model then analyzed the diseases. Some more disease detection studies for maize can be found in [152] and [153].

Potato is one of the major crops in many countries. A study in [297] detected the late blight disease of potatoes. A 512-channel spectroradiometer captured the hyperspectral images (Fieldspec Pro 2000) with a wavelength range of 325–1075 nm from a field in India. The author proposed to combine the vegetation indices with the stepwise discriminant analysis to detect early blight diseases in potato plants. A study conducted in [211] proposed novel spectral disease indices for multiple disease detection. The experiment was conducted with three key diseases found in sugar beet. The diseases are beet rust, Cercospora leaf spot, and powdery mildew. The hyperspectral leaf images were captured in different stages of pathogen development, and a range of 450–950 nm wavelength was employed for the data acquisition. After that, the images were preprocessed through RELIEF-F and a classification algorithm, which could detect three diseases at very high accuracy (85-92%).

Some studies attempted to detect disease in tomato plants. Moghadam et al. [298] proposed a probabilistic model, which combined the vegetation indices of two ranges (VNIR and SWIR) to detect the Spotted Wilt Virus in the plants. The data were collected using two headwall brand push room cameras, namely the VNIR-A series and SWIR-M series [298]. The spectral range was 400–1000 nm (324 spectral bands) of the VNIR camera and 900–2500 nm (124 spectral bands) for SWIR. At first, the leaves with diseases were segmented, and then, a grid removal algorithm was applied to process the image. The preprocessed images were then fed to the probabilistic model to detect the diseases. The results indicate that the proposed algorithm could effectively detect the diseases [298]. Harvesters operating in commercial (large-scale) tomato fields need location-precise detection of the diseases so that the spread of the diseases can be controlled [299]. Zhang et al. [299] proposed a discrimination analysis using the hyperspectral data obtained through the AVIRIS imagery platform. The analysis was conducted through the data obtained from California, USA. The images were first preprocessed with a minimum noise fraction transformation (MNFT) algorithm and then classified using the acquired images' spectral bands. After that, the images are visualized to observe which spectral bands had higher MNFT values. Based on that, the diseases were detected.

Although the aforementioned studies achieved satisfactory performance for disease detection, some challenges still need to be considered. First, machine-learning- or deep-learning-based algorithms require large data. Insufficient data and class imbalances can significantly lower the performance of the models [300]. Therefore, it is essential to ensure the quality of the data before machine learning algorithms are used for disease detection.

2) Disease Classification: The main goal of disease classification is to classify the pathogens or disease types obtained from hyperspectral images. Classification of diseased and healthy plants by employing the nondestructive technique is relatively challenging to comprehend the early symptoms of diseases. This is because several disease symptoms may visually look similar to each other. Simultaneously, single pathogen-infected plants may appear in different colors, shapes, and morphology in different areas of plants or fruits. Hence, to overcome this issue, a wide variety of images of leaves, stems, and fruits from different angles should be taken and annotated by experts in the fields. Once the annotated images are trained with computer-aided models, the models can also identify unidentified images. Generally, disease classification can be broadly divided into two categories: 1) classification based on selected wavelengths of hyperspectral images and 2) classification based on full-spectrum information of hyperspectral images. The classification based on selected wavelengths includes feature selection techniques, which involve the selection of specific wavelengths or bands to differentiate between healthy and diseased plants. This category often includes statistical analysis, vegetation indices [such as Normalized Difference Vegetation Index (NDVI)], and discriminant analysis. The selection of relevant wavelengths can improve the accuracy and provide more insights into classifications [301]. On the other hand, feature extraction is a technique that translates the original data into a new set of features to capture the essential information concisely. Feature extraction can combine multiple wavelengths of information to create new features representing important classification characteristics. The main aim is to reduce the dimensionality of the data and improve classification performance [302]. Hence, feature extraction techniques complement: 1) classification based on selected wavelengths of hyperspectral images and 2) classification based on full-spectrum information of hyperspectral image categories.

For classification based on selected wavelengths, a subsample of the spectral information is manually or automatically chosen for a specific range of wavelengths. An extensive literature study shows that vegetation indices are employed to estimate the discrete wavelength values located at different positions in the spectrum. An extensive literature study shows that vegetation indices are employed to estimate the discrete wavelength values located at different positions in the spectrum. A study shows that NDVI was employed using the statistical technique ANCOVA to select the wavelengths containing diseases. After that, quadratic discriminant analysis (QDA) is employed to classify spectra between wheat's diseased yellow rust leaves and healthy plants. The accuracy based on four spectral information (wavelength) reached 92% [303]. Moshou et al. [265] employed multilayer perceptron (MLP) to detect yellow rust at the range 460–900 nm with a spectral resolution of 20 nm. The images were collected through a hand-held platform and selected four wavelength bands. The wavelengths were selected through discriminant analysis and vegetation indices (NDVI). Then, a ten-layered neural network is applied to classify diseased plants (yellow rust). The accuracy of disease plants was 99.4% and that of healthy plants was 98.9% [265]. Deep-learning-based algorithms are also applied for disease classification [304]. A CNN is employed to detect 26 types of disease for 14 different crops. The entire dataset consisted of 54 306 RGB images and then trained AlexNet and GoogleNet. For AlexNet, 97.82% accuracy was achieved, and for GoogleNet, 98.36% accuracy was achieved. Another popular model named CaffeNet is also used to detect 13 different plant diseases for pear, apple, and