International Journal of Computing and Digital Systems
2025, VOL. 17, NO. 1, 1-13

http://dx.doi.org/10.12785/ijcds/1571029493

Deep Learning in Plant Stress Phenomics Studies - A Review

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Received 12 May 2024, Revised 5 October 2024, Accepted 25 October 2024

Abstract: Efficient crop management and treatment rely on early detection of plant stress. Imaging sensors provide a non-destructive and commonly used method for detecting stress in large farm fields. With machine learning and image processing, several automated plant stress detection methods have been developed. This technology can analyze large sets of plant images, identifying even the most subtle spectral and morphological characteristics that indicate stress. This can help categorize plants as either stressed or not, with significant implications for farmers and agriculture managers. Deep learning has shown great potential in vision tasks, making it an ideal candidate for plant stress detection. This comprehensive review paper explores the use of deep learning for detecting biotic and abiotic plant stress using various imaging techniques. A systematic bibliometric review of the Scopus database was conducted, using keywords to shortlist and identify significant contributions in the literature. The review also presents details of public and private datasets used in plant stress detection studies. The insights gained from this study will significantly contribute to developing more profound deep-learning applications in plant stress research, leading to more sustainable crop production systems. Additionally, this study will assist researchers and botanists in developing plant types resilient to various stresses.
Keywords: Deep learning, Imaging techniques, Machine vision, Machine learning, Plant phenomics, Plant stress.

1. INTRODUCTION

A. *Background and Motivation*

Plants are an essential component of life on earth, providing vital resources like oxygen. However, they can experience plant stress, which can hinder their performance and function [1]. Early detection of plant stress is crucial for farmers to reduce agriculture losses [2, 3]. There are various methods for detecting plant stress, including visual observation and artificial intelligence-based techniques [4]. By detecting crop health issues, stress on yield, and improving irrigation and fertilizer application, this technology can help develop stress-tolerant crops and combat diseases and pests [5, 6]. However, some challenges still exist in designing robust and universal models that can identify stress in different types of plants under diverse conditions [7]. Incorporating sensor data and environmental parameters into scalable and real-time plant stress detection models for large-scale farming is also necessary [8]. It's worth noting that exposure to different external elements can negatively affect plants and may be considered as plant stress [9].

B. *Bibliometric Review*

Bibliometric analysis is one of the most used and rigorous ways to explore and analyze extensive scientific information. It also helps us to untangle the developmental perspectives of that particular domain and reveal the new development directions within the same field [10]. To conduct a thorough literature review, one can explore several databases, including Scopus, Science Direct, Mendeley, Research Gate, and Google Scholar, among others. In this particular study, we opted to utilize the Scopus database, and the database was accessed on 28 April 2024. The literature review presented in this paper encompasses all relevant studies available up to that date. This paper uses a keyword-based search approach for the literature study. The keywords employed in this literature review include "plant stress detection", "abiotic stress," "biotic stress," "plant stress," "deep learning," and "machine learning." For a broad search "plant stress detection" keyword is used with "Abiotic stress" and "Biotic stress" keywords to further categorize studies based on plant stress types. Other keywords such as "plant stress," "machine learning," and "deep learning" are used to narrow down and restrict the research to automated vision-based applications in plant stress detection. TABLE I presents a list of primary keywords used to carry out this plant stress study review. Visualization of bibliometric keyword-based analyses using VOSviewer software is shown in Figure 1. The survey of the literature

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is carried out for a period of 2020 to 2024.

TABLE I. List of keywords for bibliometric review

Keywords	Number of Publications
Plant stress detection	1,972
Abiotic stress	121
Biotic stress	63
Plant stress	87
Machine learning	69
Deep learning	56

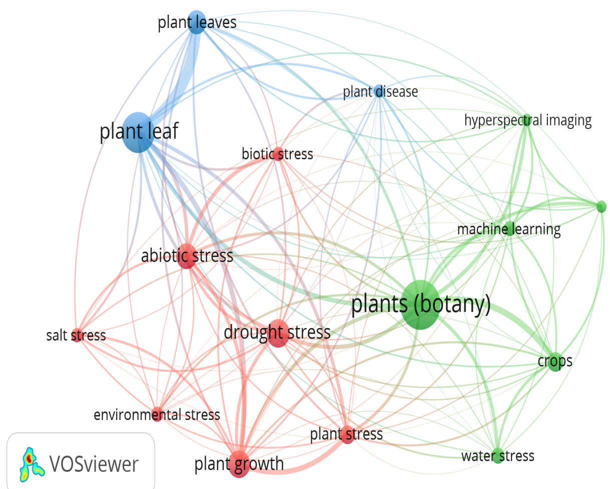

Figure 1. Keyword analysis visualization

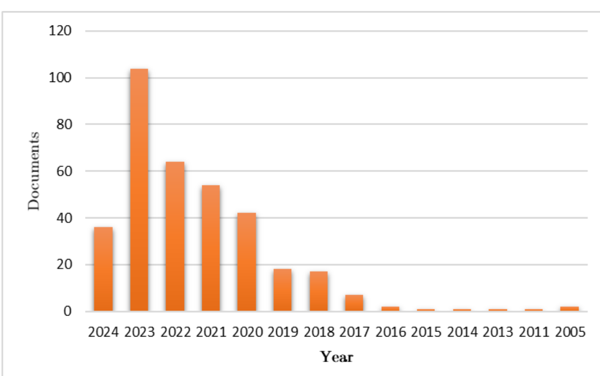

Figure 2. Plant stress using deep learning (DL) documents by year

According to the results of this bibliometric analysis, plant stress research is a rapidly evolving area in the scientific community, with a growing number of researchers focusing on deep learning (DL) as evident from Figure 2. In this review paper, the objectives are:

1) To identify the publication trends in deep learning-based plant stress studies using keyword-based bibliometric analysis.
2) To review, analyze, and categorize the deep learning-based plant stress studies based on stress type and imaging techniques.
3) To present a brief summary of publicly available datasets for plant stress detection.

This paper presents a general deep-learning pipeline for plant stress detection and commonly used deep-learning models for plant stress detection in section 2. The next section 3 discusses applications of deep learning studies based on image types. Section 4 presents deep learning studies based on plant stress types. Publicly available datasets for plant stress detection are covered in section 5. Lastly, Section 6 presents conclusions and future research directions in the study area.

2. DEEP-LEARNING PIPELINE FOR PLANT STRESS DETECTION

According to Latif et al. [11], traditional plant stress detection involves manual inspection and relies on experience. This approach can be time-consuming and requires trained personnel, as noted by Khalifani et al. [12]. Fortunately, recent advancements in deep learning techniques have made it possible to automate the process using a UAV-based camera system, significantly reducing the time required.

Plant stress detection using deep learning relies primarily on plant or plant leaf images as input. The process involves several stages, beginning with image acquisition. The next step is image pre-processing, which includes noise reduction, contrast enhancement, image resizing, colour correction, segmentation, feature extraction, and more [13]. Once completed, an image dataset is created with different sets for training, validation, and testing. These sets are then fed into the deep learning model for training and testing. The Figure 3 below illustrates the general methodology for plant stress detection using deep learning. Advanced technology can be utilized to detect plant stress, which can be detrimental to their health and growth.

A. *Image Acquisition and Pre-Processing*

Plant stress detection involves different image acquisition techniques; each technique covers a various range of electromagnetic spectrum. Visible images are used to detect stress by leaf color or chlorosis. In multispectral imagining, images are captured in different spectral bands. Hyperspectral images capture detailed information but require high computational power to process [14]. Thermal images capture temperature changes in plants, but they are affected by environmental temperature [15]. Fluorescence imaging detects photosynthesis efficiency by measuring chlorophyll fluorescence [16]. Also, X-ray or MRI imaging can be used to examine internal structures, but it is costly. Image pre-processing is an essential task in deep learning-based plant stress detection. It involves processing raw image datasets to prepare for training artificial neural networks. Techniques involved are image enhancement, formalization, noise reduction, color space conversion, image resizing,

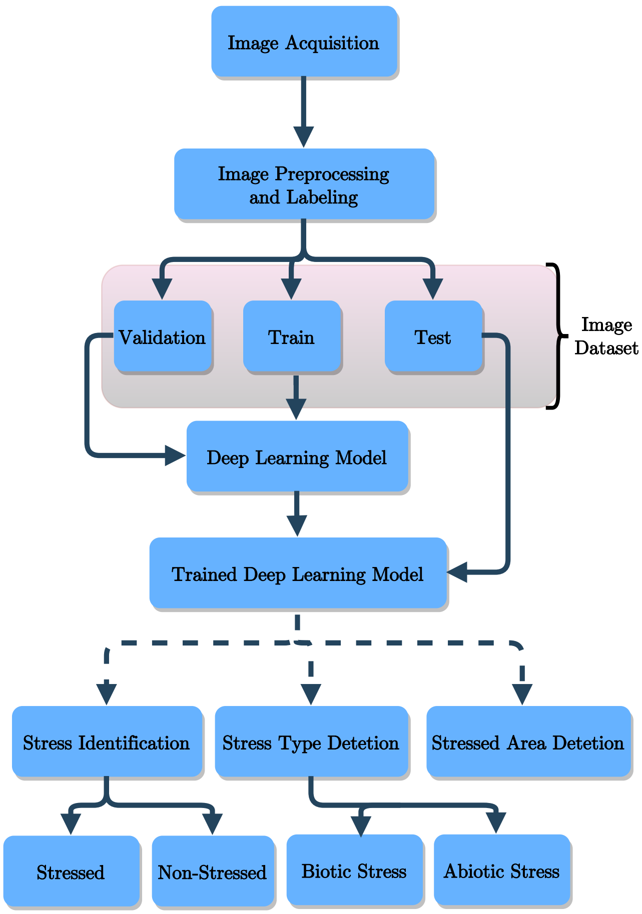

Figure 3. Plant stress detection using deep learning

data balancing, edge detection, and feature extraction. Image dataset augmentation increases the diversity of dataset [17].

B. *Common Deep Learning Models for Plant Stress Detection*

Deep learning is a powerful tool that can help identify and categorize different stress conditions that can harm plants [18] [19].

1) *Convolutional Neural Networks*

Among the most commonly used deep learning architectures is the convolutional neural network (CNN), which is highly effective in extracting spatial characteristics from images related to plant stress [20]. By implementing CNNs, plant stress symptoms can be detected with greater precision due to their advanced pattern and texture recognition capabilities in visual data [11]. Ünal [21] used various image processing techniques, including noise reduction, contrast augmentation, and image normalization. They then used shape detection, texture-based analysis, and color-based image segmentation for feature extraction. By utilizing the VGG16 and VGG19 models, they could classify rice salinity stress based on its severity. The study found that combining image enhancement, feature extraction, and deep learning resulted in an accuracy of 99.04% in detecting salinity stress with severity.

Classic CNN is less effective on complex patterns and large datasets. ResNet is a deeper version of CNN that performs well on vanishing gradient problems compared to classic CNN [22]. ResNet performance remains as it is after increasing the depth of the network. It detects fine features in images and avoids performance degradation due to the deepness of the network [23]. ResNet can be used in multiclass plant stress classification, but it requires high computation power due to depth. Inception networks like GoogleNet include multiple convolution layers in one layer due to these local and global features being captured simultaneously. GoogleNet can be used for pant stress images of different resolutions and fewer features for classification [24]. In agriculture, Chandel et al. [25] created a mobile device that employs artificial intelligence to detect crop water stress in real-time using the Raspberry Pi board and a camera equipped with GoogleNet. The device underwent successful tests on wheat and maize crops, achieving an accuracy rate of 92.9% and 97.9%, respectively. Inception types of networks have the disadvantage that their training is complex due to multiple convolutions in one layer. U-Net architecture is used for image segmentation and accurate detection of feature location. U-Net is used for exact stress area detection in images of higher resolution. DenseNet uses fewer parameters and reuses features. Due to this, DenseNet is good for a small number of datasets in plant stress classification. EfficientNet can achieve high accuracy with less computational power, so it can be easy to apply on the field of the farm on portable devices with low cost [26].

2) *Attention-based Models*

Attention-based models focus on the part of the image, which is important for classification. In one of the studies, Alirezazadeh et al. [27] employed the convolutional block attention module (CBAM) in CNN to achieve high classification performance. CBAM was applied after output feature maps of CNN to highlight more features. The study discovered that EfficientNetB0 with CBAM attained a high classification accuracy of 86.89%. In another paper, Dong et al. [28] conducted a study in which the ResNet50Evo-SE model with channel-wise attention mechanism (SE) achieved the highest accuracy of 98.97%. Further, the YoloV8-CBAM model with image data helped to obtain a recognition accuracy of 0.9653 in water-nitrogen stress recognition [28]. Additionally, Swaminathan and Vairavasundaram [29] proposed a two-stage deep convolutional neural network to identify plant stress symptoms.

3) *Recurrent Neural Networks*

Recurrent neural networks (RNN) analyze sequential data in plant stress detection. Continuous data from sensors can be analyzed for symptoms of stress [30]. RNN can process soil, temperature, and humidity datasets for initial stage detection of disease or stress on plants. Long-short term memory (LSTM) cells are advanced versions of RNN, and it has an advantage over classic RNN in analyzing long-term dependencies in the data. LSTM can store information for a long time, and can detect slowly changing signs of stresses on plants. Gated recurrent units (GRU) are simplified versions of LSTM, which require low computational power but less efficiency [31].

3. DEEP LEARNING FOR PLANT STRESS DETECTION USING DIFFERENT IMAGE TYPES

Plant health can be evaluated using various imaging techniques. These methods involve capturing images of the plant and processing them to determine whether the plant is experiencing any stress [32]. Additionally, leaf color and shape can be assessed using imaging techniques and compared with a pre-existing dataset of healthy and stressed plants to make an informed decision [33].

A variety of images that are employed during the detection of plant stress come with strengths and weaknesses. Red, green, and blue (RGB) images are the most commonly used imaging types, which a low-cost ordinary digital camera can take, and even now, mobile also has powerful RGB image cameras inbuilt [34] [35]. Stress in plants can be identified by color and patterns in RGB images. The yellow color on the plant leaf may indicate nutrition deficiency or an unhealthy plant [36] [37]. Near-infrared (NIR) images are used in plant stress detection due to their capability to collect information that is not visible to the naked eye [38] [39]. NIR images are more sensitive to physiological changes in plants than RGB images [40]. RGB images are more affected by environmental conditions, but NIR images are more resistant to environmental conditions. Water content in plants and chlorophyll levels are easily detected by NIR images, helping to detect drought stress and nutrition deficiency in plants [41]. It can detect abnormal physiological changes in plants, which can indicate stress or diseases in plants [42].

Hyperspectral imaging is effectively used for plant stress detection because of its capability to capture a larger range of spectral information [43]. Hyperspectral imaging gives information about large bands of spectra that show small changes in plats physiological, color, or water content, which indicates stress in plants [44]. Hyperspectral imaging can detect highly accurate physiological changes that other imaging techniques can not [45] [46]. As it is a non-destructive method, it can be used to monitor plants continuously [47]. It is fast analyzed using image processing, so onsite uses are possible [48]. Overall, hyperspectral imaging is an effective method for plant stress detection [49]. The thermal camera can capture temperature changes in a leaf of plants, which indicates stress or diseases in plants [50]. It can also be used to monitor how effectively water is used by plants and the photosynthesis performance of plants [51]. A recent study by Ruffing et al. [52] successfully identified the presence of salt, copper, and cesium stress in Arabidopsis thaliana plants through the use of hyperspectral reflectance imaging and multispectral curve resolution (MCR) analysis [52]. This method accurately distinguishes between different types of metal stress in plants [53]. In another study, Ruan et al. [54] employed meta-learning to detect drought and freeze stress in tomatoes, resulting in high detection accuracy with fewer training images required. Compared to other methods, this approach requires fewer image datasets. Shao et al. [55] utilized hyperspectral imaging to analyze the stages of infections caused by Fusarium root rot fungi in chili pepper leaves. Their use of successive projection algorithms (SPA) on hyperspectral images enabled the detection of biotic stress. By utilizing two wavelengths of the spectral model, they achieved an impressive prediction accuracy of 87%. Dutta et al. [56] used satellite-based hyperspectral imaging to detect diseases in Canjanus cajan plants. Their two-step wilt detection method and disease-specific spectral index allowed for earlier disease detection by two to three weeks compared to the multispectral imaging method [56]. Experts have employed thermal imaging to identify water stress in various plant species. A recent study by Watt et al. [57] utilized thermal imaging to examine the effects of water stress on radiata pine by withholding water for nine days. The study aimed to determine the physiological characteristics of radiata pine affected by water stress. Normalized canopy temperature, which measures the difference between the temperature of the canopy and the surrounding air, was used to observe physiological changes. The results revealed that three physiological traits displayed a significant difference one day after treatment, indicating the potential of thermal imaging for early detection of water stress in radiata pine. Another study by Kurunc et al. [58] used thermal imaging to detect water stress on wheat crops; it was used for four irrigation levels from no water stress to severe water stress. Pre-irrigation images were found to reflect water stress conditions more than post-irrigation conditions. Seng et al. [35] used a Dalbergia cochinchinensis sepsis plant for a water stress detection experiment in this study.

A combination of physiological parameters and an infrared thermal imaging system was used to achieve high efficiency [59]. It was found that using a combination of physiological parameters and infrared thermal imaging gives high efficiency and can be used for stress detection. The water needs of plants can be detected, which helps in irrigation management. Orzechowska et al. [60] uses Arabidopsis thaliana plants to detect light and salt stress. The plant was exposed to four different levels of salt concentration. The study found that thermal imaging has a high efficacy on slat stress detection and light stress detection. Park et al. [61] in this study experimented on the ginger plant for abiotic environmental stress detection using chlorophyll fluorescence imaging. The researchers established the physiological stress indicators using the spectral chlorophyll ratio approach. Their findings indicate that partial least squares discriminant analysis (PLS-DA) outperformed other fluorescence imaging methods currently in use.

TABLE II. Deep learning based plant stress studies using various image types

Study	Plant used	Model used	Dataset	Findings of studies
		RGB Images		
RGB Images Ghosal et al. [62]	Soybean	CNN	private	It gives highest classification accuracy of 94.13%.
Anami et al. [63]	Paddy crop	CNN VGG-16	private	The VGG-16 achieved stress classification accuracy by learning of 95.08%.
Esgario et al. [64]	Coffee tree	CNN AlexNet, GoogLeNet, VGG19, ResNet50	private	Trained network ResNet50 obtained maximum success results at 94.05% accuracy for biotic stress classifications and 84.76% accuracy for severity estimations.
Butte et al. [65]	Potato plant	Retina-UNetAg, is a variant of Retina-UNet	public	Archive Dice score coefficient of 0.74 for distinguishing between a stressed and healthy plant
		Thermal Images		
de Melo et al. [66]	Sugarcane	Inception-Resnet-v2 network	private	Accuracy of 83% detection.
Bompilwar et al. [67]	Tomato	CNN	private	Achieve 93% test accuracy
Abdulridha et al. [68]	Avocado Multi-spectral and RGB image	K-nearest neighbor (KNN) and Multilayer perceptron (MLP) neural network	private	Among other methods, MLP gave the highest classification accuracy of 86% in symptomatic
		Hyperspectral images		
Yu et al. [69]	Lettuces	Inception based Deep learning model	private	Classifications accuracy of 98.86%.
Zhu et al. [70]	Rice	De-Striping CNN (DS-CNN) and Nitrogen diagnosis CNN (ND-CNN)	private	Got 99.56% classification accuracy
Feng et al. [71]	Soybean	Dilated convolution neural network (DC2Net)	private	Accuracy of 96.87%, 97.77% and 97.77% for detecting of asymptomatic, healthy and symptomatic plant images.
		Fluorescence Image		
Shomali et al. [72]	Tomato	artificial neural network (ANN)-based algorithm	private	Separation of stressed and non stressed plant with 93.67% accurately.
Li et al. [73]	Arabidopsis thaliana	CNN with DeepLearnMOR (Deep Learning of the Morphology of Organelles)	private	Accuracy of 97% to detect abnormalities.

Arief et al. [74] conducted a study utilizing chlorophyll fluorescence imaging to detect drought and heat stress in strawberry plants. They devised an innovative imaging system that analyzed the maximum quantum efficiency of photochemistry. Their research revealed a robust correlation between the chlorophyll meter and the developed system. The results of the study demonstrate that the chlorophyll fluorescence imaging system can accurately detect spatial and temporal dynamics. TABLE II provides a summary of studies on plant stress detection using deep learning with various imaging techniques.

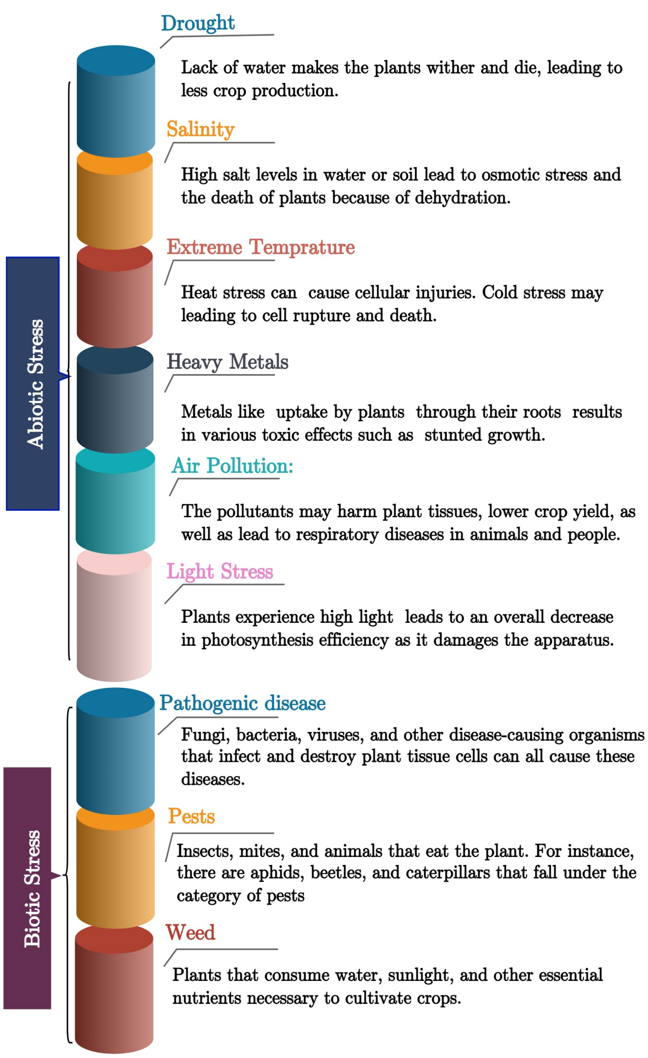

Figure 4. Plant stress types and sub-types

4. DEEP LEARNING STUDIES BASED ON PLANT STRESS TYPES

Abiotic stress is a term used to describe stress caused by non-living factors, such as drought, extreme temperatures, salinity, and nitrogen scarcity. Among these, drought is one of the most common and devastating types of abiotic stress, which can cause plants to wilt, shrink, or die altogether. Similarly, temperature extremes like freezing can cause frost damage to plants, while heat waves can cause scorching [85]. In a study by Azimi et al. [75], they concentrate on detecting abiotic types of stress due to nitrogen deficiency. Nitrogen deficiency affects plant growth, shape, and color these changes are detected by imaging techniques. This study compares deep learning methods with machine learning methods for abiotic stress detection and found that deep learning methods outperform machine learning. Another study by Azimi et al. [76] uses two variants of Chickpea plant JG-62 and Pusa-372. They studied the effect of water stress, which comes under the abiotic stress type, using the deep earning model CNN-long short-term memory (CNN-LSTM) and got 14% more accuracy than other models known at that time. In one other study by An et al. [77], they performed an experiment for maize drought stress detection. They used the CNN model for Abiotic stress detection and found that the training time required for ResNet50 is less than the ResNet152 model. They also compared deep learning with the machine learning method and found that deep learning has 10.05% more accuracy.

The causes of biotic stress are pathogens, pests, and weeds, which compete with plants for resources, damage plant tissues, and spread among plants [86] [87]. Biotic stress can significantly impact plant growth, yield, and quality [88] [89]. In a study by Nazeer et al. [80] biotic stress detection on cotton by Cotton Leaf Curl Gemini Virus (CLCuV) using deep earning model CNN was performed. They used publicly available datasets from Kaggle and private datasets and achieved a maximum accuracy of 99%. Another study by Zhang et al. [81] used hyperspectral and chlorophyll fluorescence imaging for stress detection. They found that high-level fusion-based CNN has more accuracy than single source-based CNN. Subeesh and Chauhan [82] conducted a study on tomato plants to detect biotic stress by pest infestation. They used different CNN models and found that the proposed attention-based CNN mode has high accuracy.

Deep learning studies based on plant stress types and their sub-types summarized information provided in TABLE III. Additionally, Figure 4 provides a graphical representation of these stress types and sub-types.

5. PUBLIC PLANT STRESS DATASETS

With the recent advancements in computer-based tools and sensor technology, the engineering sector and plant research have been able to collaborate and share open datasets for detecting plant stress. This joint effort has resulted in the development of public datasets and computer vision challenges that are solely focused on detecting plant stress. As a result, multiple methods can be compared on shared datasets, developing and ensuring optimal performance. This section highlights some of the most prominent imaging datasets used in studies on detecting plant stress. A comprehensive database of grapevine leaves was compiled by Ryckewaert et al. [90] through the capture of hyperspec-

TABLE III. Summary of deep learning studies based on stress types

Study	Plant used	Image type	Model used	Highlights of studies
		Abiotic stress studies		
Azimi et al. [75]	Sorghum	RGB digital image	CNN ResNet18, NasNet large model, proposed 23 layer CNN model are used	Proposed model has 4.5% less accuracy than NasNet large model
Azimi et al. [76]	Chickpea plant	RGB digital image	CNN-long short-term memory (CNN-LSTM) network	Classification performance achieved 98.52%.
An et al. [77]	Maize	RGB digital image	DCNN, ResNet50, ResNet152	Drought stress detection and classification accuracy levels 98.14% and 95.95%, respectively.
Azimi et al. [78]	Chickpea plant	RGB digital image	Residual Neural Network ResNet-18	ResNet achieve classification performance 86%
Zeng et al. [79]	Rubber tree	Hyperspectral image	multi-scale selective attention (MSA-CNN) model	Highest accuracy obtained for this model 98.44%
		Biotic stress studies		
Nazeer et al. [80]	Cotton	RGB digital image	CNN	Maximum obtained accuracy of 99%
Zhang et al. [81]	Rice	Fluorescence and Hyperspectral image	High-level fusion-based CNN	The training, validation, and testing datasets performed classifications with an accuracy of 100%, 97.7% and 97%.
Subeesh and Chauhan [82]	Tomatoes	RGB digital image	Attention-based CNN model	Obtain accuracy of 97.87%
Gautam and Rani [83]	Mango	RGB digital image	CNN model VGG16, VGG19, and RestNet	Accuracy of 98.12% for proposed model
Malvade et al. [84]	Rice	RGB digital image	CNN models namely VGG-16, InceptionV3, ResNet50, DenseNet121 and MobileNet28 are used	RestNet50 model gives higher efficiency of 92.61%

tral imagery. The leaves were meticulously measured under controlled conditions using a hyperspectral camera with the visible and near-infrared spectrum. The dataset comprises of hyperspectral acquisition from seven grape leaf varieties, including healthy leaves and those exhibiting symptoms of grapevine diseases, which could indicate biotic or abiotic stress on any organ. In Menegassi et al. [91] research, a collection of thermographic images was employed to investigate the impact of subsurface drip irrigation on arborio rice's stress levels under different soil moisture and salt concentrations. The study was structured into three blocks, each containing thirty plots, to gauge the salinity level of the soil solution and calculate the normalized relative canopy temperature (NRCT) index. The findings indicated a heightened vulnerability to saline stress during several critical stages of plant development, such as flowering, grain filling, and harvest [91]. A recent study by Gupta et al. [92] resulted in the creation of a freely accessible image dataset. This dataset showcases images of both water-stressed and controlled wheat plants, specifically capturing chlorophyll fluorescence images of Raj 3765 wheat plants over a period of sixty days [92]. Each set of images includes twenty-four images featuring both control and drought conditions.

Similarly, Sandhu [98] developed an image dataset that showcases control and drought conditions for wheat plants, with images having a resolution of 72 dots per inch (DPI). Moreover, a feature dataset was also constructed and made available to ensure that the dataset remains useful for future studies. According to Butte et al. [65], the dataset comprises aerial agricultural images of a potato field. The images display both healthy and diseased plants and have

TABLE IV. Publicly available datasets for plant stress

Dataset	Types of images	No of images	Unique identifier
Sandhu [93]	RGB images	2880	https://doi.org/10.17632/jnjd835ncg.2
Pabuayon et al. [94]	Hyperspectral images	984	https://doi.org/10.5061/dryad.2jm63xsrm
Bacher [95]	Hyperspectral and NIR images	7524	https://doi.org/10.25739/eztp-dj42
MA [96]	Chlorophyll fluorescence images	98	https://doi.org/10.21227/7eck-8z89
Ryckewaert [97]	Hyperspectral images	204	https://doi.org/10.57745/WW7TY7

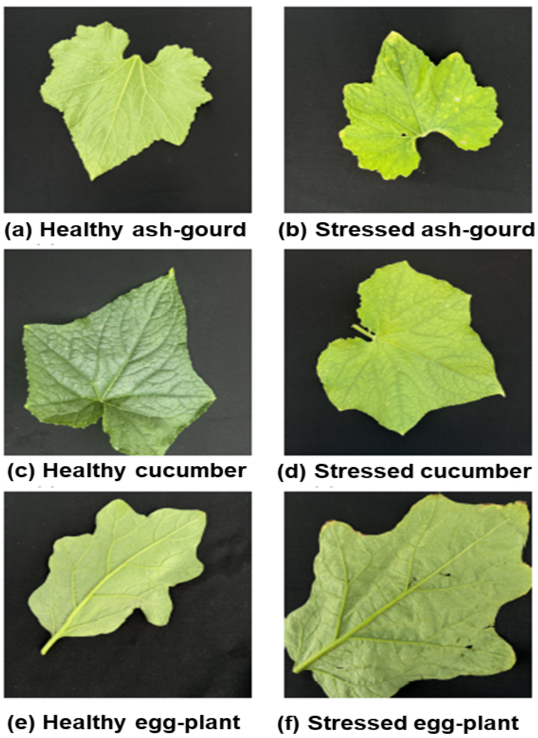

Figure 5. Sample plant stress images in the dataset [99]

manually delineated boundaries. The images were captured by a three-dimensional recording (3DR) Solo drone at a height of three meters, utilizing a Parrot Sequoia multi-spectral camera. The RGB images measure 750 × 750 pixels, while the spectral monochrome red, green, red edge and near-infrared images measure 416 × 416 pixels [65]. Furthermore, each image has a corresponding XML file containing the labeled boundaries. According to the research conducted by Pabuayon et al. [100], the dataset includes images of plants that were captured using a spectral range of 550 and 1700 nm. This range covers the green-red region up to the proximal part of the SWIR region, with each individual image taken at a spectral interval of 4.77nm. The images were taken daily in the afternoon, from 1400H to 1600H, for a total of eighteen times over nineteen days during the salinity stress experiments [100]. However, there was a seven-day gap in the image collection due to the imaging system not working.

Machado et al. [101] conducted a study that featured a dataset designed to assess the impact of abiotic stress on soybean crops in the Brazilian state of Minas Gerais. The dataset utilized advanced image processing techniques for vegetation, leaf, and soil sensors, as well as climate data. The research was carried out over two growth stages, with UAV flights being used to generate maps of chlorophyll, soil moisture, and pH levels. TABLE IV offers a comprehensive list of publicly available plant stress datasets, complete with image types, the number of images, and their unique identifiers. For a glimpse of what's available, we've included sample images from Orka et al. [99] publicly available dataset in Figure 5.

Obtaining research-specific datasets is a crucial task in deep learning-related research. Collecting image datasets of plants has many challenges, including environmental conditions, natural lighting conditions and water supply to plants. These conditions affect the collection of data and their quality. Noise in data due to different environmental conditions and more time required to collect data from areas of farm or forest. The environmental condition also varies symptoms of the same stress on the plants due to changes in temperature, natural light and humidity.

The plant stress dataset has more possibility of suffering from sampling biases due to challenges in data collection. Most data is collected from one geographical location, and it will not be exactly the same for other locations with different environmental conditions. Also, in the field or in laboratory conditions, common stress class image datasets are easily collated, but stress from rare diseases has a very small number of images, which will lead to class imbalance.

Transfer learning has the ability to overcome problems due to less numbered image datasets and sample biases of the datasets. In transfer learning, the pre-trained model is used on similar but new datasets and fine-tuned for new datasets. If the pre-trained model was trained on a large dataset, then for a new small or imbalanced dataset, it can be used with transfer learning to get results in very little time because initialized weights are on the boundary of the final weights.

6. CONCLUSIONS AND FUTURE WORK

According to this literature review, deep learning has proven to be an effective method for identifying and assessing plant stress through the analysis of intricate patterns within extensive datasets. The review highlights noteworthy progress in the examination of plant morphology, physiology, and spectral response under stress conditions. The article also emphasizes the numerous potential applications of deep learning in the realm of plant stress research, including:

1) Images and spectral data show different aspects of stress. Thus, deep learning models can distinguish between these aspects and identify stress types for prompt interventions and mitigations.
2) By utilizing this deep learning approach, it is possible to determine the degree of damage caused by the prevailing stress and its effects on the resulting yield loss.
3) These deep learning-based approaches for analyzing huge volumes of plant images promote quick and reliable stress-tolerant plant breeding.
4) Agricultural managers can integrate deep learning models into their operations as a source of information for optimal resource allocation, thereby providing an opportunity to conduct targeted interventions guided by real-time stress detection.

Despite these remarkable achievements, several challenges remain to be addressed:

1) Training of robust and large models is based on publicly available datasets related to particular crop varieties and stress types. Hence, understanding how deep learning models arrive at a specific decision and building trust in these results is challenging.
2) In low-resource environments, training and deployment of deep learning models require substantial computation and, thus, act as barriers to adoption.

Using deep learning for plant stress detection has limitations due to the unavailability of high-quality datasets and domain-specific data. Acquiring high-quality images of plants under different stress conditions is difficult due to changes in light conditions, environment and geographical areas. Data annotation requires experts in that area, and it is a time-consuming process. Plan stress symptoms visualized may vary in different environmental conditions. The deep learning model's decision-making prediction is difficult due to its black box process. Environmental conditions like light, temperature, rain and wind vary with time, which makes it difficult for deep-learning models to accurately detect plant stress. The computational cost of deep learning implementation on farms is high, which can not be afforded by small farmers or researchers. Over-fitting and unitability of an effective transferring model is also one challenge.

Future advancement in plant stress detection includes automation in annotation by using semi-supervised or weak supervised models can be used for to get annotate data. To deal with the black box problem in deep learning, advancement in explainable AI can give a solution. Research in techniques that can highlight part of the image that indicates stress, like Grad-CAM, makes model results more predictable. By not depending on one type of data, processing multiple types of data, like multimodal deep learning, can increase accuracy. Hybrid modeling combines deep learning with other techniques and develops a lightweight model that can be implemented in small farms with portable devices. Detecting changes in signs of stress on the plants and their progress can detect stress early using time series data using improved RNN or LSTM networks.

In order to tackle the challenges that modern agriculture faces and promote sustainability and reliability, it is crucial for various stakeholders to collaborate. These stakeholders may include botanists, engineers, farmers, and researchers in machine vision. The present paper offers an extensive overview of deep learning research that pertains to detecting plant stress. This knowledge can be applied to disease detection and prevention in agriculture, ultimately leading to early intervention and reduced losses.

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