**Table 2**: Published claims of stress identification from hyperspectral imaging since 2018, along with the chosen multivariate data processing technique and accuracy reached. “Plant stress” refers to both (i) the classification or modelling of stressful conditions and (ii) the plant phenotyping.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Plant stress** | **Species** | **Techniques** | **Accuracy** | **Reference** |
| Chilling | blueberry | PLS-DA  | >75% | Gao et al. (2019) |
| Salinity | wheat | Novel approach | -- | Moghimi et al. (2018) |
| Drought | grapevine | PLS-DA PLS-SVM | >97% | Zovko et al. (2019) |
| Drought | grapevine | RF (Deep learning) | 80-83% | Loggenberg et al. (2018) |
| Drought | rice | PLSR-MLR | >90% | Krishna et al. (2019) |
| Drought | tomato | Derived SRIs | -- | Elvanidi et al. (2018) |
| Drought*Meloidogyne incognita* (Nematoda) | tomato | PLS-DA PLS-SVM | 90-100% | Susič et al. (2018) |
| Insect herbivory | maize | SLDADiscriminant classification model | 79.0% | do Prado Ribeiro et al. (2018) |
| Powdery Mildew | grapevine | PLS-DA  |  | Pérez-Roncal et al. (2020) |
| Stripe rust | wheat | PCABPNN | ~92% | Yao et al. (2019) |
| *Fusarium* head blight | wheat | Derived SRIs | -- | Mahlein et al. (2019) |
| *Septoria tritici*  | wheat | PLS-DA | 93% | Yu et al. (2018) |
| Powdery mildew | barley | SiVMNon-linear SVM | ~95% | Thomas et al. (2018) |
| *Magnaporthe oryzae* | barley | LDACARS | >98% | Zhou et al. (2019) |
| Charcoal rot | soybean | SVM | 97% | Nagasubramanian et al. (2018) |
| *Sclerotinia* stem rot | oilseed rape | PLS-DASVM | >90% | Kong et al. (2018) |
| *Alternaria solani* | potato | PLS-DASVM | 92% | Van De Vijver et al. (2020) |
| Citrus canker | tangerine | RBSKNN | 94-100% | Abdulridha et al. (2019) |
| tomato spotted wilt  | sweet pepper | OR-AC-GAN (Deep learning) | 96% | Wang et al. (2019) |
| N content | tea  | PLS-DALS-SVMPLSR | >90% | Wang et al. (2020) |
| N content | apple | PLSRMLR | 77-78% | Ye et al. (2019) |
| shikimic acid concentration | transgenic maize | PLSR | 82% | Feng et al. (2018) |
| Cadmium content (model) | tomato | WT-LSSVR (Deep learning) | -- | Jun et al. (2018) |
| Lead concentration (model) | lettuce | WT-SAE (Deep learning) | -- | Zhou et al. (2020) |
| Dicamba | soybean | RF (Deep learning) | -- | Zhang et al. (2019) |
| BPNN, back propagation neural network; CARS, competitive adaptive reweighted sampling; FNN fully-connected neural network; KNN, K nearest neighbor; LDA, linear discriminant analysis; LS-SVM, least squares-support vector machines; MLR, multiple linear regression; OR-AC-GAN outlier removal auxiliary classifier generative adversarial nets; PCA, principal component analysis; PLS-DA partial least squares-discriminant analysis; PLS-SVM, partial least squares-support vector machine; PLSR, partial least-squares regression model; RBF, radial basis function; RF random forest; SiVM, simplex volume maximization; SLDA, stepwise linear discriminant analysis; SRIs, spectrum reflectance indices; SVM, support vector machine; WT-LSSVR wavelet transform and least-square support vector machine regression; WT-SAE wave-let transform and stacked auto-encoders. |

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