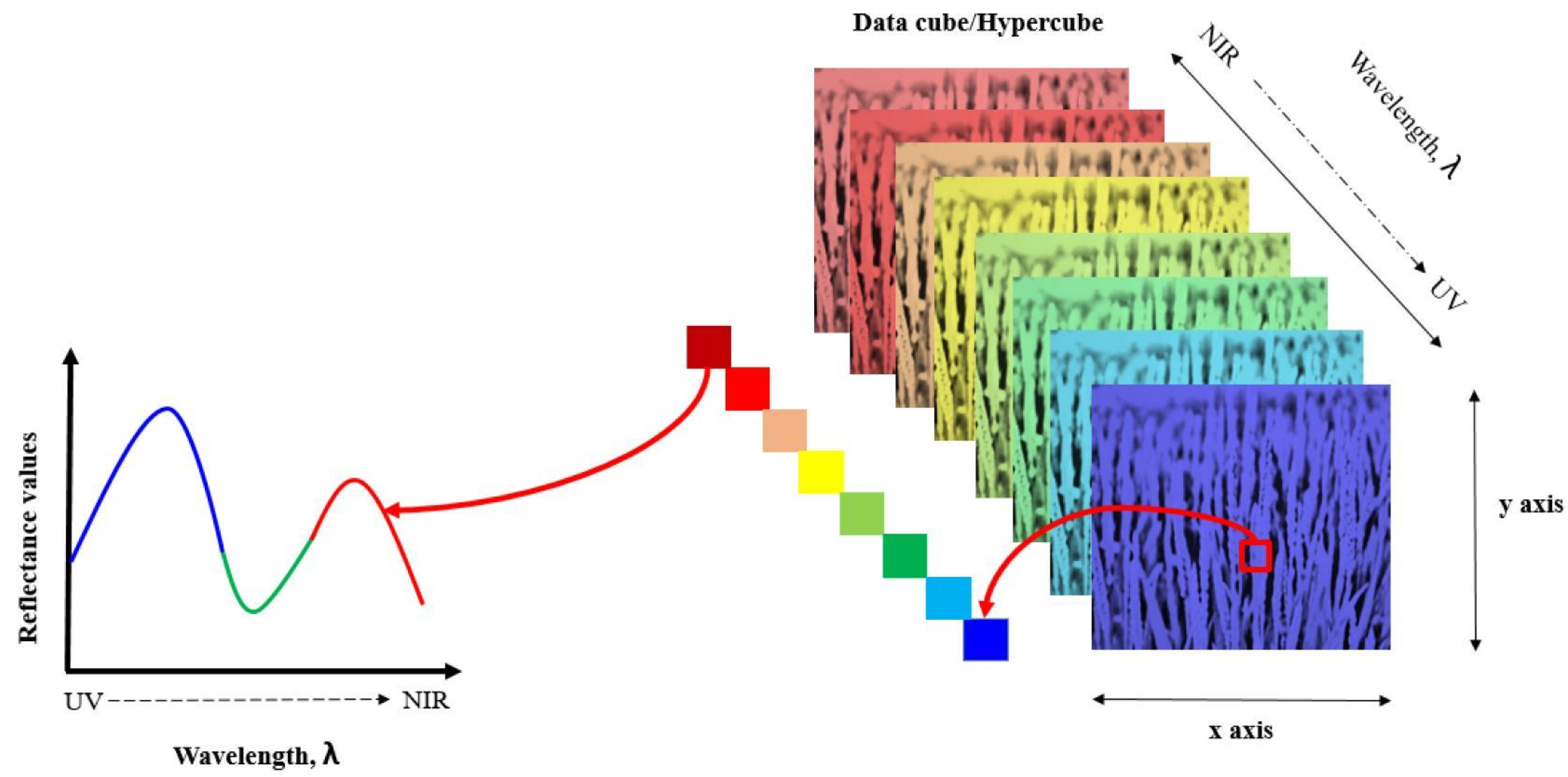

Fig. 1. Hyperspectral data cube/hypercube and spectral signature [23].

The principle of hyperspectral sensors is similar to that of RGB camera sensors. The RGB camera sensors measure the light that reaches the sensor. The sensor then stores the information. Hyperspectral sensors operate similarly. The only difference between RGB and hyperspectral sensors is that RGB measures the electromagnetic spectrum of red, green, and blue (three bands). In contrast, hyperspectral sensors can measure hundreds of electromagnetic spectrum bands. Hyperspectral sensors measure a spectral band in nanometers of electromagnetic wavelength, providing high spectral resolution. Hence, each pixel in a hyperspectral image contains reflectance information of a diverse set of electromagnetic spectral bands. For plant disease detection, the reflectance information usually refers to the biochemical components that are found in the physical aspects of the leaves [20]. This reflectance information is added to each other and called spectral profile (spectral signature). The spectral profile of healthy and diseased plants exhibits variations due to the change in biochemical properties of plant tissues. This causes changes in the shape and color of the leaves, canopy morphology, and transpiration rate, eventually leading to alterations in the plant's spectral attributes [21]. Nonimaging hyperspectral sensors quantify this spectral profile without any spatial information. The hyperspectral imaging sensors measure through the spectral bands, and each image pixel is obtained through the combined spatial and spectral resolution information. Hence, each image pixel has its spectral profile and all the reflectance information of all electromagnetic spectral bands. The resulting image is a hyperspectral data cube/hypercube, which includes 2-D spatial and 1-D spectral information of the plants. Fig. 1 presents the data cube/hypercube. Each pixel in the data cube has its inimitable spectral features. In the data cube, images at the adjacent wavelength are similar, but images at the faraway are not very similar. The distant wavelength images may contain independent information. Therefore, hyperspectral imaging is very beneficial as each unique spectrum of different wavelengths can capture the details of the images [22].

In addition to the visible electromagnetic spectrum (400–700 nm), hyperspectral image sensors can measure NIR (700–1100 nm) spectrum and SWIR (1100–2500 nm) [15], [24]. Generally, the VNIR wavelength range is considered the most useful for plants and crops. In the visible spectrum, the changes in the pigments of the leaf can be captured as the plant surface exhibits low reflectivity due to the light absorption through the photosynthetic pigment such as anthocyanins, carotenoids, and chlorophylls [7], [25]. In the NIR waveband, changes in the mesophyll cell structure can be captured as light scattering in the intercellular space of the plant increases the reflectance value [7], [25]. Nevertheless, to observe the changes in the plant water content, SWIR wavelength is required [25]. The plant water content is an important factor in understanding leaf mesophyll structure. If a plant is severely dehydrated, the impact will be on the leaf mesophyll structure, and it should be detected in the NIR range [7].

However, hyperspectral image sensors collect a large amount of spectral data, which increases the difficulty of obtaining relevant and valuable spectral information. A large amount of high-dimensional data and complex information generated by hyperspectral image sensors require advanced data analytics to efficiently process, interpret, and apply the gathered information [15], [24]. These advanced data analytics are responsible for transforming high-dimensional spectral data into meaningful information, distilling it into practical, and providing useful insights for decision making. Some examples of application of advanced data analytics in hyperspectral imaging from the literature include machine learning techniques [26], [27], [28], deep learning techniques [29], [30], [31], and dimensionality reduction techniques [32], [33]. For instance, Nguyen et al. [26] proposed a 2-D convolutional neural network (CNN) that combines a support vector machine (SVM) to identify and classify the viral diseases of grapevine. Nagasubramanian et al. [29] employed a 3-D deep CNN to detect fungal diseases in soybean plants. Sahoo et al. [33] applied principal component analysis (PCA) to reduce the dimension of the hyperspectral data