grapevine. For pear fruits, leaf spot disease, and for apple, powdery mildew, rust, and grapevine mites, wilt, downy mildew, and powdery mildew disease were detected. Around 30 000 images were used for training, and the accuracy of disease detection reached 96.3% [173]. Jin et al. [305] employed a two-layered CNN with a bidirectional gated recurrent unit neural network to classify Fusarium blight head diseases of wheat at the pixel level. The model obtained the accuracy of 74.3% and the F1-score of 75% [305].

In addition to deep learning techniques, some statistical methods are employed to classify diseases. A study showed Fisher's linear discriminant analysis (FDA) was used to detect powdery mildew and yellow rust on wheat crops using remote sensing hyperspectral images. Different wavelengths, such as 531, 570–654, and 687–717 nm, were selected to classify the diseases. The accuracy of the disease classification reached 93% [306]. Another popular statistical algorithm PCA is sometimes also used for disease classification. One such study can be found in [307], where the labeled image of cucumber leaves with downy mildew disease is used to perform the analysis. PCA is used to reduce the complexity of the hyperspectral images. This study only used 20 leaves (ten infected and ten healthy) to train and obtained 90% detection accuracy [307]. However, this analysis might not be very suitable as the training with fewer hyperspectral images could result in biased results.

On the other hand, classification based on the full spectrum aims to divide the images into specific categories/classes. Abdulridha et al. [170] compared two classification techniques, namely radial basis function (RBF) and kNN, to detect citrus canker diseases in citrus plants. The experiment was conducted using images from different disease development stages of plants using UAVs. Around 31 vegetation indices were included to be detected using the RBF and kNN algorithms. The results show that RBF could detect the citrus canker better than kNN. Also, among all the vegetation indices, only the photochemical reflectance index and the water index were accurately detected [170]. QDA analysis is one of the most popular techniques, which estimates a covariance matrix and correlates each class. QDA was employed to study avocado plants' Laurel wilt disease (fungal). The hyperspectral images were collected from the glasshouse and field, which resulted in an accuracy of 94% [308]. A study on celery crops was conducted by Huang and Apan [213] to detect the Sclerotinia rot diseases. The author employed PLSR algorithms to perform the disease classification, resulting in an accuracy of 88.92%. A combination of FDA with Savitzky–Golay was performed to classify the yellow rust diseases in wheat. The classification accuracy reached 92% [7], [309], showing a promising statistical technique.

Despite the promising performances, classification algorithms may suffer from vanishing gradient and exploding gradient issues, which may cause the model to overfit or underfit. Overfitting of a model is defined as the instances when the model is trained with a large number of data, and instead of focusing on the essential features, it focuses on the noise. Thus, the correct classification of the data is not achieved due to the extensive information and noise. In short, the model obtains low bias and high variance values. On the other hand, underfitting of a model is defined as the instances when the model cannot learn the underlying information or trend in the dataset. This occurs due to high bias and low variance value and also due to the insufficient number of data. Sometimes, the underfitting may happen when nonlinear data are used to develop a linear model [300]. Hence, based on the quality of the dataset, a classification algorithm should be chosen.

3) Disease Severity Analysis: Once the plant diseases are detected and classified, the next step is to understand the severity of the conditions on the plants. Therefore, a quantitative plant disease assessment is critical for hyperspectral image analysis. Disease index is a function of disease incidence and disease severity. For example, for wheat Fusarium head blight, i.e., $FHB\, index = incidence \times severity$. In addition, water content, pigment content, and pathogen types and symptoms are used as indirect evaluation indices [17].

A comparative analysis of hyperspectral images' spectral and temporal information can estimate plants' pathological stress. A study was conducted by Muhammed [310] to evaluate the fungal disease severity in wheat leaves. The crop reflectance data and complementary diseased leaf vectors are first normalized through bandwise and spectralwise normalization techniques. Then, kNN algorithms are applied to classify the types of wheat diseases. After the classification step, the images are fed to a linear transformation model so that the correlation factor can be obtained to define the severity rank of the diseases [310]. Spectral assessment and interpretation are also used to determine the disease severity assessment index. One such study was found in [296], where the disease severity of powdery mildew in wheat plants was estimated. A spectroradiometer evaluated the hyperspectral reflectance of the healthy and infected leaves in a laboratory setting. Nine ranks of disease severity scales were defined by using the disease index. Multivariate linear regression (MLR) and PLSR assessed the disease severity. Once the models were run and validation of the model was completed, the images were evaluated through the relative root-mean-square error (RMSE) metric. Results show that the PLSR model had lower relative RMSE and a higher coefficient of determination score than MLR models [296].

Spectral reflectance ratio (SRR) models are also used to assess the disease severity in plants. One such study was conducted to assess the severity of rice blasts from the hyperspectral images [270]. At first, the average spectral reflectance of the hyperspectral images (healthy and diseased) was obtained. Then, by the SRR reconstruction method, the severity of the rice blast was ranked. Once the ranking is obtained, the images are fed to the SVM model to classify the diseases based on the development stages of rice (such as jointing, booting, and heading stages). The SRR reconstruction method proved effective for disease severity assessment during the later stage of the vegetative growth [270].

The distribution of carotenoid and chlorophyll pigment distribution in leaves is a crucial factor in determining how healthy the plant leaves are. A study was conducted on cucumber leaves to understand the distribution of the carotenoid and chlorophyll content to assess the angular spot disease [165]. The chlorophyll content was measured through the biochemical analyzer. After that, a PLSR model was employed to establish a