

REVIEW ARTICLE

Machine vision and artificial intelligence for plant growth stress detection and monitoring: A review

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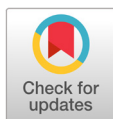
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Abstract

The agricultural sector faces increasing challenges in ensuring food security and optimizing crop yield, necessitating innovative solutions for early detection and mitigation of plant growth stress. The integration of advanced imaging technologies with artificial intelligence (AI) has emerged as a powerful tool for non-invasive, real-time monitoring of plant health. The objective of this paper was to review the application of machine vision and AI in identifying and classifying plant growth stress, with a focus on stressors, datasets, and the use of intelligent algorithms. The significance of plant growth stress induced by environmental variables, including temperature, light, nutrient deficiencies, and water supply were addressed and the conventional stress detection methodologies, underscores their inherent limitations, and establishes the groundwork for the exploration of state-of-the-art technologies in stress assessment. Various sensor technologies were explored, encompassing traditional RGB cameras, multispectral and hyperspectral sensors, and thermal imaging, each capable of capturing distinct stress signatures. Machine vision, leveraging high-resolution imaging and spectroscopy, offers detailed insights into plant physiological responses. Coupled with AI approaches such as deep learning, neural networks, and pattern recognition, machine vision enables the automated analysis of vast datasets, enhancing the accuracy and speed of stress detection. The recent advancements in image processing techniques tailored for plant stress identification were focused and discussed the role of feature extraction, classification, and predictive modelling in achieving robust results. The potentials of AI in plant stress physiology and its role in overcoming the limitations of traditional methods, and the use of unsupervised identification of visual symptoms to quantify stress severity, allowing for the identification of different types of plant stress were studied. Moreover, the potentials of machine vision technology and AI for real-time monitoring and decision support systems in precision



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agriculture were discussed. The findings of this review would contribute to the growing field of agricultural technology, offering insights into the development of automated tools that could aid farmers and researchers in mitigating the impact of abiotic stressors on crop/plant health and productivity.

Keywords: Precision agriculture, abiotic stress, deep learning, image processing, stress detection

Introduction

In the current era, agriculture stands as a key contributor to the global economy. The expanding population, coupled with urbanization, is progressively shrinking cultivable land, intensifying the challenges faced by the agricultural sector (Tian et al., 2020; Wang et al., 2019). The increasing demand for efficient and safe food production methods necessitates a shift towards innovative sensing, driving technologies, and enhanced information and communication technologies (Liakos et al., 2018). To address these challenges, traditional agricultural management approaches need supplementation with advanced technologies to boost productivity accurately, fostering the evolution of high-quality and high-yield agriculture (Balaska et al., 2023). Furthermore, there is a growing need to adopt sustainable technologies that can improve agricultural efficiency and address environmental concerns.

Plant stress refers to external conditions that adversely affect the growth, development, or productivity of plants (Lichtenthaler, 1998). Plant stress poses a major threat to crop yield and quality, making the rapid and robust detection and diagnosis of plant stress essential for the application of precision agriculture (Gao et al., 2020). The effects of plant growth stress on crop yield can be significant, with various factors such as temperature, light, nutrient, water and other environmental stressors leading to reduced productivity (Kopecká et al. 2023; Fahad et al., 2017). Water supply and temperature stress can cause damage to the reproductive growth phase of crops, resulting in a substantial decrease in yield (Seleiman et al., 2021). These stresses can also lead to damaged photosynthetic process, oxidative damage, and membrane instability, further impacting crop productivity. For instance, temperature stress has been observed to cause substantial yield reductions in crops such as common beans, peanut, and tomato (Hussain et al., 2018). Additionally, prolonged exposure to water stress during the reproductive stage can significantly affect grain quality and yield.

In this context, optical imaging methods have gained prominence for detecting plant diseases and stressors. These advanced techniques enable the rapid and non-contact measurement of physiological changes in plants caused by various stressors, including abiotic and biotic factors. Commonly used imaging technologies for detecting crop stress include digital, fluorescence, thermography, LIDAR, multispectral, and hyperspectral imaging techniques. Digital imaging sensors capture RGB coloured images, providing valuable information on plant attributes like canopy vigour, leaf color, texture, size, and shape for disease detection (Mahlein et al., 2016). Color and texture features, including RGB, LAB, YCBCR, HSV spaces, contrast, homogeneity, dissimilarity, energy, and entropy aid in distinguishing between healthy and symptomatic plants (Gao et al., 2023). The high spatial resolution images provided by RGB cameras make them a valuable tool for studying plant phenomena and assessing visual symptoms related to plant stress. Thermal cameras detect radiation in the infrared wavelength range and produce measurements displayed as false-color images, allowing for the visualization of temperature variations in plants (Pineda et al., 2020). These sensors have been employed to detect a variety of plant growth stresses, such as pathogen infections, water scarcity, and nutrient deficiencies. Fluorescence imaging sensors and multispectral sensors are valuable tools for plant stress detection. These sensors offer a comprehensive approach to assessing plant health and detecting various types of stress, contributing to improved crop management and yield (Zubler et al., 2020). Fluorescence imaging evaluates spatiotemporal changes in leaves and detecting plant stress. It can provide early-stage detection of both biotic and

abiotic stresses before visible symptoms appear (Kumar et al., 2021). Multispectral and hyperspectral imaging across visible, near-infrared, and infrared wavelengths detect changes in leaf reflectance linked to plant stresses (Weng et al., 2023). Hyperspectral offers finer spectral detail than multispectral, enhancing stress identification.

The integration of optical sensors and machine learning has shown promise in the proximal detection of plant stress, allowing for the evaluation of plant health using various optical sensors. These sensors provide valuable data that can be analyzed using machine learning algorithms to detect and assess plant stress. Machine learning techniques, such as artificial neural networks and support vector machines, are employed for data processing and analysis, enabling the rapid and accurate detection of plant stress. Additionally, machine vision technologies, including deep learning and image processing techniques, have been increasingly utilized for the detection of stresses and diseases in precision agriculture. These advancements hold significant potential for enabling early and accurate identification of plant stress, thereby contributing to improved agricultural efficiency and productivity. The objective of this paper was to conduct an overview of the application of machine vision and AI for plant growth stress detection, and provide insights that can inform future research, innovation, and practical applications in sustainable agriculture and food production.

Types of plant stress

Stress is a changed physical state brought on by biotic or abiotic causes that upset a plant's natural balance. In consequence environmental stress causes massive agricultural losses (Bechtold et al., 2018). Plant stress encompasses adverse conditions that impact a plant's metabolism, growth, and development (Gull et al., 2019). Diverse factors contribute to plant stress, including extremes in temperature, light fluctuations, pathogenic infections, pest infestations, nutrient deficiencies, and stresses like salinity, drought, and heavy metal exposure. These stressors can induce alterations in gene expression, disrupt cellular metabolism, affect growth rates, and ultimately result in diminished crop yields. Plants have evolved an array of mechanisms to cope with these stresses, underscoring the importance of comprehending their responses for devising effective strategies to mitigate their impact on agricultural production (Kollist et al., 2019). Plant stress also leads to alteration of the leaf structure, which adjusts light reflection on the leaf surface and modifies the color and texture of the leaf (Ghosal et al., 2018).

There are two types of plant growth stress, named biotic stress and abiotic stress. The term "biotic stress" refers to living organisms that harm crops, such as fungi, bacteria, viruses, weeds, parasites, insects, and diseases (Dhingra et al., 2019). Abiotic stress is the result of non-living elements including nutrition shortages, floods, and other environmental variables like drought, temperature, humidity, light. Fig. 1 shows various types of stress on crop and plant growth significantly impact agricultural production. As a defence strategy against the threat posed by the stresses they encounter, plants have special ways of reacting to stress (Czedik - Eysenberg et al., 2018). Plant senescence, leaf curling, and wilting caused by biotic stress result in decreased leaf area, which lowers harvest weight, increases plant diameter, and produces fewer leaves (Saakre et al., 2017). Affected tissues or plants may experience abiotic or biotic stress due to nutrition and water shortages, insect infestations, or cell architectures that prevent photosynthesis and transpiration (Virlet et al., 2016). It is essential to prevent plant stress in crops that require substantial water for growth and yield. This stress can occur when there is excessive water supply in the field, leading to issues such as waterlogging and clogging (Zhao et al., 2017). Water delivery to plants during the period of growth and during the time when mature harvests are being harvested can also contribute to plant stress (Duarte-Galvan et al., 2014). Lack or excess of nutrients leads to plant stress, which is brought on by a lack of nutrients required for plant growth (Nachtigall et al., 2017).

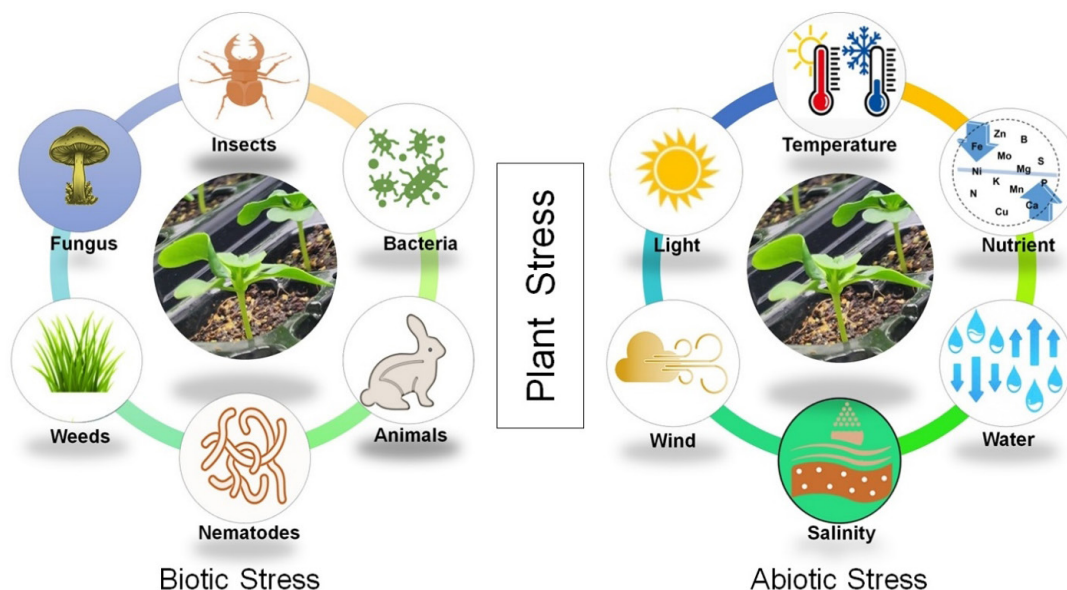


Fig. 1. Various forms of stress on crop and plant growth significantly impact agricultural production.

Numerous aspects of the effects of abiotic stress on plant performance are being investigated, including metabolic/physiological reactions, molecular signalling pathways, ecophysiology, and crop breeding research. Abiotic stress significantly affects plant growth and productivity. Various factors such as drought, salinity, extreme temperatures, and heavy metals can limit crop productivity and lead to great yield losses (Islam et al., 2021a). Plants have developed potent adaptive tactics to combat these stresses, including cellular, physiological, and morphological defences (He et al., 2018; Cramer et al., 2011). The effects of abiotic stress on plants are dynamic and complex, impacting the synthesis, concentration, metabolism, transport, and storage of sugars, as well as causing ionic toxicity, osmotic pressure, oxidative damage, and nutritional shortage (Cramer et al., 2011). As a result, it is imperative to develop crops with multi-stress tolerance to alleviate the pressure of these adverse environmental conditions. In the majority of abiotic stress condition plant metabolism is disrupted and accumulates reactive oxygen species (ROS) causing oxidation and dysfunction of cellular components and finally cell death (Obata et al., 2012). Therefore, assuring optimal crop yields with minimum losses from plant environmental stressors including light, temperature, nutrition, and water is essential for the agricultural industry's sustainability as the global population continues to grow.

For various plant parts like flowers, leaves, stems, fruits, canopies, and roots, plant phenotypic criteria include color, size, texture, and shape (open to be observed) (Story et al., 2009). This information is useful for plant growth and stress monitoring in horticulture systems since it indicates the growth stage and health levels of plants. In order to determine the growth rate or annual growth cycle of plants cultivated under various or similar weather or nutrient circumstances, plant height is a quantitative morphological characteristic (Chaudhury et al., 2018; Gupta et al., 2019). Fall foliage is a qualitative indicator of a plant's overall health (Kumar et al., 2019). The fresh and dry weight of the plant may also be connected to the upper canopy area (Shimizu et al., 1995; Lee et al., 2018). The growth and health status of the plants are reflected in this data. It is beneficial for horticulture systems management and decision-making. The information was previously gathered via visual inspection or physical measurement techniques, which calls for a high degree of experience from producers by measuring the size of seedling and determine whether it has grown to a sufficient level before transplantation. Early plant stress detection is essential in order to reduce both acute and chronic productivity loss. When stress develops in plants, quick diagnosis and decision-making are required to alleviate the stress and avoid financial loss.

Quantification of plant growth stress symptom

When a plant grows under less-than-ideal conditions that put more demands on it, it is said to be under stress. The quantification of plant growth stress symptoms involves measuring various physiological, morphological, and visual parameters to detect the effects of stress on plants (Galieni et al., 2021). These parameters can include biomass production, growth, visible stress symptoms, root, and shoot biomass, root-shoot ratio, leaf area, plant height, leaf number, wilting symptoms, and presence of flowers. Fig. 2 shows the effects of abiotic stress on different types of seedlings. The key indicator to determine the type of stress cause the relative distribution of symptoms at the leaf, branch, and crown levels. With the changes of environment, internal activities of plant metabolism changes to survive in the new environment. The effects of abiotic stresses can occur either in molecular level or morphological level. The physiological reaction to plant stress is leaf wilting, leaf abscission, decrease of leaf area etc. Environmental stress suppresses cell elongation in consequence with decreasing leaf area, plant height, and other developments of crops owing to cell elongation.

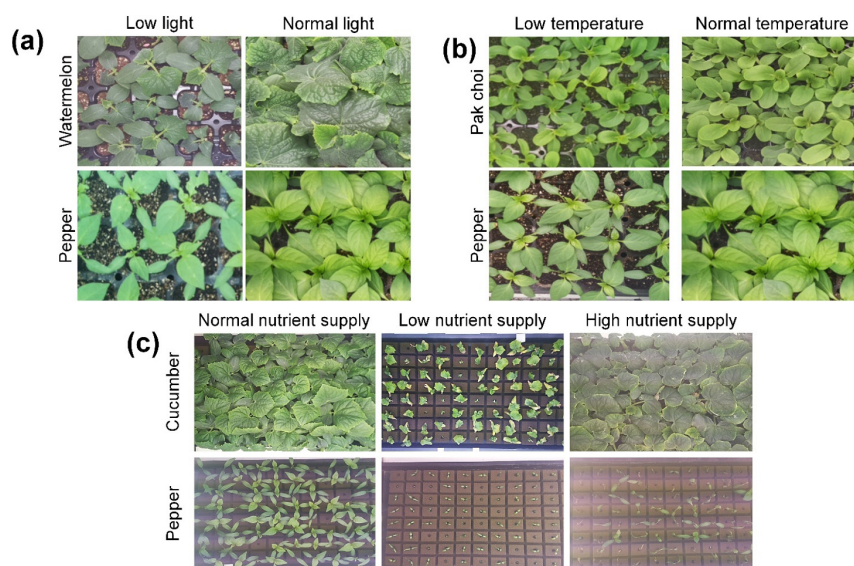


Fig. 2. Visual effects of abiotic stresses on different types of seedlings.

Rafique et al. (2020) showed the response of different growth parameters (leaf area, plant height, and stem diameter) under drought stress. Lack of water reduces the number of leaves on a plant, their size, and their lifespan. Temperature, acclimation, and leaf turgor pressure are necessary for the creation and increase of the leaf area index. Drought reduces the leaf zone, which is thought to be caused by the leaf extension being hidden, which lowers the photosynthetic rate. A common adverse effect of water stress on rice plants is a reduction in both fresh and dry biomass (Zhang et al., 2006). Francesca et al. (2022) showed the difference of tomato plant height, leaf number, leaf area, shoot fresh weight and shoot dry weight between drought and heat stressed and non-stressed plants. López-Marín et al. (2013) exhibited pepper plant height, leaf area, leaf weight decreased under thermal stress condition than normal condition. Temperature, light intensity, and photoperiod all affect plants actively; all three variables working together can boost biomass, promote growth, and enhance plant morphology.

Islam et al. (2021b) proposed an image processing algorithm for ice-plant leaf area calculation under different light condition. Different LED combination affects the growth and leaf size. The purpose of one study was to identify the ideal photo-thermal settings

and examine the impact of various photoperiods, light intensities, and day/night temperatures on the growth and quality of lettuce cultivated in glasshouses (Iqbal et al., 2022). Study shows photosynthetic rate can suppress in high salt concentration can limit stomatal activities resulting in available CO₂ restriction with discoloration and freshness in lettuce plants (Neocleous et al., 2014). Abdullah et al. (2018) showed impact of infrared lighting and water stress on growth and quality of cucumber. The obtained outcomes showed using infrared light and any of the commonly used irrigation schedules (used 70, 85, or 100% of the water) improved every measurement of vegetative development (plant height, number of leaves per plant, fresh and dry weight, whole plant). Chowdhury et al. (2023) investigated the effects of light quality, photoperiod, and light intensity on Chinese kale growth and glucosinolate content during different growth stages of cultivation in an aeroponics plant factory. The light significantly affect the growth and glucosinolate contents of Chinese kale leaves.

Image-based plant growth stress symptom detection

Plant phenotyping refers to the systematic and comprehensive analysis of observable traits or characteristics (phenotypes) of plants throughout their life cycle. Plant phenotyping is ideal in environmentally controlled greenhouses and glasshouses since they provide a variety of automatic control techniques to monitor and record ambient parameters (temperature, relative humidity, light, and water content) in plants (Basak et al., 2019). There are few research to investigate environmental stress detection in indoor farming such as classifying water stress (Hendrawan et al., 2021), looking for tip-burn stress (Gozzovelli et al., 2021), grading lettuce light sensitivity (Hao et al., 2020), and categorizing odd leaves (Wu et al., 2021). Nondestructive plant phenotypic image collections are available using imaging and image processing techniques with illumination sources ranging from the visible to near-infrared. For modeling and predicting plant growth and development, these techniques have improved precision, boosted throughput, and produced high-dimensional phenotypic data (Tardieu and Tuberosa, 2010, Goltzarian et al., 2011). Better performance and a novel viewpoint for improving plant phenotypes have been attained through the employment of integrated image-based innovative tools and techniques in phenomics and environmentally controlled platforms and facilities (Granier et al., 2014). In recent years, machine vision has become widely used in plant industries' intelligent systems (Dewi et al., 2020, Schor et al., 2017, Bechar et al., 2010, Valente et al., 2019). Almost every aspect of production is covered by this technology, including fruit grading and seedling raising, transplanting, management, and harvesting. By mimicking human vision, it gathers information from images, evaluates it, and provides guidance for actual production (Ren et al., 2007, Yang et al., 2019).

Unlike chemical and physical procedures, machine vision systems gather information about plants without causing harm to the plants. It also operates continuously at a low cost and excellent efficiency. Machine vision systems, also known as computer vision systems, have been increasingly used for non-invasive plant information gathering. These systems utilize various techniques such as image processing, pattern recognition, and deep learning to identify plant species based on visual data (Oppong et al., 2022). For instance, research has been conducted on the development of computer vision systems for automatic plant species identification using techniques like deep learning, leaf image analysis, and feature extraction (Wäldchen et al., 2018). These systems allow for the non-destructive collection of plant data, enabling tasks such as species identification and monitoring without causing harm to the plants (Oppong et al., 2022). Machine vision applications have certain obstacles because the illumination environment varies based on the needs of the plant. Instead of considering the needs of the plants, environmental factors including air temperature, relative humidity, and lighting intensity were changed in a traditional greenhouse based on farmer observations or predetermined thresholds (Lakhiar et al., 2018; Kim et al., 2010). Machine vision can assist with this limitation by providing the optimal method for plants to receive nutrition, water, temperature,

and light based on continuously recorded growth data. Fig. 3 shows different imaging systems for plant stress detection. Application of genomics and cutting-edge technical advancements improve current plant breeding programs to create plants with larger biomass, greater nutrition, and stronger tolerance to biotic and abiotic stressors. Significant breakthroughs in genetic tools and methodologies have enabled the production of high-yielding, stress-tolerant. However, progress in this area is hampered by the difficulty in accessing phenotypic data. In addition, the current phenotyping technologies are slow, expensive, labor-intensive, and primarily harmful (Furbank et al., 2011).

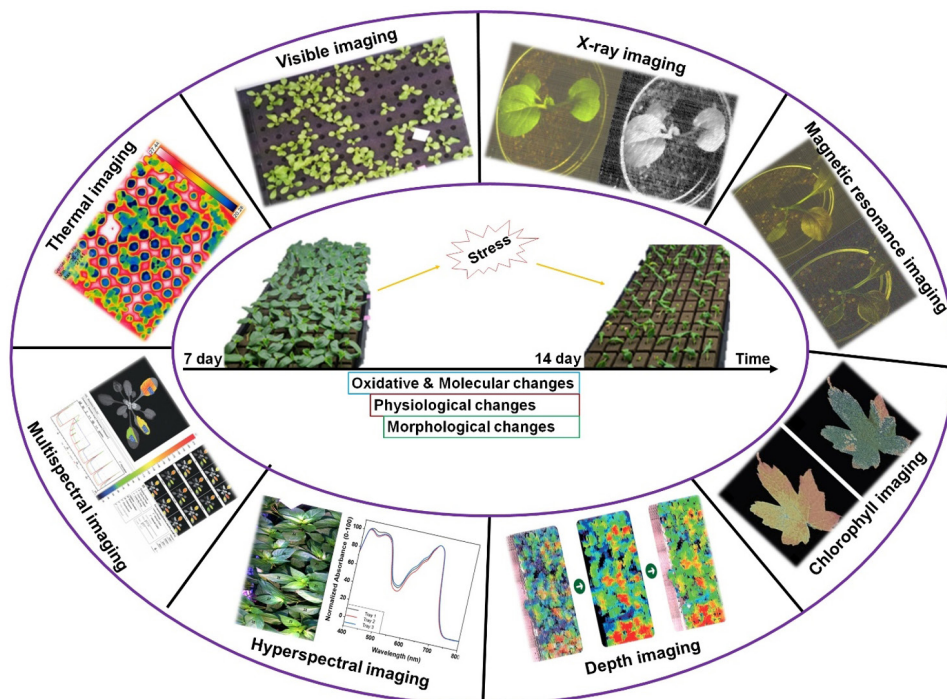


Fig. 3. Different imaging systems for plant growth stress detection.

Utilizing various imaging methods and methodologies, symptoms can be efficiently monitored (Sankaran et al., 2015). Utilizing sensors, static scanning, fisher discrimination analysis, and three-dimensional modeling are just a few examples of imaging technologies. To detect phenotypic reactions during plant under stress condition magnetic (Gout et al., 2001), soft x-ray imaging (Numajiri et al., 2021), and ultrasound (Yakupoglu et al., 2023) have been used. Static scanning technologies have been used for drought stress detection by collecting images and working on parameters using RGB mean value functions (Wu et al., 2021). Chen et al. (2014) used fisher discrimination analysis for the identification nitrogen, phosphorus, potassium stress in plant (Chen et al., 2014). For the water stress measurement of plant infrared thermal imaging has been commonly used in recent days (Vadivambal et al., 2011; Egea et al., 2017; Garcia-Tejero et al., 2016; Garcia-Tejero et al., 2018). When water stress occurs, plants respond with a limited stomatal closure, limiting stomatal conductance, restraining leaf transpiration, and aiding in the reduction of the evaporative chilling procedure, resulting in high leaf temperature. Visible light imaging is also a simple and inexpensive imaging technique by using traditional color cameras with wavelengths from 400 to 750nm in the electromagnetic spectrum. This imaging systems also can investigate the effects of plant under stress condition before the appearance of visible symptoms (Raza et al., 2015). Visible imaging techniques in glasshouses, greenhouses, and screen houses are very useful in assessing leaf biomass, crop traits, panicle traits, inhibition and growth rates, leaf physiology and

structure, seedling strength, coleoptile length, and biomass at kernel morphology, and root structural mechanism under controlled conditions (Li et al., 2014).

Spectrometry (hyperspectral imaging) is a proximal and remote sensing method for determining crop status and health (Khan et al., 2018). Multispectral or hyperspectral sensors, which can periodically scan wavelengths of interest, can be used to gather spectral measurements of the electromagnetic spectrum (Fiorani et al., 2013). Absorption waveband in the infrared range from the multispectral and hyperspectral measurements are frequently employed to explain various water statuses that measure the canopy water content (Cabrera - Bosquet et al., 2012). Susic et al. (2018) used hyperspectral imaging to discriminate between abiotic and biotic drought stress in tomatoes. Positron emission tomography (PET) imaging technology has advanced and introduced to get exact visualization of plants. By recognizing a pair of gamma rays emitted by a positron-emitting tracer injected into the plant, positron emission tomography creates 3D images. It primarily focuses on physiological changes and is used to evaluate how well photosynthetic function and environmental stress are occurring (Baker et al., 2008).

Chlorophyll a, a fluorophore that is sensitive to a variety of environmental stressors, is present in high concentrations in plants by nature. Chlorophyll fluorescence is a tool that can measure photosynthetic efficiency and detect various types of stress that impact the photosynthetic apparatus. Chlorophyll fluorescence is directly related to the efficiency of plants' photosynthetic processes as here are three different outcomes for the energy of photons that have been absorbed by photosynthetic pigments. Energy from photons can be transformed into heat, used to power the light processes of photosynthesis (electron transport), or reemitted as fluorescence by chlorophyll a. The variability in chlorophyll fluorescence can thus be used as a measure of photosynthetic efficiency as well as stress identification. Legendre et al., (2021) used Chlorophyll fluorescence imaging (CFI) to visualize stress induced by the photosystem II-inhibitory herbicide atrazine. The reflectometer observations based on wavelengths with the highest (741.2 nm) and lowest variability (548.9 nm) in response to atrazine damage were used to create a fluorescence-based stress index (Legendre et al., 2021).

Image processing techniques for plant stress symptom identification

Pre-processing, feature extraction, selection, and classification are few of the steps involved in image processing for plant stress detection. One crucial step in implementing image processing techniques is pre-processing image data. Pre-processing techniques that range from simple background removal, contrast enhancement, and cropping to more complex procedures like clustering and principal component analysis (PCA)-based dimensionality reduction that greatly increases the performance of computer vision based analysis. Principle Component Analysis (PCA) is a statistical technique that turns correlated variable data into a set of linearly uncorrelated variables known as principle components by the application of an orthogonal transformation. Unfold Principal Component Analysis (UPCA) is a tool used to identify plant stress conditions and/or help farmers prevent or limit plant damage caused by stress on plants by identifying these conditions in a timely manner.

In order to improve the signal-to-noise ratio and enable the machine learning model to more readily identify patterns and trends that will help categorize the data into the right groups, pre-processing depends on the concentration of information. Pre-processing helps identify pertinent image elements that are essential for model training by utilizing domain knowledge. In order to identify the photograph, this involves removing any tags, dirt, or soil from the foreground image of either leaves or fruits. Image segmentation, contrast enhancement, thresholding to binary data, image conversion from RGB to greyscale or RGB to hue saturation value (HSV) are examples of pre-processing operations that can be applied. Other pre-processing operations include de-noising images using filters

such as band-pass, low-pass, and fast Fourier transform (FFT); feature extraction at different scales using image transforms such as FFT, wavelet transforms, Hough transform, Harr transforms, and Radon transforms; pixel-based classification, image clustering into classes, and dimensionality reduction of images. Using image data generator in Keras for pre-processing, the images were scaled and denoised based on the observation of changes in the leaf and fruit surface response to the various biotic and abiotic stress (Li et al. 2020).

In earlier research on plant stress detection, Scale-invariant feature transform (SIFT), histogram of oriented gradients (HOG), and local binary pattern (LBP) feature extractors were used for classifiers such as adaptive boosting (AdaBoost) (Schapire et al., 1999) and support vector machine (SVM) (Iqbal, 2022). (Marceau et al., 1990) assessed the grey level co-occurrence matrix (GLCM) for evaluating texture representations that can be examined in spatial attributes retrieved from digital images. This is the connection between the grey levels that now exist in nearby pixels that affect the overall appearance of image. In order to characterize particular textural aspects of the image or to generate a new texture image or band that may be included in spectral feature space for classification, GLCM can be used to measure statistical metrics including homogeneity, contrast, and entropy (Marceau et al., 1990). During co-occurrence computing, the GLCM technique makes judgments based on variables such as inter-pixel distance and angle, spectral and quantization level of the picture, moving window size, and statistics utilized as texture measurements. Fig. 4 shows a detailed schematic representation of machine vision and image processing fusion for comprehensive detection of plant growth abiotic stress symptoms.

Feature selection is another important part of image processing is essential for improving computational efficiency, reducing noise, enhancing interpretability, and ensuring the effectiveness and generalization of image processing algorithms. Sun et al. (2019) used sequential feature selection algorithm was employed to select chlorophyll features that could represent the responses of three genotypes caused by drought stress for each day post drought stress affected plants.

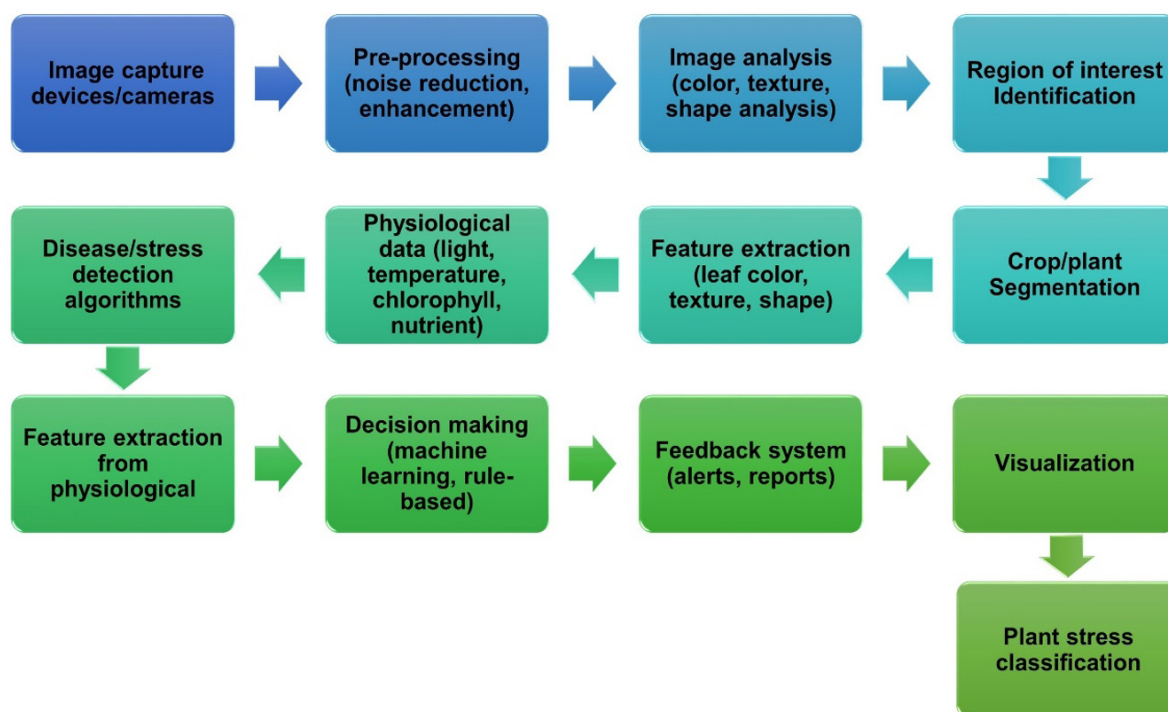


Fig. 4. A detailed schematic representation of machine vision and image processing fusion for comprehensive detection of plant growth abiotic stress symptoms.

Classification in plant stress detection involves building models that can automatically categorize plants into different stress classes based on various features extracted from images or sensor data. The goal is to develop robust and accurate algorithms that can assist in identifying and managing plant stress conditions. Naik et al. (2017) utilized several classification algorithms, namely classification trees (CT), random forests (RF), Naïve Bayes (NB), linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), multi-class support vector machines (SVM), k-nearest neighbors (KNN), and Gaussian mixture models (GMM). Building on the findings, they applied the concept of hierarchical classification to create two more models using a combination of linear discriminant analysis (LDA) and SVM algorithms.

Artificial intelligence application for plant stress symptom detection

The technologies of artificial intelligence (AI), machine learning (ML), and deep learning (DL) have had a significant impact on the topic of plant phenotyping. AI was first defined as the science and engineering of making intelligent machines, especially intelligent computer programs (Buchanan et al., 2005). In recent years, the fusion of AI, ML, and DL technologies has revolutionized plant stress symptom detection. Machine learning algorithms, a subset of AI, have been important in plant stress symptom detection. By analysing vast datasets of plant images, ML models can identify precise indicators of stress, such as leaf discoloration or wilting, with remarkable accuracy. These models learn patterns and features from labelled data, allowing them to classify plants based on their health status and detect deviations from the norm that may signify stress.

Deep learning, a sophisticated branch of ML, has further enhanced the capabilities of plant stress detection systems. Deep neural networks, inspired by the structure of the human brain, excel at processing complex data and extracting intricate features. In plant phenotyping, convolutional neural networks (CNNs) have emerged as a powerful tool for image analysis. By traversing multiple layers of abstraction, CNNs can discern nuanced variations in plant physiology, enabling precise identification of stress symptoms even amidst diverse environmental conditions. Fig. 5 shows a schematic representation of a deep learning framework for plant stress classification through image analysis and feature extraction.

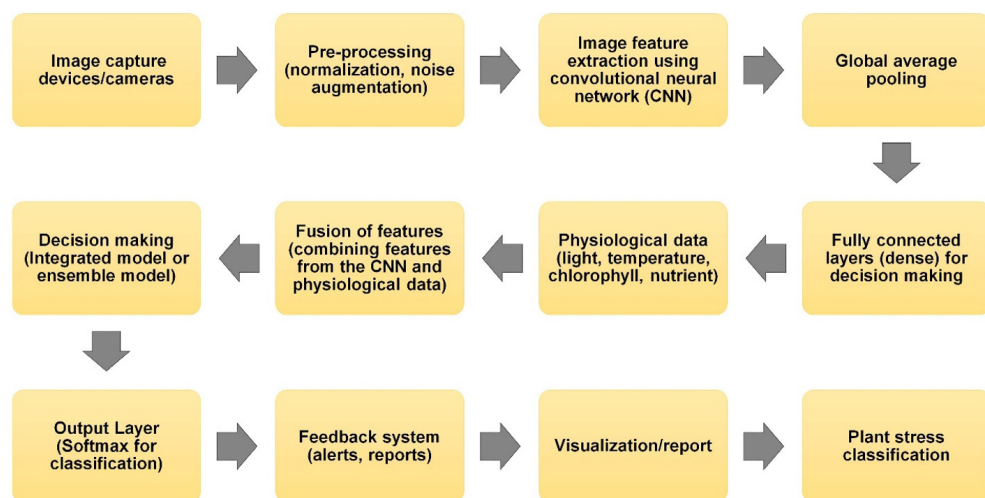


Fig. 5. A schematic representation of a deep learning framework for plant stress classification through image analysis and feature extraction.

Recent developments in big data have accelerated the development of AI by combining vast data sets with intelligent algorithms, enabling AI software to automatically learn from the patterns or features in the vast datasets. A form of artificial intelligence is machine learning is used to carry out particular task by computer systems. It is typically divided into supervised and unsupervised learning techniques. The expression of augmented learning techniques uses an input matrix with independent x and dependent y variables. When dealing with classification problems, y is often a scalar to represent the category labels and a vector of continuous values when using regression (Harrington, 2012). According to the current status of the research, there are not many datasets that support fine-grained instance segmentation that are available for autonomous crop disease and pest detection. Fig. 6 shows the application of real-time monitoring and detection of seedling stress symptoms using sensor fusion and CNN based algorithm. Afzaal et al. (2021) presented a novel dataset consisting of 2500 photos representing seven different types of strawberry diseases. In order to enable the development of deep learning-based autonomous detection systems capable of segmenting strawberry diseases under intricate background settings. Khanna et al. (2019) contributed a generic framework for remote plant stress phenotyping. In this research, a machine learning-based methodology for methodically inferring these stress conditions from the remotely measured data was presented, along with a dataset containing spatiotemporal-spectral data following sugar-beet crop growth under optimal, drought, low and surplus nitrogen fertilization, and weed stress conditions. Naik et al. (2017) investigated ten different classification strategies; a hierarchical classifier with a mean per-class accuracy of approximately 96% was found to be the best classifier. By linking the automatically extracted features of canopy traits with the plant stress severity rating, a population canopy graph" that has phenotypical significance. They integrated the image capture, image processing, and classification workflow into a smartphone app to allow digital photographs of the canopy to be used for automatic real-time iron deficiency chlorosis score evaluation.

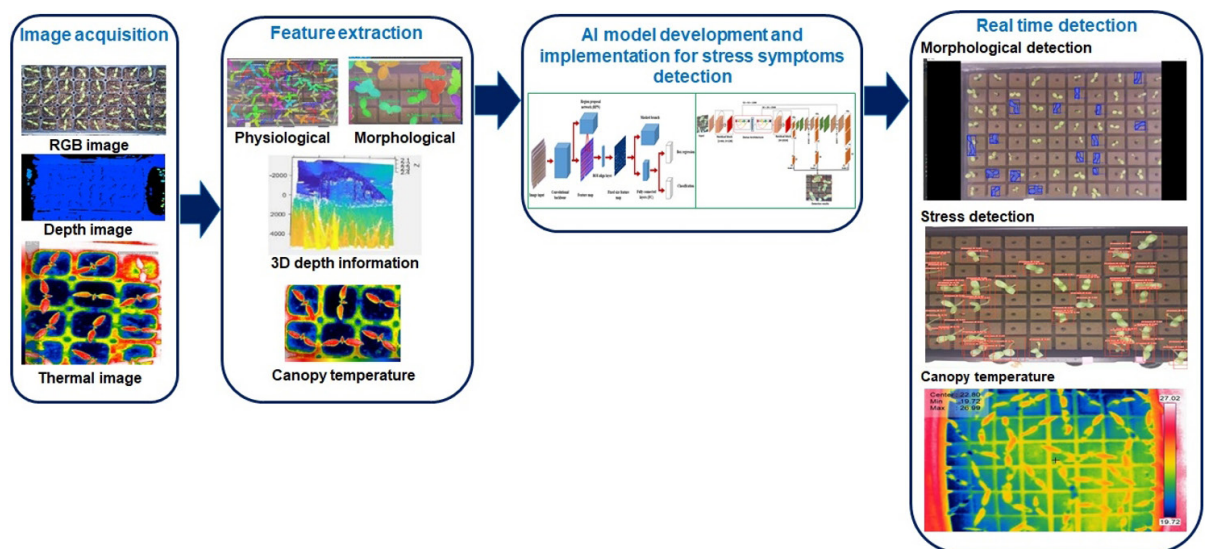


Fig. 6. Application of CNN based algorithm for seedlings stress symptoms detection at the Agricultural Production Machinery and Precision Agriculture Lab, Chungnam National University, Republic of Korea.

Another effective supervised machine learning technique that may be used to identify people in high-dimensional space is the Support Vector Machine (SVM) (Cortes et al., 1995). Moshou et al. (2014) discriminated between healthy and water stressed wheat canopies under greenhouse conditions. They developed stress type detection algorithms based on the combination of least-squares support vectors machine with sensor fusion. With the classification performance of 99% the model was developed for automated recognition of different biotic and abiotic stress. Pujari et al. (2016) detected and quantified plant disease symptoms in the initial stage and developed algorithms for color and textures features extraction from the sample images of plant disease and used to train support vector machine (SVM) classifiers. The findings show that SVM classifier is more suited for identifying and categorizing plant diseases that impact crops in horticulture and agriculture. Some researches were conducted for detecting and classifying drought stress (Behmann et al., 2014), weed and nitrogen stress (Karimi et al., 2006), cadmium stress (Zhou et al., 2019), disease and insect stress (Zhao et al., 2022) of crops by using hyperspectral images image based SVM classification model. For eliminating water stress discrimination method for plant root zone water status in greenhouse was developed by Guo et al. (2017) by integrating phenotyping and machine learning classification model Random Forest (RF), Neural network (NN), Support Vector machine (SVM). For the dimensionality reduction of a high dimensional dataset, feature selection selects discriminative features to capture most valuable information with minimum redundancy.

Moghimi et al. (2018) used six feature selection methods to provide remarkable results to observe health status of plants. Among them the best results were achieved by ReliefF, SVM-RFE, and Random Forest model respectively. Another form of artificial intelligence is Deep Learning (DL) which is a statistical learning technique that extracts features from unprocessed datasets (Sarker 2021). To achieve this goal a multi-layered artificial neural network with hidden layers stacked one after another is used by DL. Due to its complex algorithms, DL calls for strong computational resources. There are three popular DL models such as Recurrent Neural Networks (RNN) (Concepcion II et al., 2020), Generative Adversarial Networks (GAN) (Qi et al., 2019), Convolution Neural Networks (CNN) (Yang et al., 2019). To achieve high accuracy in tasks like object detection (Oh et al., 2020; Lu et al., 2021), language translation (He, 2020), speech recognition (Zheng et al., 2018), as well as in measuring plant stress and other biotic and abiotic conditions that affect plants, deep learning (DL) uses multi-layered artificial neural networks (ANN). There are five key artificial neuron components make up the fundamental feed forward neural network. The input nodes, connections, weighted sum, transfer or activation function, and output node are among them. The numerical value linked with the input node is often a real number. Weights (w) are connected to connections, which can be any real number. The values and weights from the input nodes of the connections are entered into the weighted sum. The transfer or activation function will take the weighted sum's output as an input.

CNNs are frequently used in Deep Learning for applications involving image processing or computer vision. The most well-known technique among the deep learning methods is the CNN model, which has demonstrated outstanding success and performance in the fields of computer vision and pattern recognition, designed for visual recognition, image annotation and retrieval as well as plant stress detection (Azimi et al., 2021). Convolutional neural network (CNN) and long short-term memory (LSTM) network were utilized by Rojanarungruengpom et al. (2021) to detect the early stage of nutrient deficiency-induced plant stress. They made use of sorghum datasets, which are made up of more than 40,000 photographs of the crop in growth that were taken in three views at the phenotyping facility. The use of deep learning is expanding in the field of precision agriculture rapidly (Tian et al., 2020, Li et al., 2021). Wang et al. (2021) proposed an automatic extraction algorithm for crop images based on Mask RCNN. 360 datasets of several types of fruits were pre-processed and additionally an improved Mask RCNN network model structure was established to the network design to enhance functions and optimize region extraction network, and feature pyramid network. Finally, by using the Sobel operator to forecast the target edge, adding the edge loss to the loss function, and adding a micro-fully connected layer to the mask branch of the

ROI output, the edge accuracy of the segmentation mask is further improved. The proposed algorithm demonstrated better precision, recall, average precision, mean average precision, and F1 scores of crop image extraction. Chu et al. (2021) reported the creation of Suppression Mask R-CNN, a revolutionary deep learning-based apple detection system. In order to suppress non-apple features produced by the original network, a suppression branch was added to the conventional Mask R-CNN in their innovative suppression Mask R-CNN for apple detection. The developed model showed a higher F1-score of 0.905 and a detection time of 0.25 second per frame.

Jia et al. (2020) applied a model of harvesting robot vision detector based on Mask R-CNN, which shows good performance of feature extraction and target detection applied in deep learning to fruit identification in orchards. To make the model better suited for identifying and segmenting apples that overlap, it was updated. A random test set including 120 photos is used to evaluate the approach; the precision rate is 97.31%, and the recall rate is 95.70%. Additionally, the identification speed is quicker, which satisfies the vision system requirements of the apple harvesting robot. Yu et al. (2019) introduced Mask Region Convolutional Neural Network (Mask-RCNN) to enhance machine vision performance in fruit detection for a strawberry harvesting robot. The method put forth shows increased universality and resilience in a non-structural context, especially for overlapping and buried fruits as well as those under different lighting conditions. Kaneda et al. (2017) proposed a novel multi-modal sliding window-based support vector regression (multi-modal SW-SVR) method for accurate water stress prediction from environmental and plant image data. It included SW-SVR and deep neural network (DNN) as a feature extractor, which performed better and features for precise and stable water stress prediction.

Weng et al. (2023) proposed a drought stress (DS) identification method using hyperspectral imaging (HSI) and subsample fusion. Reflectance spectra from HSI images of young and mature leaves at different DS levels were extracted, and effective wavelengths (EWs) were determined using a genetic algorithm. DS identification models were constructed using EW spectra and image features from RIS by LeNet-5, support vector machine (SVM), random forest, and dense convolutional networks (DCN). SVM and subsample fusion achieved global optimal classification performance, with a classification accuracy of 95.90% and 95.78% for calibration and prediction sets, respectively. Tran et al. (2019) used used artificial neural network models to recognize, classify, and predict the nutritional deficiencies occurring in tomato plants (*Solanum lycopersicum* L.). A total of 571 images were captured used and the accuracy of 87.273% and 79.091% for Inception-ResNet v2 and Autoencoder, respectively, and 91% validity using Ensemble Averaging were observed.

Khatoon et al. (2021) proposed an AI-based system for real-time detection of diseases in tomato plants, utilizing various deep learning models trained on a large dataset of plant images. ShallowNet, a shallow network trained from scratch, and DenseNet, a state-of-the-art deep learning network fine-tuned via transfer learning, were compared. DenseNet consistently showed high performance, with an accuracy of 95.31% on the test dataset. Taha et al. (2022) combined color imaging with deep convolutional neural networks (DCNNs) to diagnose nutrient status in aquaponics grown lettuce. The method involved multi-stage processes, including plant detection and nutrient deficiency classification. Using 3,000 lettuce images categorized into four nutrient classes, DCNNs outperformed traditional machine learning methods, achieving 99.1% accuracy for segmentation and 96.5% for classification. Ruan et al. (2023) introduced meta-learning to hyperspectral imaging and crop detection, utilizing 88 hyperspectral images of drought-stressed tomato plants and 68 images of freeze-stressed tomato plants. Results showed that meta-learning, with a minimum of eight target domain samples, achieved a 69.57% detection accuracy, 59.29% precision, 66.32% recall, and 62.61% F1-score for classifying frost stress severity. Shomali et al. (2023) conducted a study comparing the chlorophyll fluorescence (ChlF) features of tomato plants under high light ($1200 \mu\text{mol m}^{-2} \text{s}^{-1}$) with control plants ($300 \mu\text{mol m}^{-2} \text{s}^{-1}$). Three artificial neural networks (ANNs) based algorithms, Boruta, Support Vector Machine (SVM), and Recursive Feature Elimination (RFE) were used to identify the most reliable ChlF features

which demonstrated the effectiveness of these features for phenotyping plants under high light stress. Long and Ma (2022) explored a method for identifying drought stress in tomato seedlings by using chlorophyll fluorescence imaging. They collected chlorophyll fluorescence parameters and corresponding images for four different drought stress levels. The features with high Pearson correlations were input into three models—Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), and k-Nearest Neighbor (KNN) to classify drought stress classes. The recognition accuracy rates were 86.8% for LDA, 87.1% for SVM, and 76.5% for KNN. Kuo et al., (2023) developed the 1D-ResGC-Net, a convolutional neural network with an embedded residual global context (ResGC) block, to analyze visible and near-infrared (Vis/NIR) spectroscopy data of tomato leaves for early drought stress detection, and utilizing gradient-weighted class activation mapping to identify the most informative feature bands, showed an accuracy of 90%. Kumar et al. (2021) demonstrated the effectiveness of image-based phenotyping for water-stress classification and identified genomic loci for horticultural traits, chlorophyll fluorescence, and spectral vegetation indices. They found 25 quantitative trait loci (QTLs) for horticultural traits, 26 for chlorophyll fluorescence, and 34 for VI, explaining 6.41% to 19.5%, 6.93% to 13.26%, and 7.2% to 17.19% of phenotypic variation, respectively. Yang et al. (2021) explored the potential of machine learning models, including Multiple Linear Regression (MLR), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM), to detect yellow and rotten leaves in hydroponic lettuce. They used one-way analysis of variance to select color features for training these models and applied it to reduce the number of RGB, HSV, and Lab* features in hydroponic lettuce images. MLR and SVM provided the highest detection accuracies of 89.48% and 99.29%, and 98.33% and 97.91% for yellow and rotten leaves, respectively. Concepcion II et al. (2020) proposed advanced computer vision and machine learning techniques to predict lettuce water stress indicators using 330 samples from an aquaponic system. Color components, canopy area, and a thermal index were the key components for an RNN optimized by evolutionary strategy (ES) model, which showed high prediction accuracy ($R^2 = 0.81$ to 0.82) with an efficient inference time of 7.5 seconds. Yee-Rendon et al. (2021) used four well-known pre-trained deep-learning models, namely VGG-16, Xception, Inception v3, and MobileNet v2, to classify jalapeño pepper leaves with two diseases: Tobacco Mosaic Virus (TMV) and Pepper Huasteco Yellow Vein Virus (PHYVV). They introduced new vegetation indices, Normalized Red-Blue Vegetation Index (NRBVI) and Normalized Green-Blue Vegetation Index (NGBVI), and employed data augmentation to enhance model accuracy. The Xception model using the NGBVI dataset exhibited the highest performance, achieving an average accuracy of 98.3%. Table 1 shows the key indicators and detection algorithms for plant growth stress detection using machine learning algorithms.

Table 1. Key indicators and detection algorithms for plant growth stress detection.

Crop	Key indicator	Stress type	Sensor	AI Method	Reference
Tomato	Stem diameter	Water	RGB	Multi-modal support vector regression (SW-SVR)	Kaneda et al. (2017)
Tomato	Fruit and leaf (color)	Nutrient	RGB	Deep convolutional neural network (CNN)	Tran et al. (2019)
Tomato	Fruit and leaf (color)	Nutrient	RGB	CNN	Khatoun et al. (2021)
Lettuce	Leaf area	Nutrient	RGB	Deep convolutional neural network (CNN)	Taha et al. (2022)
Lettuce	Leaf	Water	RGB	Multiple linear regression (MLR), KNN, SVM	Yang et al. (2023)
Pepper	Leaf	Water	RGB	VGG-16, Xception, Inception v3, MobileNet v2	Yee -Rendon et al. (2021)
Tomato	Leaf	Water	Hype rspectral	Support vector machine (SVM), random forest (RF), dense convolutional network	Weng et al. (2023)
Tomato	Canopy	Tem perature	Hype rspectral	SVM, PLS-DA	Ruan et al. (2023)
Tomato	Leaf	Water	Mult ispectral	1D CNN	Kuo et al. (2023)
Lettuce	Leaf	Water	Thermal	Recurrent neural network (RNN)	Concepcion II et al. (2020)
Tomato	Leaf	Light	Ch lorophyll flu orescence	ANN, SVM, Recursive Feature Elimination (RFE)	Shomali et al. (2023)
Tomato	Leaf	Water	Ch lorophyll flu orescence	LDA, SVM, KNN	Long and Ma (2022)
Lettuce	Leaf	Water	Ch lorophyll flu orescence	RF	Kumar et al. (2021)

Challenges and limitations of using machine vision techniques

Using machine vision for plant stress detection comes with its own set of challenges and limitations. Fig. 7 shows the summary of the characteristics and pros and cons of AI technologies for plant stress detection. While this technology has shown promising results in various applications, there are certain issues that need to be addressed for its successful implementation in plant stress detection. As the morphological characteristics of plant change with the growing time period it is challenging to detect stress symptoms in very early stage with images due to the dynamic nature of plant phenotypes. Similar physiological changes of plants can be exhibited due to different abiotic stresses which limits the machine vision systems to differentiate between different causes of plant abnormalities. Creating a universal model that works well across diverse plant types and growing environments is challenging. In the domain of image based plant stress detection systems, image data quality and variability in imaging techniques can affect the performance of machine vision algorithms. Obtaining labeled datasets that cover a wide range of stress conditions can be challenging.

Additionally, data collection may be hindered by factors such as weather conditions or restricted access to certain plant locations. Plant stress can manifest in subtle and complex ways, such as changes in color, texture, or morphology. Developing algorithms that can accurately interpret these diverse symptoms is a complex task. Deploying machine vision systems on a large scale, especially in extensive agricultural fields, can be logistically challenging and may require significant investment.

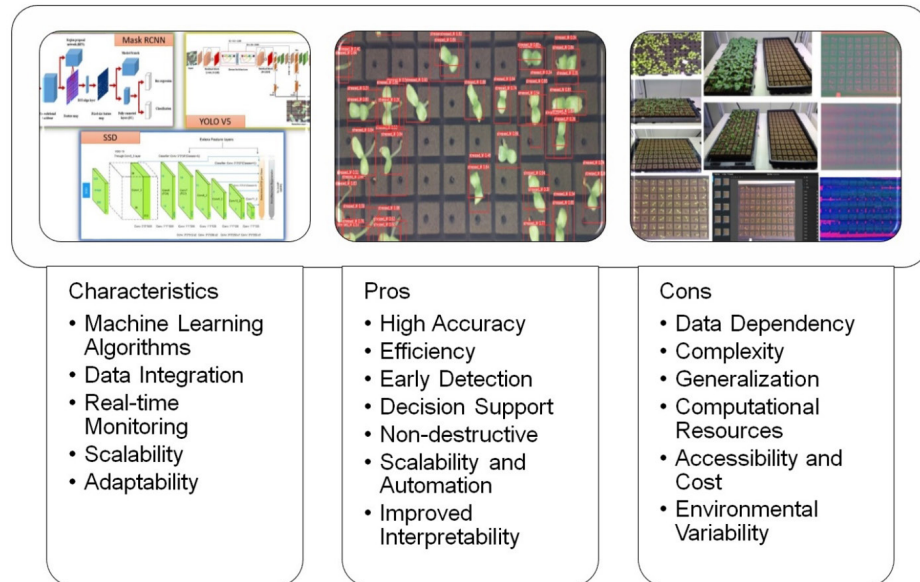


Fig. 7. A schematic representation of the characteristics and pros and cons of AI technologies for plant stress detection.

Future of machine vision in agriculture

The future of machine vision in plant stress detection holds several exciting possibilities, driven by advancements in technology, research, and interdisciplinary collaboration. Continued development of high-resolution imaging technologies, including hyperspectral and multispectral imaging, will provide more detailed information about plant characteristics. These technologies can capture a broader range of wavelengths, enabling better discrimination of stress-related changes. Machine vision systems are likely to be integrated into larger sensor networks. Combining data from various sensors, such as environmental sensors, drones, and ground-based sensors, will enhance the accuracy of stress detection by providing a more comprehensive view of plant and environmental conditions. Further advancements in deep learning techniques and neural network architectures will contribute to improved image recognition and feature extraction. These advancements can enhance the ability of machine vision systems to accurately detect subtle and complex stress symptoms.

The development of real-time decision support systems will enable quick responses to detected stress conditions. This is particularly important in precision agriculture, where timely interventions can mitigate the impact of stress and optimize crop yields. Automation in agriculture, including autonomous drones and robotic systems equipped with machine vision, will become more prevalent. These systems can efficiently monitor large agricultural areas, identify stress conditions, and take appropriate actions without human intervention. Collaboration between machine vision systems and human experts will continue to be crucial. Interactive systems that allow plant scientists and farmers to provide feedback and guidance to machine learning models will contribute to more accurate and interpretable results.

Conclusions

Plant stress detection represents a critical aspect of modern agriculture, where early identification of stress factors can significantly impact crop yield, quality, and overall plant health. The integration of image processing techniques for plant abiotic stress symptoms detection represents a significant progress towards addressing the pressing challenges in modern agriculture. The advancements in computer vision and machine learning have enabled the development of robust algorithms capable of extracting valuable information from high-resolution images, facilitating the accurate identification of stress indicators. Despite the natural challenges associated with the variability in plant responses to abiotic stressors, ongoing research in this domain holds promise for enhancing the precision and adaptability of detection models across diverse plant species and environmental conditions. Furthermore, bridging the realms of plant biology, computer vision, and data science, underscores the importance of collaborative efforts in addressing complex challenges in agriculture. Moving forward, the continuous refinement of image processing techniques, coupled with advancements in sensor technologies and artificial intelligence, holds the potential to revolutionize crop management practices, contributing to global food security and the sustainable cultivation of crops in the face of changing environmental conditions.

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