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Hyperspectral imaging and its applications: An Overview

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Recording of the spectral information together with spatial information is useful for many applications. Hyperspectral Imaging (HSI) is a recently developed imaging modality which is capable of recording both the spatial (x, y) and spectral (λ) information of a scene. Thereafter, several applications have been shown using HSI. In this review, we discussed some of the recent implementations of HSI that aimed at addressing several scientific research problems. We also brief about some of the existing types of HSI cameras. In some of the recent works, Deep Learning (DL) frameworks have been extensively used for several HSI related problems. We have provided insights on some of the recent implementations of DL on HSI based problems.

Keywords: Hyperspectral imaging, Deep learning, Biomedical imaging, Spectral imaging.

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1 Introduction

Hyperspectral Imaging (HSI) refers to recording of many spectral informations from a scene of interest. In general, human eyes are capable of recognizing or clearly distinguishing only three bands of wavelengths from the visible region such as Red (R), Green (G), and Blue (B). However, capturing wider wavelength information, that covers at least from visible to infrared, aids in several scientific applications. HSI gathers a wide range of spectra for each captured pixel spurring among Visible and Infra-Red (IR) regions [1]. Figure 1 shows the electromagnetic spectrum where the HSI can range up to visible and IR.

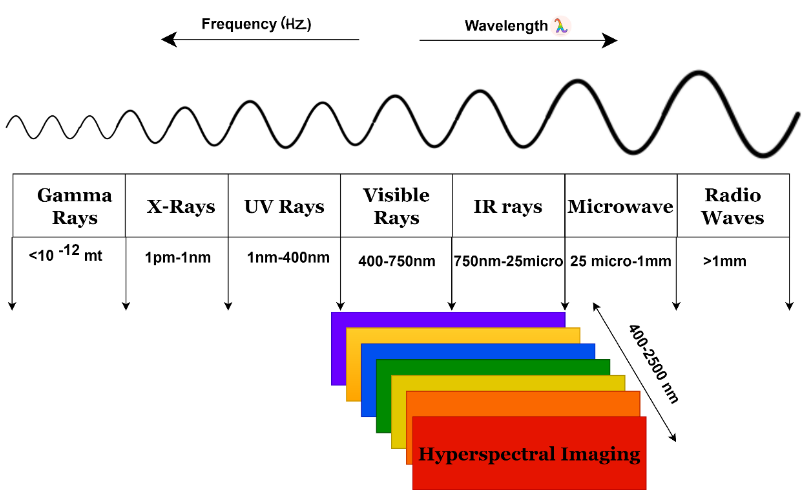

Fig 1. Electromagnetic Spectrum [2]

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In HSI, we represent each pixel of an image with a unique fingerprint called a spectral signature [3]. In general, every material or an object has a different spectral signature that can be visualized using Hyperspectral Sensor. HSI can have a continuous spectrum of information instead of some discrete bands like Multispectral images [4], thus HSI finds many applications as compared to multispectral imaging in different areas of science. To note, HSI stacks up a set of 2D images which is represented as a 3D hypercube with coordinates (x, y, λ), where x and y represent spatial information and λ indicates the spectral information [5]. Figure 2 shows the differences among classical RGB, Multispectral, and Hyperspectral images.

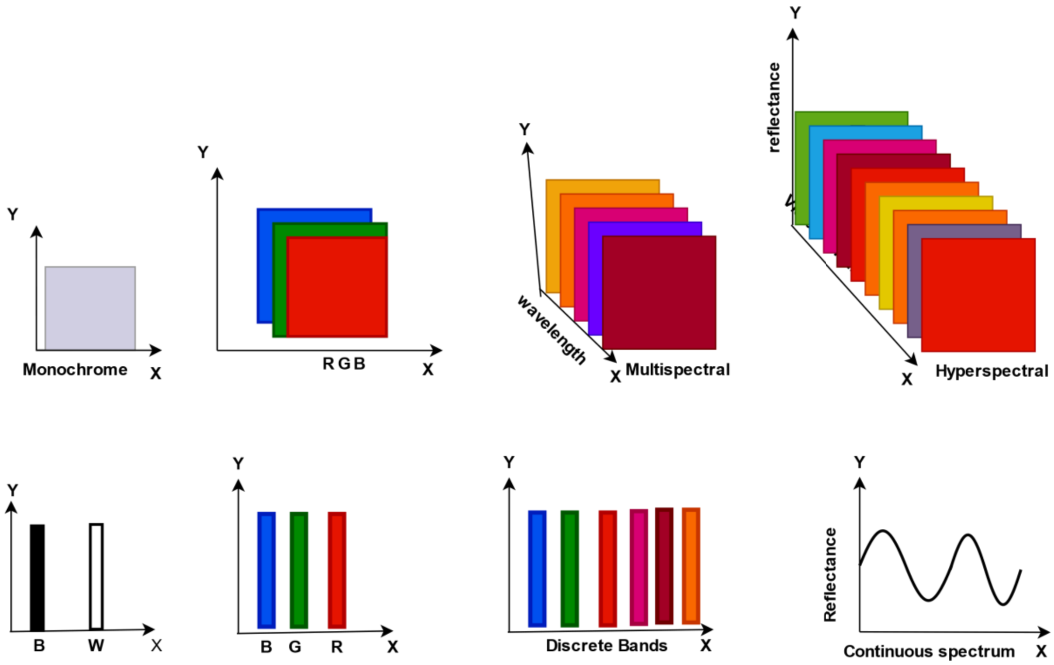


Fig 2. RGB vs Multispectral vs Hyperspectral Imaging [6].

The primary focus of this article is to review the applications of Hyperspectral Imaging in various scientific fields. The rest of the paper is organized as follows. In Section 2, we introduce Hyperspectral based image acquisition and types of HSI sensors. Section 3 presents the applications of HSI in various research areas. Section 4 demonstrates the utilization of Machine Learning (ML) and Deep Learning (DL) methods in Hyperspectral Image processing and finally, we present our conclusion with some future insights in Section 5.

2 Image acquisition methods of HSI

Figure 3 depicts the schematic of the HSI image acquisition process under controlled environment i.e., inside the laboratory and at open space i.e., outside the laboratory.

Figure 3(a) shows a leaf sample kept on a moving stage which allows to take the images from different angles. In laboratory environment, Halogen lamps are commonly used, at the either side of the setup, for proper illumination. The captured images can be processed with several software packages such as Environment for Visualizing Images (ENVI) [9], SPECIM -IQ Studio [10], and/or MATLAB. The output from ENVI can also be converted as mat files which can then be processed using MATLAB. Figure 3(b) represents the setup when the image is taken outside the laboratory environment. HSI imagers can be broadly classified into four types as shown in Fig 4 below.

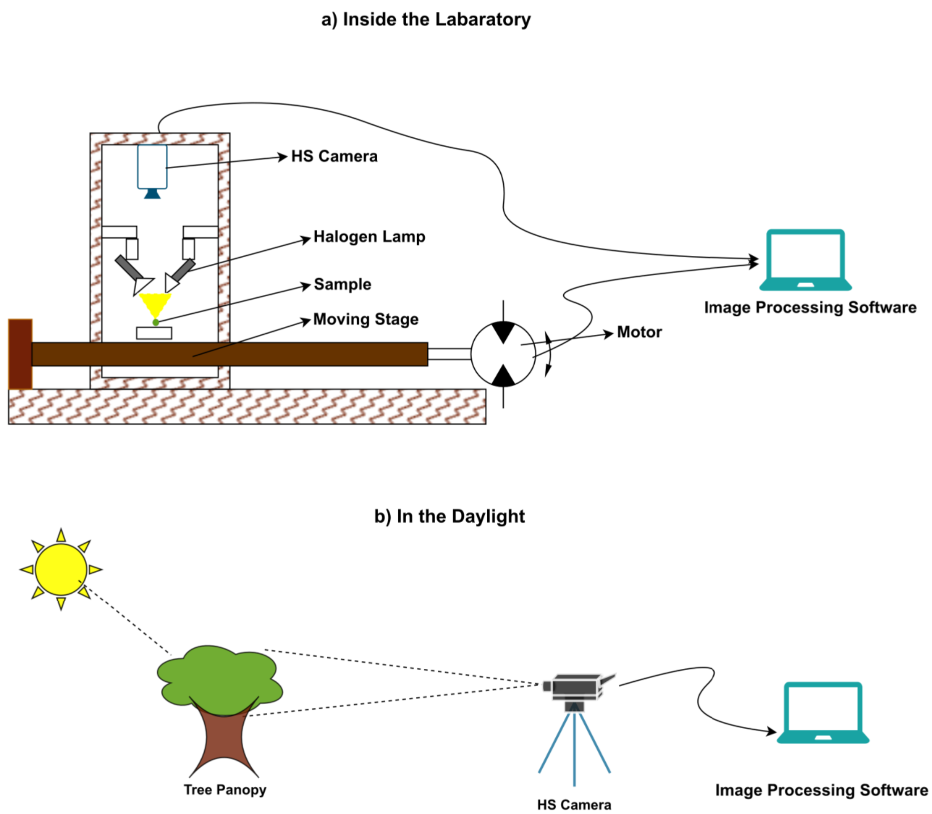


Fig 3. (a) Image acquisition process inside Laboratory (b) in Daylight [8].

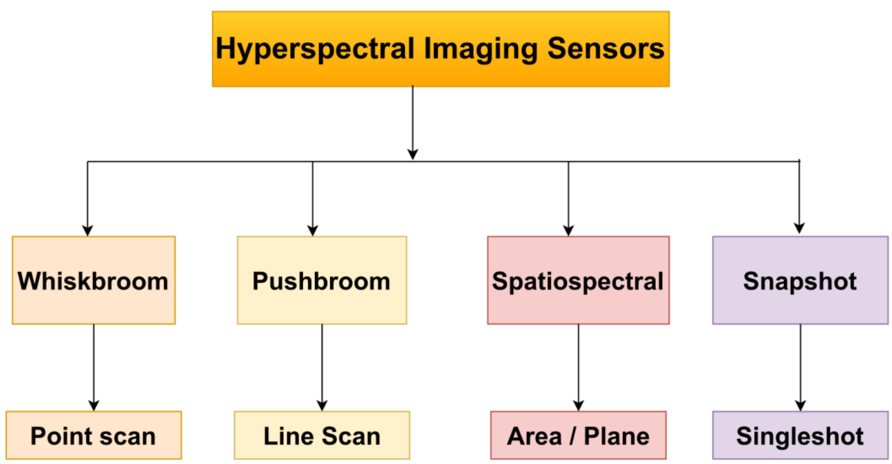


Fig 4. Classification of HSI Sensors.

2.1 Whiskbroom Scanners

Whiskbroom scanners are also known as Point scan cameras [11]. Whiskbroom camera captures the scene point-wise as it moves to and fro in a particular scene. Generally, these types of cameras find their applications in satellite imaging where continuous ground tracking is required.

2.2 Push broom Scanners

These are also called as Line scanning cameras [12]. These sensors scan each line at a time, and it follows the top-down approach. For instance, for a particular scene, it captures line by line from top to bottom. These sensors find their applications in areas such as food and feed quality detection, and seed quality examination [13]. A push broom scanner gathers more photons than a whiskbroom scanner as it exposes the sensor for a longer duration. Push broom sensors have varied sensitivity and the resolution is lower than that of a whisk broom scanner.

2.3 Spatio-spectral scanners

Spatio-spectral scanners are also called area or wavelength scanning cameras [14]. These scannars scans a particular area at a time and covers all corners of the scene. Such scanners can be used for the applications such as plant disease detection [14], and fruit and species abnormality detection. The advantage of spectral scanning is being faster than the Whiskbroom and Push broom, nevertheless the accuracy is limited.

2.4 Snapshot Scannars

Working principle of these scannars are just like commercial cameras [15] which capture the entire spectral and spatial information, in a single shot. Snapshot scannars are used mostly in the daylight scenarios. They have found applications recently in soil monitoring [16] and vegetation. These types of scannars are newly invented and have not yet been widely used as others. Figure 5 depicts the working principle of different types of scannars.

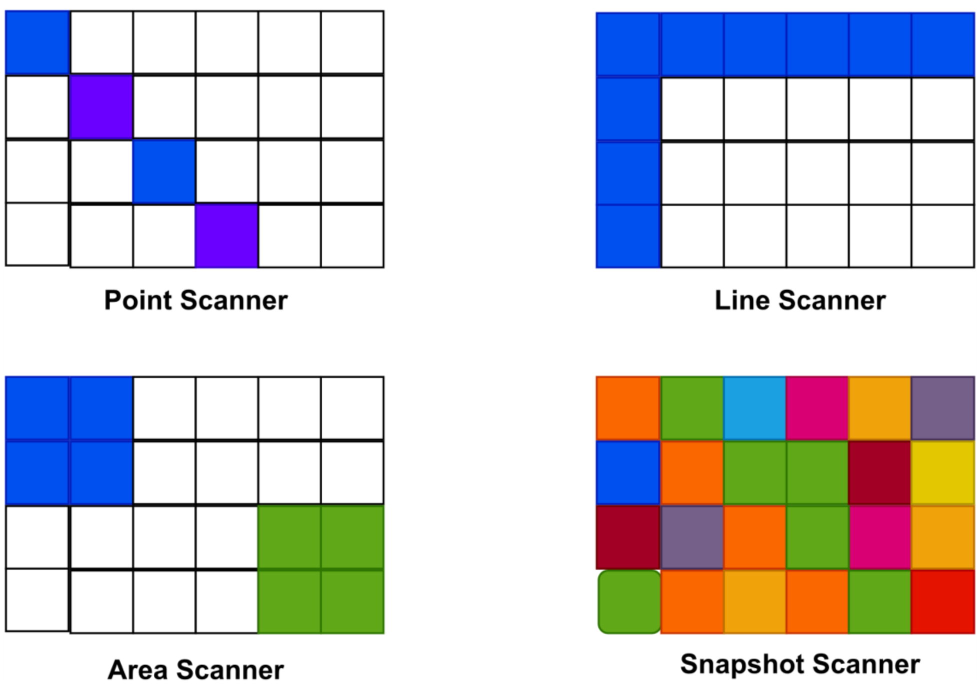


Fig 5. Different Types of Scanners [17].

3 Applications of Hyperspectral Imaging

As mentioned earlier, Hyperspectral Imaging (HSI) possesses the distinctive ability to assign a spectral signature to each individual pixel. This makes it highly valuable across various scientific domains. In the following, we discussed some of the recent applications of HSI.

3.1 Remote Sensing

Remote Sensing is one of the most beneficial areas of Hyperspectral imaging. Particularly in satellite imaging, at least one hyperspectral sensor is used for earth monitoring [18]. In addition to this, HSI have been used extensively in Agriculture, where crop protection is needed, and precision in detecting the infected part of a leaf is essential [19], mineral extraction [20], and land mines detection [21], to name a few. To note, there are few publicly available resources of HSI for remote sensing applications. They are Indian Pines Salinas Pavia center and University, Kennedy Space Center [22-24]. Figure 6 depicts how an image is taken using a spaceborne Hyperspectral sensor. Data for remote sensing is abundantly available; people who are interested in the earth data can consider visiting USGS Earth Explorer [26], for further investigations.

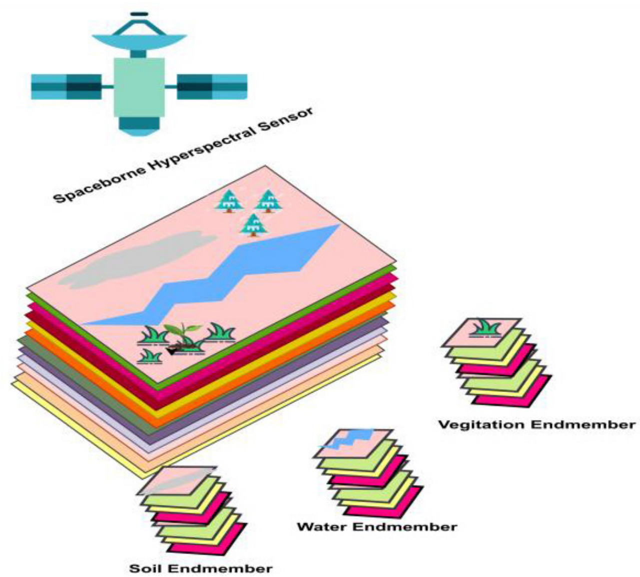


Fig 6. Imaging using Spaceborne Hyperspectral sensor [25].

3.2 Food and Feed Quality Detection

Detection of the quality of food and feed is vital for the well-being of humans and animals. Food quality inspection needs real-time monitoring of the production and storage process, without actually disturbing it. HSI provides such a contactless solution that researchers were able to detect the quality of food grains, fruits, child probiotics, and animal feed too [27]. Seed quality inspection is particularly useful for farmers to improve their productivity in agriculture [28]. Figure 7 depicts how food grain quality can be measured inside a bin using an area scanning sensor.

3.3 Plant Disease/ Stress Detection

Plant disease prediction is important for sustainable crop production and the improvement of vegetation [30]. For this application, several standardized vegetation indices are used to predict the quality of the plants. Of them Normalized Difference Vegetation Index (NDVI) is widely used to remotely separate the different plants over a wide area, based on the characteristics of the leaf. Using such indices, HSI aids in the early detection of the plant disease and when fitted to Drones they are capable of identifying the affected leaves in a larger crop area. Hyperspectral 3D fusion models are also being developed to differentiate the normal leaves and infected (stressed) leaves. Authors in [30] were able to differentiate different classes of the leaves using the standard K-means clustering algorithm. Figure 8 depicts the use of K-means clustering on sugar beet leaves.

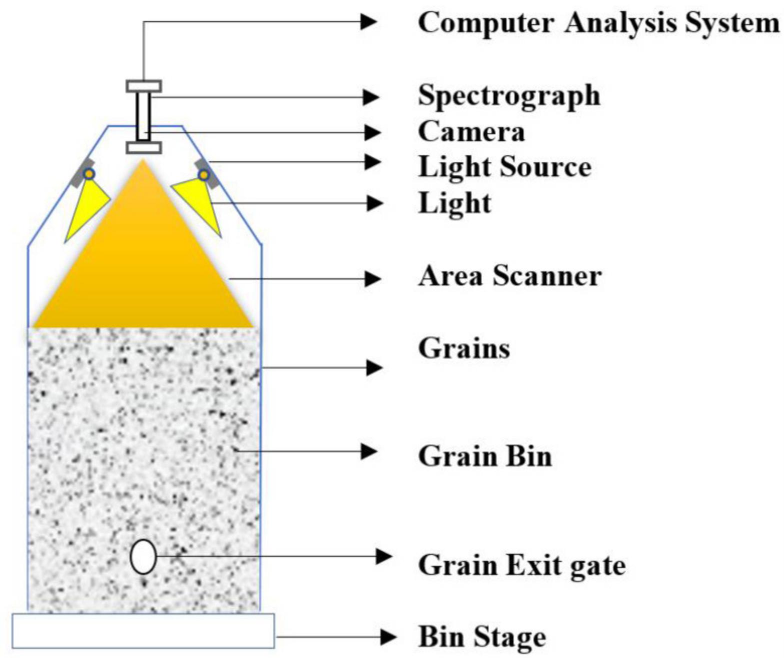


Fig 7. Inspection of grains under a bin [29].

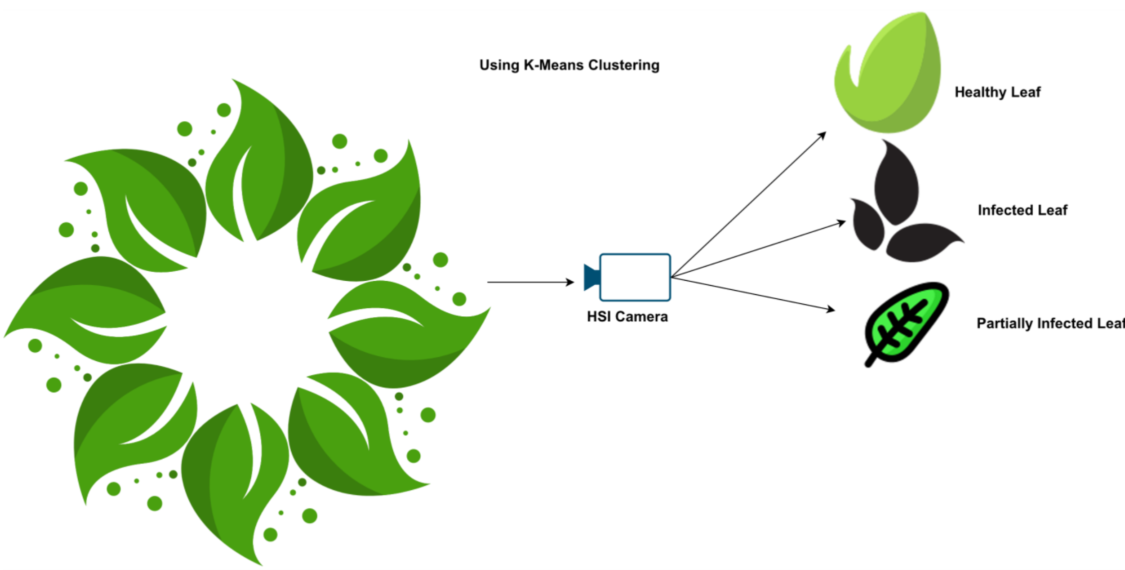


Fig 8. Classification of the leaf using K-Means clustering [30].

3.4 Crime Scene Investigation/Forensic Analysis

HSI is also being used in forensic analysis and crime scene investigations to find clues that the human eye fails to perceive. When imaged with Hyperspectral sensor, HSI was able to find out some clues such as the age of the blood stains and the extent of it. A study in [31] states that HSI can detect the age of the blood for up to two hundred days. This is very much useful in the crime scene investigation and forensic analysis to follow. As we know the sensors not only investigate in the visible region but also spans across the IR region, which gives the missing information to the authorities. Hence, this assists in solving the investigation faster. Gunshot residues can also be found via spectral imaging in a non-contact manner [32] instead of using some chemicals which destroy the other valuable information present at a crime scene. Figure 9 depicts what a crime scene can look like when imaged using HSI.

Fig 9. Crime scene analysis using HSI [31].

3.5 Medical Imaging

Medical imaging using hyperspectral sensors is gaining much more interests among the research community in recent years. Using HSI, we can take the images of biological samples in two ways [32]. One is *in-vivo*, and the other is *ex-vivo*. Generally, *in-vivo* represents the experiments that are performed inside the human/animal body, in its intact state, without really touching it. On the other hand, *ex-vivo* refers to the technique where the tissue is taken outside the body (with biopsies) and perform experimentation on those resected tissues. In some cases, tissues stained with some chemicals and/or stored, cultured under specific laboratory conditions. Such an investigation is commonly known as *in-vitro*.

3.5.1 Cancer Detection

In cancer detection, a lot of work has been already proposed in the literature using *ex-vivo* (for human tissues) and *in-vivo* (for animals such as Mice). In [33-37] authors performed breast cancer detection, where all of them used HSI to perform analysis on the resected tissues (humans). They also have demonstrated the feasibility of using Artificial Intelligence techniques along with HSI for classification of the tissues i.e., benign or malignant. In [38-40] authors discuss about Head and Neck cancers in which they were able to identify different classes of tissues that are existing especially inside the oral cavity. Apart from this, the detection of different types of cancers such as skin, colon, and cervical cancer was also performed by different research groups [41-43]. All of the above studies were performed by exploring a wide range of Visible and Infrared spectra. Figure 10 depicts the setup for *ex-vivo* analysis of the cancer tissues inside a laboratory.

Other than Cancer detection, HSI has been extensively used in some more medical imaging applications like Retina fault detection [44], Diabetic foot analysis [45], saturation of hemoglobin in oxygenation of the blood [46]. *in-vivo* analysis is performed for identifying the Microvascular structures in mice [47]. To note, there are some publicly available medical datasets which are cited in [48,49]. However, the data availability of HSI in Biomedical imaging is very limited.

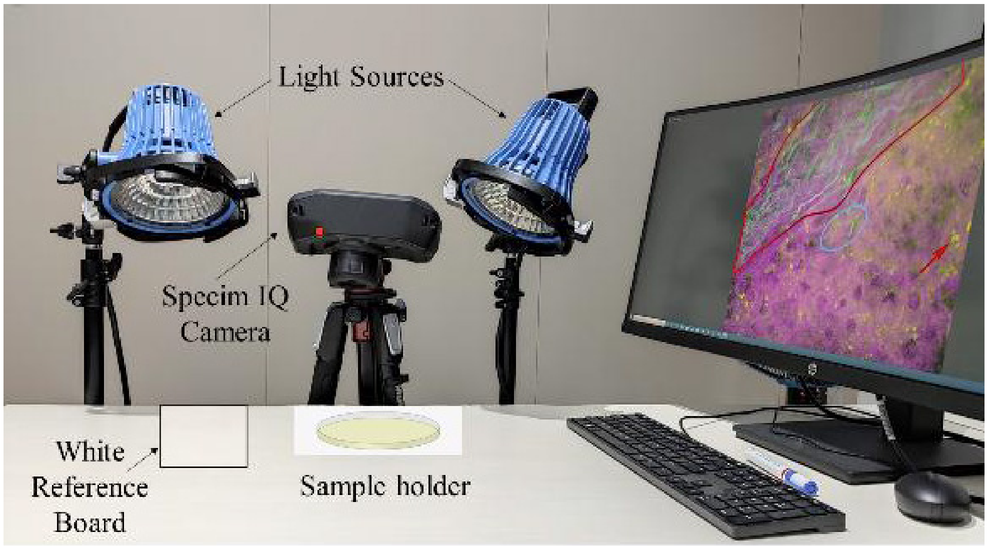


Fig 10. Typical HSI lab setup for *ex-vivo* analysis.

4 Artificial Intelligence in HSI

As aforementioned, HSI contains a 3D hypercube (i.e., 2D spatial information and 1D spectral information) which is complex to analyze with the existing techniques that are available for RGB image analysis. To alleviate, many researchers have opted AI based solutions such as Machine Learning (ML) and Deep Learning (DL) and have found some fruitful results for many complex problems. In the following, we will discuss some of the recent ML or DL based HSI data processing [50].

4.1 Machine Learning

For land cover classification, several algorithms have been proposed. One of the widely used algorithms is quadratic discriminant analysis (QDA), which is also called as a maximum likelihood classifier [51]. The authors in [52] used the standard Gaussian models to predict the quality of food grains, they performed active and transfer learning using Gaussian models for obtaining food grain quality prediction. Authors were able to classify between different grades of food grains with an accuracy of 95%. Support Vector Machine (SVM) is also used widely for hyperspectral based image analysis such as Target detection, Physical Parameter estimation, and spectral unmixing [53]. In SVM, usage of kernels is important as kernels are projected into a higher dimensional space and the decision of the classifier may be linear or non-linear based on the kernel function. One of the most used kernels is Radial Basis Function (RBF). It was demonstrated that use of multiple kernels in SVM outperforms the single kernel based SVM [54].

After SVM, latent linear models like Principal Component Analysis (PCA) [55] and Independent Component Analysis (ICA) [56] are the mostly used dimensionality reduction methods in HSI. Other than these, some other popular machine learning models are used frequently such as Linear regression (LR) [57]. Logistic regression [58] predicts the likelihood that a certain event will occur, such as voting or not voting. Given the nature of the analysis, the dependent variable is restricted to values ranging between 0 and 1 and it is mostly used for binary classification in HSI.

In medical imaging applications, the usage of ML algorithms like K- Nearest Neighbour (KNN) [59], Random Forest [60], and AdaBoost [49] have been extensive. Since KNN predicts the new data based on the similarity of the existing data, thus it is widely used in the pixel-wise classification of an image. Random Forest is used in solving the issues of Classification and Regression. It generates decision trees from sample size and uses the results of most of the samples for classification or the average in the case of regression. The AdaBoost algorithm combines a set of weak classifiers to make it a strong classifier. In general, the weak classifiers are the nodes with the lowest weights and vice-versa. By utilizing bagging techniques on data samples, the Random Forest algorithm constructs an ensemble of decision trees that leverage a variety of characteristics and factors. Like AdaBoost, which is also an ensemble learning algorithm, decision stumps are utilized in the construction of this collection of learning algorithms.

Although machine learning (ML) algorithms are extensively utilized and computationally efficient, they encounter a challenge when it comes to analyzing the significantly larger hypercube generated by HSI. To alliviate, several recent works [33,34,61] have been performed using DL algorithms. In the following section, we discuss some of the widely used DL methods for hyperspectral image analysis.

4.2 Deep Learning **(***D L***)**

DL is the preferred choice when it comes to medical image analysis. In particular, Convolutional Neural Network (CNN) is widely used and the operation of CNN involves convolving one layer with its immediate next layer with some kernel functions. To date, it works well for image-related problems. U-shaped CNN called U-Net was used in [33,34] for the classification of benign and malignant tumors. Authors have achieved an accuracy of above 80% with CNN and with U-NET 87% accuracy was estimated. Figure 11 depicts the feature extraction and classification of CNN. In oral cancer detection U-NET is being used and in [61], authors successfully classified seven different classes inside the oral cavity.

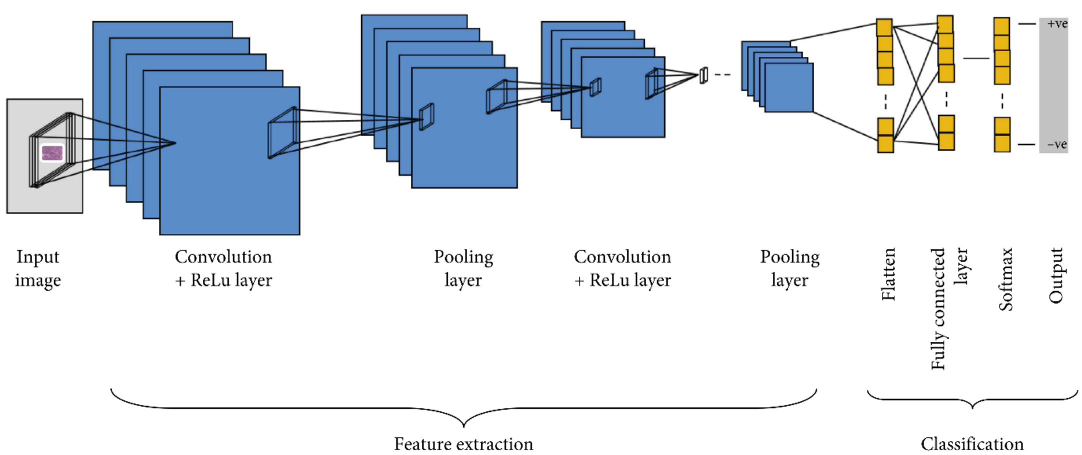


Fig 11. Convolutional Neural Network [62].

Variations of CNN have been used by different authors in Remote sensing. Indian Pines dataset has been widely used by many authors [33,34]. Some authors [62,64] used 3D-Quasi CNN to classify different crops [63] and they have achieved an accuracy of 93%. Figure 12 depicts the structure of the U-NET.

Apart from classical CNN, few other networks were also proposed such as Residual Networks (RESNET), [64] which is used for food grain quality detection. Gated Recuring Unit (GRU) is used to identify the reason for soya beans death [65].

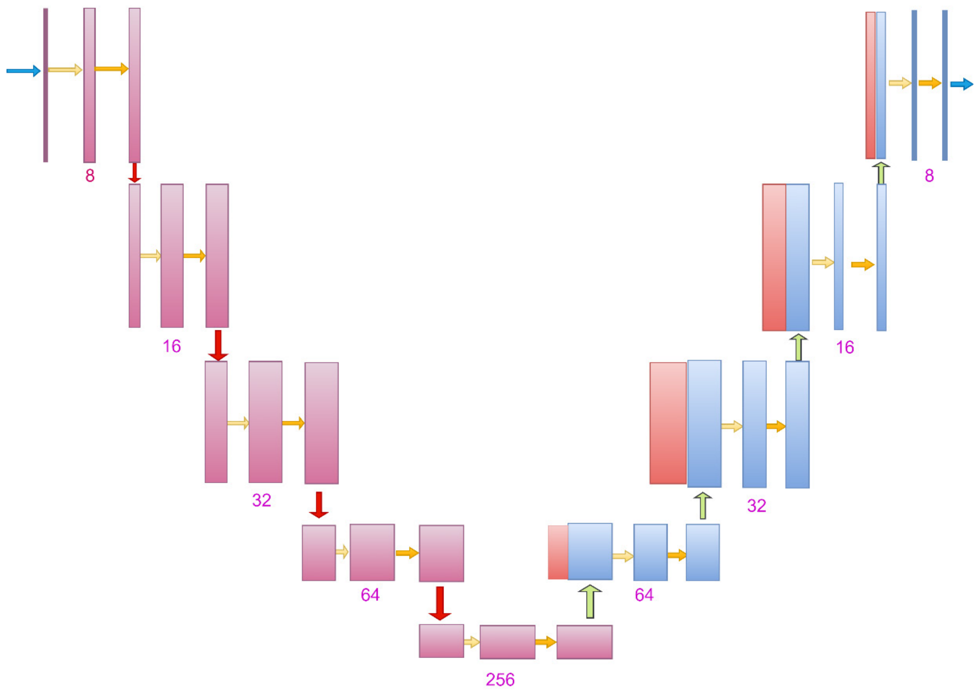


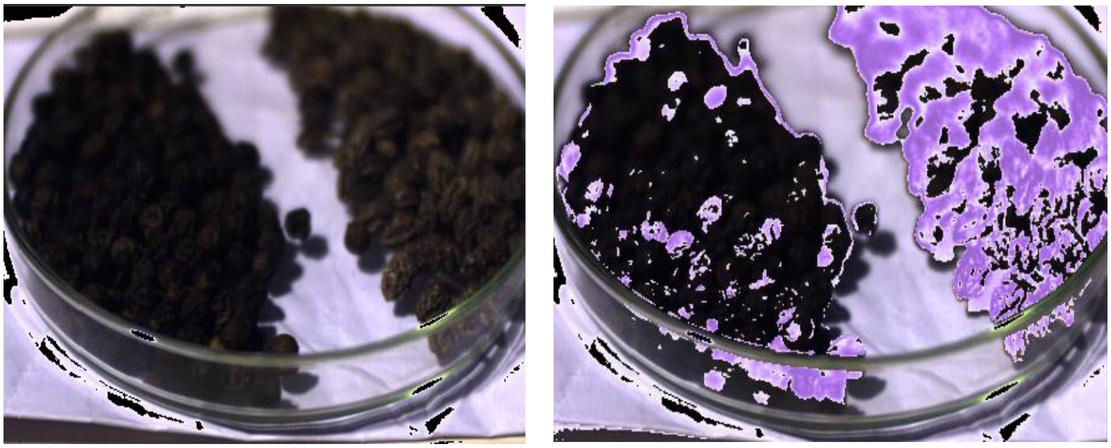
Fig 12. U-NET Architecture [63].

5 Experimental Results

Figure 13(a) illustrates the segmentation of infected sections of a leaf, while Fig 13(b) shows the segmentation of pepper and papaya seeds. The analysis was performed using the savitzky-golay algorithm, which is the default algorithm in the software.

Sample Leaf | Segmentation of infected Leaf

Fig 13 (a). Segmentation of infected part in a Natural Leaf.



Sample Black Pepper and Papaya Seeds | Segmentation of Black Pepper and Papaya Seeds

Fig 13 (b). segmentation of pepper and papaya seeds.

6 Conclusion

This article describes about different types of imaging systems such as whiskbroom, Pushbroom etc. and how we can use them for different kinds of applications. Till now HSI has been much explored in areas like Remote Sensing, where lot of research has been done and made some significant contributions with the help of HSI and there are some publicly available datasets also which were mentioned above. The applications of HSI in the area of Bio-Medical Imaging are booming now since HSI sensors were able to identify many diseases at an earlier stage.

Future work needs to be done on improving the hardware capabilities of the hyperspectral sensor, such as increasing penetration depth, and commercialization of the cameras so that more people can use them. Spectral libraries should be created especially for medical imaging so that it can be useful for the surgeons for image-guiding surgery. Open-source software can be developed to encourage research in this field.

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