as oxygen absorption, water absorption and carbon dioxide absorption .This atmosphere absorption affects the brightness or radiance, recorded over any given point on the ground.

The two ways in which atmosphere absorption affects are when a sensor records reflected solar energy. First it attenuates (reduces) the energy illuminating a ground object (and being reflected from the object) at particular wavelengths, thus decreasing the radiance that can be measured. Second, the atmosphere acts as a reflector itself, adding a scattered, extraneous path radiance to the signal detected by the sensor which is unrelated to the properties of the surface. The formula for total radiance recorded by the sensor due to reflectance of the ground images is

$$L_{tot} = \frac{pET}{\pi} + Lp \qquad \text{………………(1)}$$

Hyper-spectral data contain a substantial amount of information about atmospheric characteristics at the time of image acquisition. In some cases, atmospheric models can be used with the image data themselves to compute quantities such as the total atmospheric column water vapour content and other atmospheric correction parameters.Therefore, atmospheric correction is critical for obtaining good-quality spectral information Software or methods commonly used in previous studies for performing atmospheric correction on UAV-based hyper-spectral images include the MODTRAN model (Spectral

Sciences Inc.), ENVI FLAASH, PCI Geomatica (PCI Geomatics Corporate), SMARTS model (Solar Consulting Services).[4]

4. *Feature reduction / Band reduction / Data dimensionality reduction techniques:-*

Hyper-spectral images typically have hundreds of bands, and many of them are highly correlated. Thus bands removal of least effective feature is referred to as feature selection and the other is to transform the pixel vector into a new set of coordinates in which the features that can be removed are more evident. Therefore, feature reduction, i.e., band reduction, has become a more significant part of image interpretation process.In order to perform the band reduction, we can approach to employ some sort of linear transformation on the original dataset to produce a smaller set of factors or components.Most of the original variance is retained with a significant reduction in data volume.Therefore, dimension reduction is also an essential procedure to consider in the preprocessing of hyper-spectral imagery.

5. *Principal Component Analysis (PCA):-*

In PCA preprocessing, data analysis which transforms multidimensional image data into a new, uncorrelated coordinate system or vector space. The principal component analysis is based on the fact that continuous bands of hyperspectral images are highly correlated and often convey almost the same information about the object. The analysis is used to transform the original data so as to remove the correlation among the bands. In preprocessing we produce a space in which the data have maximum variance along its first axis, the next largest variance along a second mutually orthogonal.This variances contribute little to separability among the bands, reducing the dimensionality of the classification space and thus improving classification speed.Thus PCA will compress all the information contained in an original n – band data set into fewer than n “new bands” or components .

6. *Redundancy:-*

There is huge data gathered from the platforms, thus data does not contain any particular information for specific applications, it contains redundancies. The data recorded by hyper-spectral sensors have a large overlap of information content over the bands of data for a given pixel. In such cases, not all of the data is needed to characterise a pixel properly, although redundant data may be different for different applications. Data redundancy can take two forms; spatial and spectral. Since hyper-spectral imagery has more spectral concern, one way of viewing spectral redundancy in hyper-spectral data is to form the correlation matrix for an image; the correlation matrix can be derived from the covariance matrix. High correlation between band pairs indicates a high degree of redundancy.

7. *Minimum Noise Fraction (MNF):-*

This transformation is mainly used to reduce the dimensionality of hyper-spectral data before performing the data fusion. It is defined as a two-step cascaded PCA . The first step, based on an estimated noise covariance matrix, is to decorrelate and rescale the data noise, where the noise has unit variance and no band-to-band correlations. Then the PCA analysis is performed on noise-whitened data.The MNF transformation is a linear transformation of Principal component that orders the data according to signal-to-noise-ratio. MNF transformation determines the dimensionality of the data and segregates noise in the data and reduces the computational requirements for processing data. This partitions the data space into two parts: one associated with large eigenvalues and coherent eigen-images, and a second with near-unity eigenvalues and noise-dominated images. By using only the coherent portions in subsequent processing, the noise is separated from the data, thus improving spectral processing results.

8. *Band sensitivity:-*

Band sensitivity analysis used in hyper-spectral remote sensing to reduce the data size by selecting only the bands that are sensitive to the object of interest. Different algorithms such as a fast volume-gradient-based method that is an unsupervised method and removes the most redundant band successively based on the gradient of volume,column subset selection-based method that maximises the volume of the selected subset of columns (i.e., bands) and is robust to noisy bands, and a manifold ranking-based salient band selection method that puts band vectors in manifold space and selects a band-based ranking that can tackle the problem of inappropriate measurement of the band difference .Sensitivity analysis identifies spectral bands that are sensitive to different crop properties.

4. ANALYSIS OF HYPERSPECTRAL IMAGING IN PRECISION AGRICULTURE

After preprocessing of carefully captured images to produce a dataset of desired measurements from the images. Analysis approaches are being developed which are enabling the Hyper-spectral imaging technologies to be utilized for wider ranging applications. Hyper-spectral imaging uses high-fidelity color reflectance information over a large range of the light spectrum and thus has potential for identifying subtle changes in plant growth and development.

Machine Learning :-

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. machine learning is divided into Supervised machine learning algorithms that can apply what has been learned in the past to new data using labeled examples to predict future events and unsupervised machine learning algorithms are used when the information used to train is neither classified nor labeled.The machine learning helps in dealing with the big data to classify and come up with the solution. The machine learning models allow us to classify and organize the data so they can be analyzed. This Big data generated by the hyper spectral imaging provides farmers with useful and actionable information on weather and seasonal patterns, rain and water cycles, fertilizer requirements, and other critical information for harvesting and decision making. This enables farmers, agricultural suppliers and other stakeholders to make smart decisions such as the cycles for crops planting to increase profitability and the planning of optimal harvesting times leading to improved farm yields.

. The machine learning models contain different algorithms for different use cases and it is up to the programmer to come up with an algorithm model which will suit for the analyzing of the images. Some Machine learning Algorithms are RS image analysis , artificial neural networks (ANN), decision tree (DT) classifiers, Random Forest (RF), K means clustering and Support Vector Machines (SVM).[5]

SVM is a supervised machine learning algorithm which can be used for classification or regression problems. It uses a technique called the kernel trick to transform your data and then based on these transformations it finds an optimal boundary between the possible outputs. Simply put, it does some extremely complex data transformations, then figures out how to separate your data based on the labels or outputs you've defined. SVM is used for classifying different crop types and achieving high classification accuracy. Since there are multiple features present in the images that need to be classified to analyze. The SVM algorithm is used to group the data in the different groups according to similar features. The models need to be trained with the dataset with structured data. The model will be trained with structured data and creates groups of the same features and create boundaries from other groups.

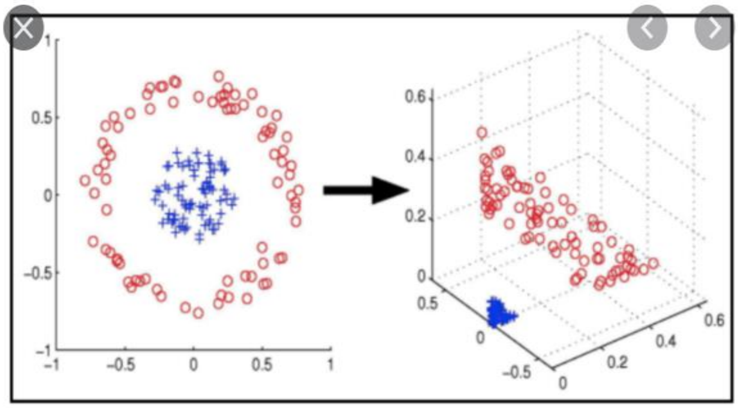

Figure 3 : SVM algorithm using kernel transformation for non-linear data.

Random Forest is another commonly used algorithm for investigating agricultural features with Hyper-spectral imagery. Random Forest is supervised machine learning used for Classification and Regression problems in ML. Random Forest consists of a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset. For example, In images taken, we need to separate weeds from the crop. We can use the RF to classify them. Using ground-based hyperspectral reflectance data acquired by an ASD spectroradiometer. RF can be used to detect maize disease with the RF model. Overall, machine learning models generally have robust performances for investigating agricultural features using hyper-spectral imagery.

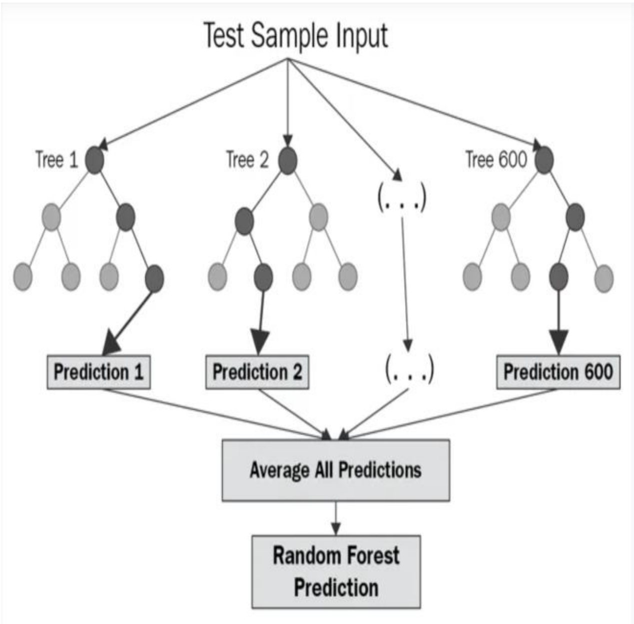

Fig:4 Random Forest Tree

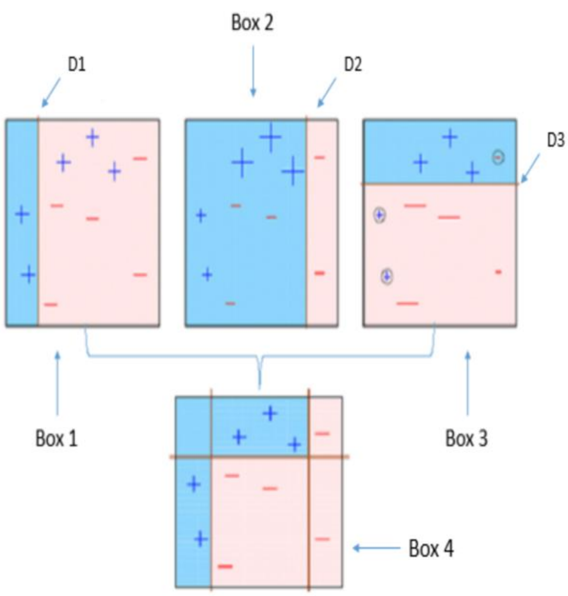

Fig:5 XGBoost Concept

5. IMPLEMENTATION OF MACHINE LEARNING MODEL-Indian Pines lands Classification.

Link : https://drive.google.com/file/d/1w8BeQt4dx6Ip7htV7GWfYZaPc_JLcUbN/view?usp=sharing

(The link for the Python Machine learning Code file)

The dataset was obtained from the Purdue website. This Image was gathered by AVIRIS sensor over the Indian Pines test site in North-western Indiana and consists of 145 X 145 pixels and 224 spectral reflectance bands in the wavelength range 0.4–2.5 10^(-6) meters. This scene is a subset of a larger one. The Indian Pines scene contains two-thirds agriculture, and one-third forest or other natural perennial vegetation. There are two major dual lane highways, a rail line, as well as some low density housing, other built structures, and smaller roads. Since the scene is taken in June some of

The crops present, corn, soybeans, are in early stages of growth with less than 5% coverage. The ground truth available is designated into sixteen classes and is not all mutually exclusive. We have also reduced the number of bands to 200 by removing bands covering the region of water

Absorption.

The Machine learning model was trained using this dataset for classification of land in Indiana for agricultural and commercial infrastructure.In the machine learning model, the process was Data visualization, Data Analysis, Training model and Testing models for Classification of pixels in the image.

First part of Data Analysis was to find the dataset shape, dataset Objects and Pixel distribution in the dataset.

In the Data Analysis, Data set shape is 21025 X 201. The dataset contained 200 bands and label associated with that row. The dataset top 5 is printed out .The rows contain the pixels associated with the respective band.

	band-1	band-2	band-3	band-4	band-5	band-6	band-7	band-8	band-9	band-10	...	band-192	band-193
0	3172	4142	4506	4279	4782	5048	5213	5106	5053	4750	...	1094	1090
1	2580	4266	4502	4426	4853	5249	5352	5353	5347	5065	...	1108	1104
2	3687	4266	4421	4498	5019	5293	5438	5427	5383	5132	...	1111	1114
3	2749	4258	4603	4493	4958	5234	5417	5355	5349	5096	...	1122	1108
4	2746	4018	4675	4417	4886	5117	5215	5096	5098	4834	...	1110	1107

Fig:6 Contents of Dataset

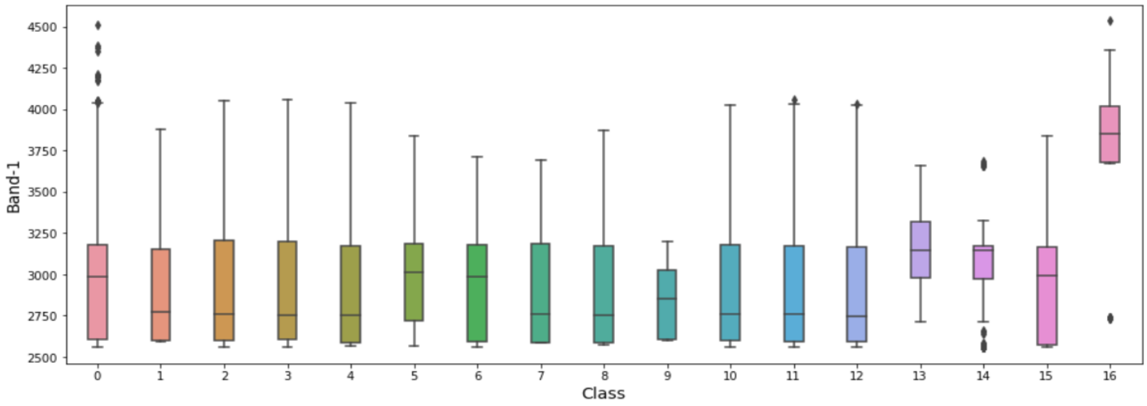

Fig:7 Amount of pixels of each class in Band 1.

We visualized the total number of pixels associated with each class label by plotting the box plot. In the Data Visualization, we wanted to analyze the pixel with respect to the label in the band, so we plotted the box plot. The plot can be shown here

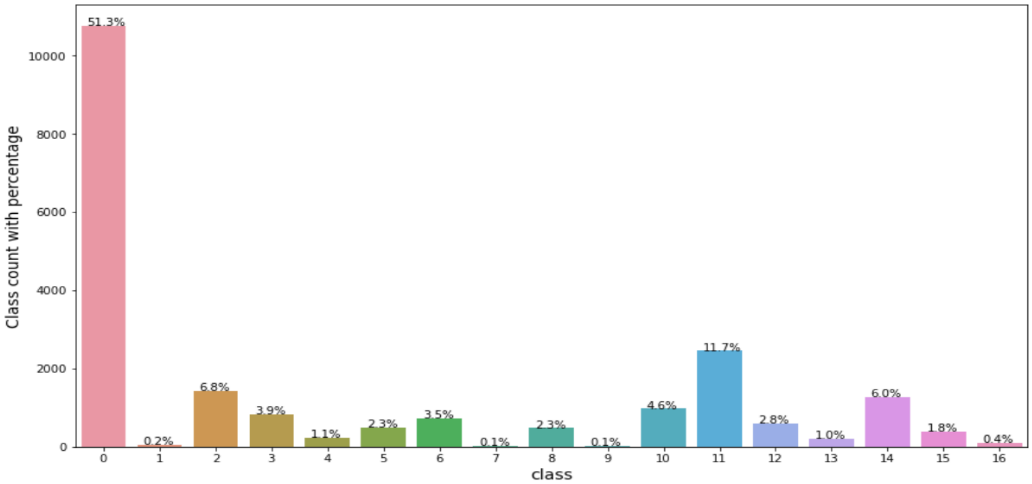

Fig:8 Box plot of pixels associated with class labels

Training the dataset, we needed to preprocess the data and reduce the dimensionality of the data, so we can eliminate the redundancy and train the model with higher efficiency and classification. We Used PCA(Principal Component Analysis), the PCA transforms the Dataset bands of 200 into 150 bands having high covariance among the pixels from each band. The PCA helps in increasing the accuracy of the model by eliminating the duplicates in the dataset.The PCA Cumulative explained variance is plotted to see the variance in the 150 bands. The Graph is shown here.

Classification report:

	precision	recall	f1-score	support
0	0.74	0.91	0.82	3236
1	0.00	0.00	0.00	14
2	0.57	0.52	0.54	424
3	0.81	0.28	0.42	232
4	0.90	0.11	0.20	82
5	0.94	0.51	0.66	142
6	0.87	0.62	0.72	226
7	0.00	0.00	0.00	14
8	0.79	0.99	0.88	133
9	0.00	0.00	0.00	3
10	0.66	0.62	0.64	280
11	0.62	0.80	0.70	711
12	0.75	0.23	0.35	192
13	0.91	0.81	0.85	72
14	0.72	0.21	0.32	385
15	0.00	0.00	0.00	131
16	0.75	0.87	0.81	31
accuracy			0.72	6308
macro avg	0.59	0.44	0.46	6308
weighted avg	0.71	0.72	0.68	6308

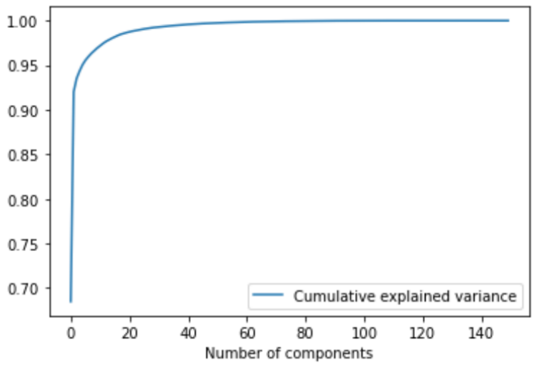

Fig:9 PCA - Cumulative explained variance Graph.

After the PCA transform, The dataset is divided into the training and test dataset by 70 % and 30% respectively.The SVM model was trained using trained dataset. The Accuracy was pixel classification was about 71.84%.The classification report was printed to see the prediction accuracy for each of the labels.

After training the model. The classification of pixels is divided and realized into the image to compare with the ground truth. As we can see, all the pixels were not able to to classify into the correct label.Thus we can see the pixels in different labels.

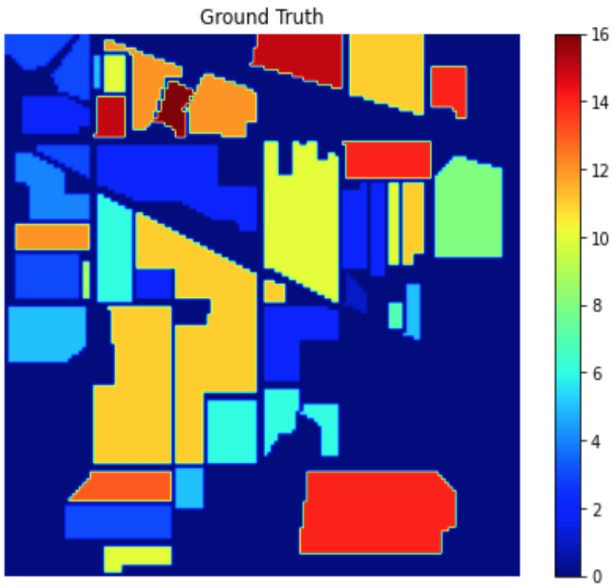

Fig:10 Ground Truth Image.

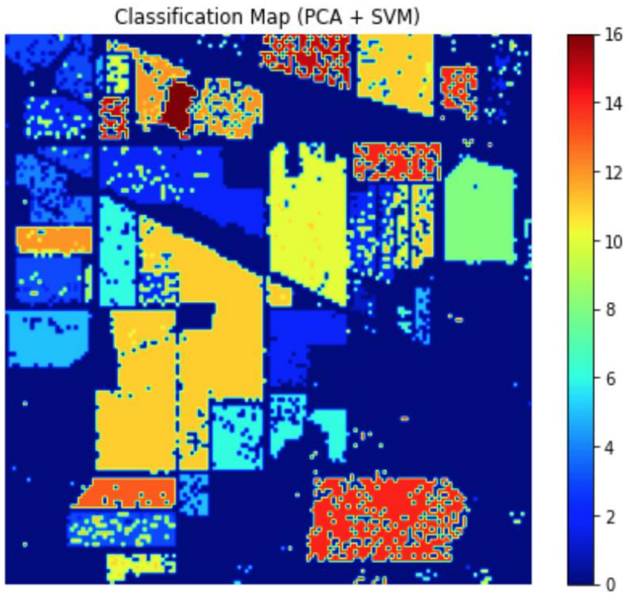

Fig:11 PCA+ SVM classification Image.

```
pipeline_lr=Pipeline([('scalar1',MinMaxScaler()),
                     ('lr_classifier',LogisticRegression(max_iter=5000))])

pipeline_dt=Pipeline([('scalar2',MinMaxScaler()),
                     ('dt_classifier',DecisionTreeClassifier())])
pipeline_randomforest=Pipeline([('scalar3',MinMaxScaler()),
                     ('rf_classifier',RandomForestClassifier())])
pipeline_SV=Pipeline([('scalar4',MinMaxScaler()),
                     ('SVC_classifier',SVC(kernel='rbf'))])
pipeline_Ada_boost=Pipeline([('scalar5',MinMaxScaler()),
                     ('ADA_classifier',AdaBoostClassifier())])
pipeline_XGBoost=Pipeline([('scalar6',MinMaxScaler()),
                     ('XG_Bosst',XGBClassifier())])
```

```
for i,model in enumerate(pipelines):
    print("{} Test Accuracy: {}".format(pipe_dict[i],model.score(X_test,y_test)))
```

```
Logistic Regression Test Accuracy: 0.7415979708306912
Decision Tree Test Accuracy: 0.6534559289790742
RandomForest Test Accuracy: 0.7370006341154091
Support Vector Machines Test Accuracy: 0.7533291058972733
ADA Boost Test Accuracy: 0.4245402663284718
XGBOOST Test Accuracy: 0.797717184527584
```

In order to Increase the accuracy of Classification, we used the pipeline model which automates the machine learning workflow by enabling data to be transformed and correlated into a model. The pipeline model allows to train models with data to tune the model and transform the predictions. Using a for loop, we put an evaluation metric such as accuracy a model score for pipe line to print out accuracy of the model.

After Training the Pipeline model,we see that the XGBoost model has higher accuracy of all models with 80% accuracy.We can decide the XGBoost is best for classification, we try to improve the accuracy by cross validation of the dataset. Cross validation is used to estimate the skill of a **machine learning** model on unseen data. That is, to use a limited sample in order to estimate how the model is expected to perform in general when used to make predictions on data not used during the training of the model.Thus we use the model to predict the K Fold = 3, which means take the train the model with three iterations of datasets in random order. This eliminates the unknown of the predicted data.As you can see the Xgboost classification of pixels has higher accuracy of predicting pixels to respective labels. These models can be trained with higher accuracy if given access to high amounts of Big data to train the model.

The Implementation of machine learning model shows that Hyperspectral Imaging is far superior to conventional imaging techniques such as satellite Imaging in Agriculture.The hyperspectral Imaging allows you to analyze crop conditions over thousands of square metres. Farmers can use machine learning for Hyperspectral data to identify soil and crop conditions and characteristics, monitor growth,

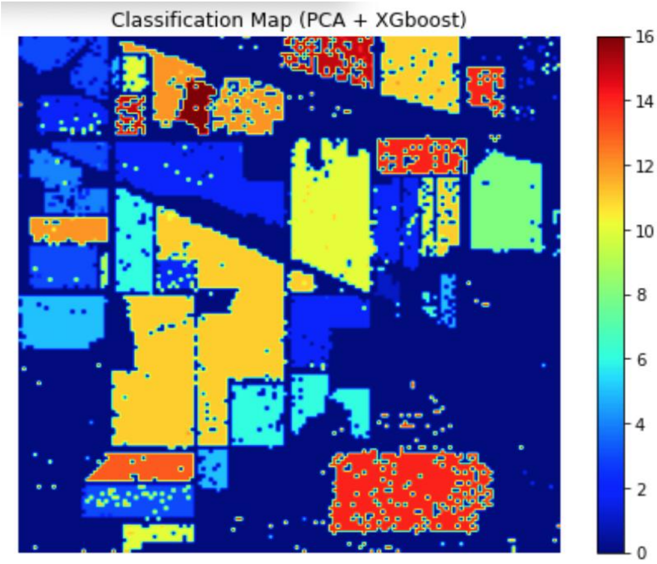

Fig:12 PCA+ XGboost Classification Image

assess soil and irrigation requirements(Nitrogen and water content).In This Machine learning model, classification of pixels to specific label allows the farmers to see the crop yield and crop pattern grown around the land.This models see the what crops can be grown to next season according to the previous yield patterns.The classification allows the farmers to map the path for automated drones and machinery in the fields for various requirements such as pesticides and fertilizer.

Fig:13 Drone Path for Fertilizing the field.

6. PAN SHARPENING ALGORITHMS

Multi-spectral and hyperspectral images have very good spatial resolution.But , due to the discontinuity in the bands,the spectral sensors need to scan a larger area in order to get the images,this would lead to larger pixel area.This would decrease the spatial resolution of the image. But,an efficient data analysis can be done only when we have images with high spectral and spatial resolution. In order to accommodate both spectral and spatial resolution in an image, techniques like pan-sharpening algorithms are used. In pan-sharpening techniques,two images of an object are captured. One, a panchromatic image which is captured in gray-scale and the other a regular multispectral image with high spectral resolution.A panchromatic image is captured on a sensor with a single band covering a continuum of wavelengths. So, the size of a pixel is small in case of a panchromatic image giving it a very high spatial resolution. The two images are fused together using few mathematical techniques in order to get a resultant image with high spectral and spatial resolution.Two algorithms implementing pan-sharpening technique have been discussed in the report.[14]They are as follows:

- IHS Algorithm
- Brovey Algorithm.

IHS Algorithm :

IHS Algorithm is one of the most commonly used techniques for Image Sharpening. It has become a standard procedure in image analysis for improvement of Spatial Resolution.IHS stands for Intensity-Hue- Saturation. In IHS, the spectral information is reflected on Hue and Saturation.

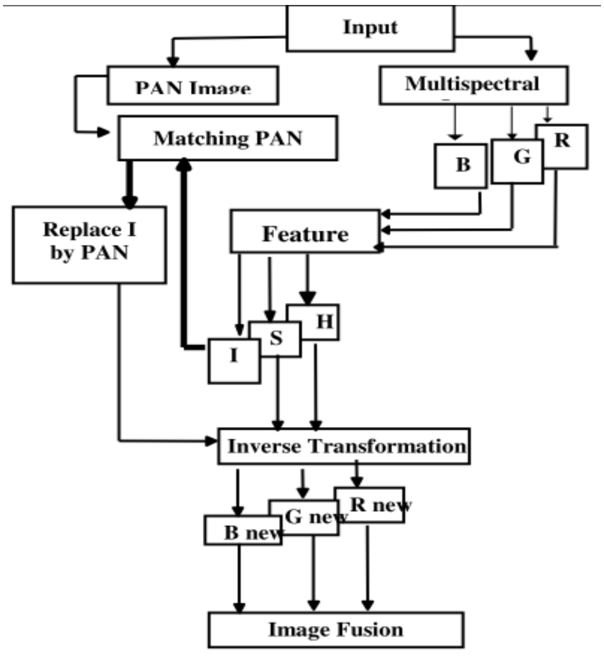

Fig.14 Flow of IHS Algorithm

The IHS Algorithm takes 2 input images PAN and Multispectral. The RGB (Red, Green, Blue) components are extracted from the Multispectral image and they are transformed into IHS components using various mathematical models. The Intensity of the Multispectral Image is mapped to the intensity of the PAN image and using this data the IHS components are transformed back into new RGB components. The Fused image is developed using these new RGB values. This Fused image contains the spatial resolution of PAN image and Spectral Resolution of Multispectral image.

$$\begin{bmatrix} I \\ v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{6}} & \frac{-2}{\sqrt{6}} \\ \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{2}} & 0 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad \begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = \begin{bmatrix} 1 & \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{2}} \\ 1 & \frac{1}{\sqrt{6}} & \frac{-1}{2} \\ 1 & \frac{-2}{\sqrt{6}} & 0 \end{bmatrix} \begin{bmatrix} I \\ v_1 \\ v_2 \end{bmatrix}$$

$$H = \tan^{-1}\left(\frac{v2}{v1}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots(2)$$

$$S = \sqrt{v_1^2 + v_2^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots(3)$$

Since hyperspectral Images are taken on a large scale, Each pixel can be viewed as a point on the Cartesian plane with axes v1 and v2. Hue is analogous to the angular component and Saturation to the radial component.Fig. 7 shows the fused image based on IHS algorithm

Brovey Transform :

Brovey Transform is a type of image Fusion technique that preserves the relative spectral contributions of each pixel but replaces its overall brightness with high resolution Panchromatic Image. Here the Intensity (Resolution) of RGB components of the Multispectral Images are scaled to the Intensity of the Panchromatic Image.

$$R_{new} = \frac{R}{(R+G+B)} \times PAN \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

$$G_{new} = \frac{G}{(R+G+B)} \times PAN \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

$$B_{new} = \frac{B}{(R+G+B)} \times PAN \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

Fig. 8. Shows the Fused image based on Brovey Transform

As observed from Fig. 7 and 8, The IHS based image does not show some blue areas when fused

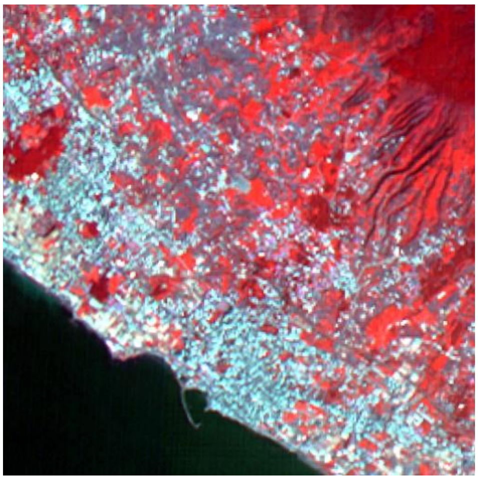

Fig.15. Multispectral Image

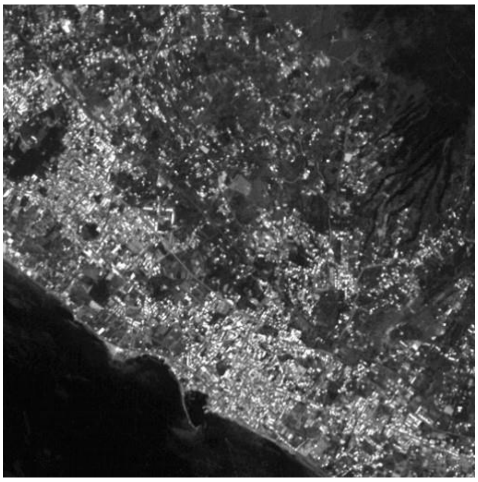

Fig. 16. Panchromatic Image

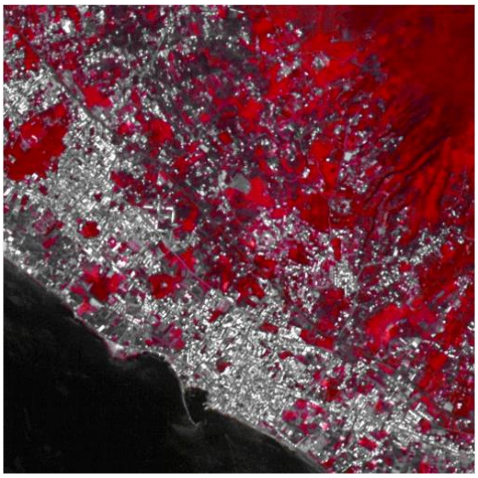

Fig. 17.IHS Based Fused Image

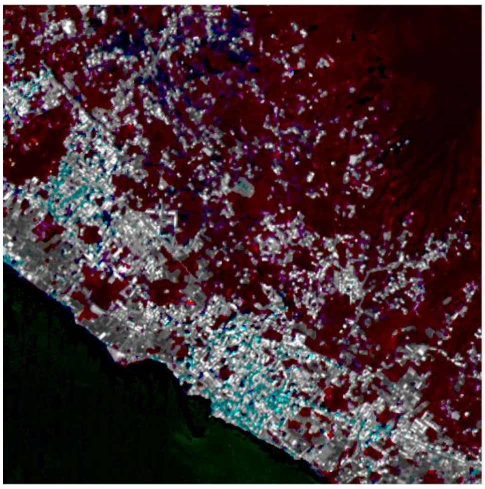

Fig. 18.Brovey Transform Based Fused Image

As observed from Fig. 7 and 8, The IHS based image does not show some blue areas when fused. This is because during the Transform and Inverse IHS Transform, there is a chance of losing some color components . This is a major drawback of IHS algorithm. So Brovey Transform is more preferable than IHS algorithm.

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7. FUTURE TREND

Deep learning

Hyperspectral images have high dimensionality, non-linear correlations, and large spatial variability of spectral signatures, can make classification and analysis a challenge even for traditional machine learning methods. Deep learning algorithms such as convolutional neural networks (CNNs) have been successful in the classification of hyperspectral images. DL outperforms the limitation of conventional ML techniques, which was the ability to process natural data in their raw form to extract high-level spatial-spectral features effectively. DL is actually everywhere in remote sensing (RS) data analyzing (e. g. image pre-processing, pixel-based classification, target recognition and recently in high level semantic feature extraction and scene understanding). DL is modelled by neural networks (NNs) with many hidden layers. Multiple hidden layers work to build an improved feature space. Higher layers make aspects of the input that are important for discrimination more relevant and suppress irrelevant variations. Second layer learns first order features, as edges; third layer learns higher order features (combination of first layer features, combinations of edges).The Constructing a pattern-recognition or ML(NLP) system required a deep knowledge for decades to build a feature extractor that could transformed the raw data into suitable internal representation or feature vector, from which the learning system could detect or classify patterns in input and output. Deep learning is used investigating the estimation of crop yield using CNN and multispectral images together with climate data , plant disease detection using CNN and smartphone-acquired images , crop classification using 3-D CNN and multi-temporal multispectral images , and classification of agricultural land cover using deep recurrent neural network and multi-temporal SAR images.

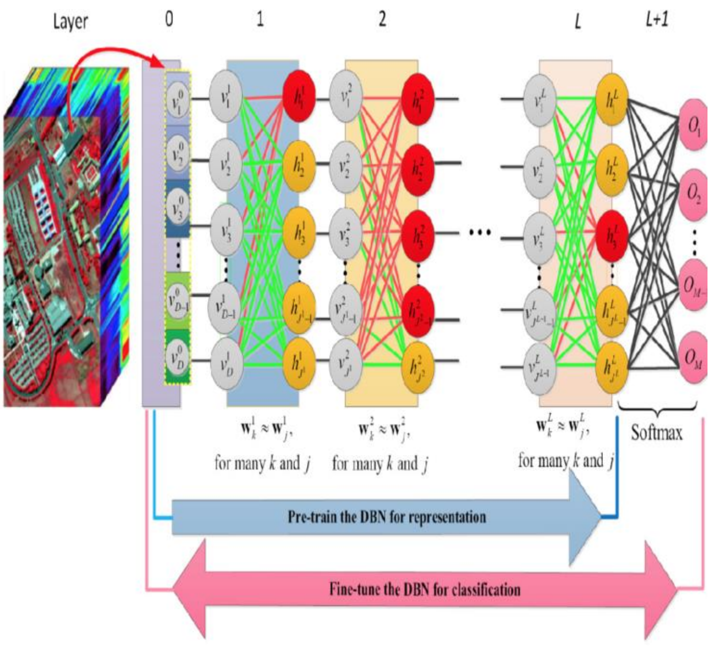

Fig:19 CNN (Convolutional Neural Networks)

8. CONCLUSION

In this report, a detailed analysis of hyperspectral imaging has been done.The advantages of hyperspectral imaging over other conventional remote sensing techniques have been discussed.The steps involved in the analysis of a hyperspectral image are explored.Analysis of datasets regarding agricultural diversity in the Indiana province of the USA has been performed using suitable machine learning models like SVM has been successfully done.The machine learning algorithms implemented have been using python.A comparative study of accuracy of various mathematical models like SVM,XG-Boost, Logarithmic regression and Decision tree to classify the pixels has been accomplished and it has been found that XG-Boost is the most accurate amongst all the other methods.A closer look at the pre-processing techniques has also been done.Here,the trade-off between spatial and spectral resolution of images has been accomplished by the implementation of a special class of pre-processing techniques called pan-sharpening algorithms.Two such pan-sharpening algorithms have been discussed in the report.The futuristic trends in this domain like the introduction of deep-learning algorithms to study the hyperspectral data of the agricultural lands have been discussed.In this way,hyperspectral imaging technique can be used to obtain the data regarding the agrarian fields and henceforth it becomes a pivotal support for precision agriculture.

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