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Assessing Crop Health via a Thorough Examination of Stress Detection and Classification Models

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Abstract—

In order to maintain sustainable agricultural practices and guarantee food security, crop health evaluation is essential. In order to keep an eye on and control the state of crops, stress detection and classification models have been getting a lot of attention lately. Our goal in this review article is to take a close look at the current crop stress detection and classification models, highlighting their best features and weaknesses as we go. Our research focuses on four primary areas: models for detecting stress, models for classifying stress, models for integrating the two, and methods for quantifying the degree of crop stress. We have outlined the feature extraction methods, algorithms, and classification strategies employed in each model type and given our critical assessment of each. Additionally, we have examined the models' comparative performance measures and benchmarks and gone over their possible real-world applications in the agricultural sector. Although stress detection and classification algorithms for crop health assessment have come a long way, our research shows that there are still many unanswered questions and limits. Problems with data gathering and labeling, robust and scalable algorithms, and interpretable and explainable models are all part of this category. In addition, we point out potential avenues for further study, including the incorporation of multi-modal data sources, the creation of standardized assessment frameworks, and the use of sophisticated machine learning techniques. Our analysis concludes with a thorough synopsis of current research on stress detection and classification models for agricultural health evaluation. We show how these models might help the agricultural sector and point out important areas for further study and improvement. Researchers, practitioners, and policymakers may all benefit from our results, which add to the ongoing conversation on AI and ML's place in the agricultural sector. Medical Conditions—Disease, strain, stress, categorization, DL, feature, detection, dataset

I. INTRODUCTION

Particularly in the field of crop disease detection and categorization, agricultural practices have seen a dramatic shift towards using state-of-the-art technology in the last few years. The advent of deep learning has been a guiding light of innovation in agriculture, as conventional approaches falter in the face of mounting threats from ever-changing diseases and environmental variables. The complex relationship between deep learning methods and the control of agricultural diseases is the subject of this critical assessment. Our goal is to provide a thorough study that highlights the progress accomplished and critically examines the benefits and drawbacks of this technological revolution by exploring the techniques' strengths, weaknesses, and possible ramifications. In order to determine how to best control diseases, pests, and environmental pressures that might impact crop development and output, crop health assessment is a crucial part of agriculture. Crop protection, increased production, and food security may all be achieved if farmers are able to recognize stress factors like drought, nutrient inadequacy, and insect infestation early on [1]. To help farmers out in a timely manner, we need reliable and accurate ways to automate crop health evaluation. An exciting new direction in automated crop health evaluation is the use of stress detection and classification algorithms. These models detect and categorize crop stressors by analyzing a variety of data types using machine learning algorithms and image processing techniques[2]. These data kinds include spectral reflectance, thermal imaging, and hyperspectral imaging. Improved precision, velocity, and efficiency in crop monitoring are a few ways in which stress detection and classification algorithms assist farmers in making better judgments on how to manage their crops. This article's key contribution is 1) a thorough examination of the existing state of crop health assessment stress detection and classification models 2) A detailed examination of many models, including information on their datasets and metrics 3)Models for Assessing the Severity of Crop Stress

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4)Gaps in the current models' research have been found. There are six sections to the paper. In the first section, you should outline the review's goals and parameters. Bring attention to the topic's importance and how it relates to the field. Fill in the blanks and provide some context. The second section details the methodology used to compile the literature for this study. Included are the databases, search terms, filters, and selection criteria used for the literature study. In sections three and four, we compare and contrast several models for crop disease detection and classification, and we discuss the advantages and disadvantages of each. The concepts and problems of crop disease severity quantification are covered in the fifth segment. Finally, the section summarizes and examines the discovered research gaps and potential topics for further study. In this analysis, we will examine the problems and potential avenues for further study by comparing and contrasting various models' performance measures and standards. This review article aims to help academics, practitioners, and stakeholders in the agricultural sector improve crop health assessment by offering insights and suggestions. The objective is to make it more effective and efficient.

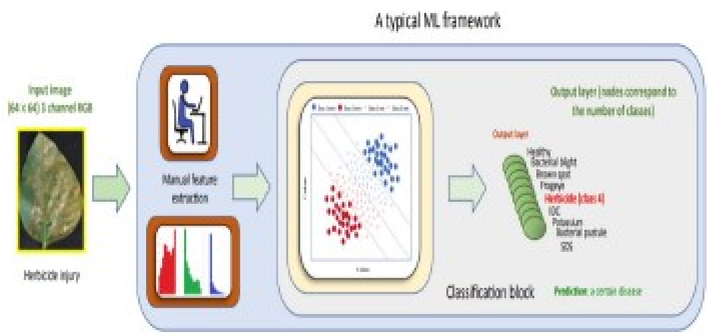

Fig. 1. A typical ML Framework.

II. LITERARUTE REVIEW

Methods for searching for relevant research and criteria for choosing studies to include in the literature review: We systematically reviewed studies that used stress detection and classification models to evaluate the health of crops. Electronic databases, conference proceedings, and scholarly publications were all part of our search technique. We used Google Scholar, Scopus, IEEE Xplore, and the Web of Science to look for relevant articles. We used a mix of terms associated with strain identification, categorization, crops, farming, and ML algorithms. Articles published in English between 2010 and 2023 were the only ones we considered. B. Key terms, databases, and filters described: Specifically, we looked for everything related to stress, health, detection, classification, crop, agriculture, machine learning, and image processing. To get appropriate search results, we combined these phrases using Boolean operators (AND, OR). Language and publication date parameters helped us further refine our search. We included studies that fulfilled the following criteria: (1) they were published in English-language articles; (2) they focused on stress detection and classification models for crop health assessment; (3) they used machine learning algorithms or image processing techniques; (4) they were published between 2010 and 2023. Duplicate, irrelevant, or inaccessible studies were not included. D. The method of data extraction and synthesis: Using a pre-established data extraction form, we retrieved information from the chosen research. The study's methodology, algorithms, performance measures, data sources, sample size, population, and design were all meticulously documented. We summarized the main points, strengths, and weaknesses of each research to create a data synthesis. In addition, we looked for patterns and gaps in the research by comparing and contrasting the outcomes of different studies.

STRESS DETECTION MODELS

Methods and algorithms utilized for feature extraction and their descriptions: Texture analysis, color analysis, shape analysis, and deep learning methods like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are among the feature extraction algorithms and approaches that have been used for stress detection[3] in crops. Extraction of texture information from crop pictures has been accomplished by means of texture analysis techniques like local binary pattern (LBP) and gray-level co-occurrence matrix (GLCM). Color characteristics have been extracted using color analysis techniques including color moments and color histograms. Features of shapes have been extracted using form analysis techniques including shape context and Fourier descriptors. In order to automatically learn and extract features from crop photos for disease diagnosis, many Deep learning approaches, such CNNs and RNNs, have been described in [4]. Barbados [5] and Lee et al. [6] discussed the idea of focusing on individual lesions and patches rather than the whole leaf since every disease location is different. One option to enhance the data is to cut the leaf picture into numerous smaller photographs, and this method also offered the advantage of identifying the presence of several ailments on a single leaf. Liu et al. [7] proposed a new convolutional neural network (CNN) structure for apple leaf disease recognition. This network was built by cascading two networks: one that was an Inception network and another that was an AlexNet precursor. Substituting the Inception network for the fully connected layers of the traditional AlexNet model significantly reduced the number of trainable parameters and, by extension, the storage requirements. Using Noverov's accelerated gradient (NAG) optimization method instead of stochastic gradient descent (SDG) to update the weights will speed up convergence. Results from SVM, BP, AlexNet, GoogLeNet, ResNet20, and VGG16 were used to measure this network's performance.

TABLE I
DATASETS USED FOR SOME OF THE CROP DISEASE DETECTION MODELS

Crop	*Dataset*	*Metric*
Rice Corn[26]	Self-Acquired	Specificity,Accuracy, sen-sitivity
Tomato[27]	AI Challenger	Confusion Ma-trix,Accuracy
Apple[28]	PlantVillage,Self-Acquired	MAP,Confusion Matrix
Tomato[29]	PlantVillage	Parametr size, Average ac-curacy
Grape[30]	AI Challenger+ Self-Acquired	Average accuracy, Model Parameter

STRESS CLASSIFICATION MODELS

A. A rundown of the models and methods used for classification: The evaluation of crop health has made use of a number of models and algorithms for stress categorization. A typical method involves training models using convolutional neural networks (CNNs) on massive datasets of tagged pictures [8]. Decision Trees (DT), Random Forest (RF), and Multi-Layer Perceptron (MLP) are a few examples. To recognize stress factors including nutrient insufficiency, drought, and insect infestation, these models may be trained utilizing a variety of data sources, including spectral, image, and sensor data [9]. By incorporating a multi-scale feature extraction module into the ResNet18, Wang et al. [10] altered the method of connecting the residual layers, proposed an improved multi-scale residual (Multi-scale ResNet) model that drastically cut down on model parameters, storage space, and computing overhead; and finally, decomposed the large convolution kernel and performed group convolution operations. The PlantVillage dataset obtained an accuracy percentage of 95.95%, while the self-collected dataset of 7 genuine environmental illnesses earned an accuracy rate of 93.15%. The model encountered minimal issues with picture shadows, occlusions, and fluctuations in light intensity. A deconvolution-guided VGG network (DGVGGNet) model was developed by Ren et al. [11] and others. It is capable of detecting plant leaf diseases and segmenting disease spots. For the 10 different tomato leaf diseases included in the PlantVillage dataset, our model achieved a recognition accuracy of 99.19%. The average intersection ratio for illness spot segmentation was 75.36 percent, while the pixel accuracy was 94.666 percent. It was also quite resilient in conditions of obstruction and poor light.

TABLE II
SUMMARY OF SOME CROP DISEASE DETECTION & CLASSIFICATION MODELS WITH IDENTIFIED ISSUES

Refference No	*Architecture/ Technique*	*Model/Approach*	*Performance*	*Challenges/Issues*
[10]	Modified ResNet18 with multi-scale feature extraction module	Multi-scale ResNet	95.95% accuracy on PlantVillage dataset; 93.05% on self-collected dataset	Model is easily interfered with image shadows, occlusions, light intensity variations
[11]	VGG network with deconvolution guidance	Deconvolution-Guided VGGNet	99.19% recognition accuracy for 10 types of tomato leaf diseases	False disease portioned segmentation may lead to incorrect results
[12]	Pre-trained GoogleNet	Transfer Learning	61% to 100% for different crops with different conditions	The number of samples associated to each disease varied greatly due to the characteristics of the symptoms and segmentation
[13]	K-means clustering, GCH, CCV, LBP, CLBP, improved SVM	K-means clustering and SVM	93% classification accuracy for three apple diseases	Only 3 kinds of Apple diseases were detected
[14]	Feature extraction using stepwise discriminant and Bayesian discriminant, PCA, Fisher discriminant	Model based on stepwise discriminant and Bayesian discriminant, PCA, Fisher discriminant	94.71% and 98.32% accuracy using PCA and Fisher discriminant	Any deviation from color, texture, and shape information of leaf may lead to different result
[15]	Unsupervised identification of visual symptoms	CNN framework with top-K high resolution feature maps	Identified and classified 8 soybean stress types	Presence of shadow and dark spots in the image; lack of focus, lack of resolution
[17]	A digital image processing based segmentation approach	Shape features of infected region were fed into K-Nearest Neighbor(KNN) classifier for disease identification	Identified and classified only 2 stress types	The recognition rates reported for brown spot (70%) and frog eye (80%),,Small dataset size,only 2 stress recognised

Reviews have shown that Support Vector Machine is a popular choice for identifying agricultural diseases [12]. Five convolutional layers and three fully connected layers make up the eight-layer deep convolutional neural network (CNN) that the authors presented as AlexNet. Capturing intricate hierarchical elements from photos was made possible by this deep architecture [13]. In their study, Dubey and Jalal [14] employed the K-means clustering method to divide up the areas affected by lesions. They then used a combination of global color histogram (GCH), color coherence vector (CCV), local binary pattern (LBP), and completed local binary pattern (CLBP) to determine the spot colors and textures. Using an improved support vector machine (SVM), they were able to detect and identify three different apple diseases with a classification accuracy of 93%. In their study on four tomato leaf diseases—early blight, late blight, leaf mildew, and leaf spot—the authors used stepwise discriminant and Bayesian discriminant principal component analysis (PCA) to extract 18 characteristic parameters, including color, texture, and shape information, from images of tomato leaf spots, respectively. To build the discriminant model and extract the distinctive parameters, we employed principal component analysis and discriminant approaches.

INTEGRATION OF STRESS DETECTION AND CLASSIFICATION MODELS

An explanation of the fusion techniques and ensemble methods used: Integrated models for crop health evaluation often include ensemble approaches and fusion techniques. To make an ensemble technique more accurate and resilient, it combines the output of several models. To provide a fuller view of the state of the crop, fusion methods integrate information from many sources. Fusion methods may be categorized into three main types: feature-level, decision-level, and classifier-level. When it comes to evaluating the health of crops, many research have used stress detection and classification models with great success. An example of this is the 92% accuracy rate achieved by a deep learning-based model for the detection and classification of wheat illnesses using aerial photos, as shown by Khan et al. (2020) [22]. In a similar vein, Hu et al. (2021) [23] achieved a 95.8% success rate in disease classification for tomato plants using machine learning methods. The symptoms of maize illnesses were correctly diagnosed with a 94.8 percent accuracy rate using a deep learning model constructed by Liu et al. (2021). Previous research has shown that support vector machines (SVMs) can accurately identify various crop kinds when used for agricultural classification tasks [24]. In order to identify signs of water stress in grapevines using multispectral imaging, the authors of[25] created a model based on machine learning.

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TABLE III
SUMMARY OF SOME CROP DISEASE DETECTION & CLASSIFICATION MODELS

Refference No	*Meethodology*	*Techniques*	*Findings*	*Strengths*	*Limitations*	*Recommendations*
[31]	UAV Imagery	Random Forest,Multilayer Perceptron	Can predict disease severity with acceptable accuracy.	High accuracy	requires the user to manually cut images from each plot to be fed to the algorithms	a preprocessing stage where the plots are extracted from the orthophotomosaic automatically
[32]	Remote Sensing Data	Vegetation Indices VI's	VI's can be used to predict disease severity	if the fields are known to be infested with a specific disease,then a map of severity levels can be created	Various stress factors, can also cause a decrease in chlorophyll content	This method can be used for other crops
[33]	BLSNet with semantic segmentation	BLSNet	High accuracy for rapid, non-destructive assessment	Accuracy estimation for level 3-5 is higher with avg accuracy of 94%	challenges associated with accuracy of low level 1-2 disease degree estimation	an advanced segmentation model can be developed for more types of plants, more types of diseases and more levels of disease severity
[34]	Smartphone App	Image Processing	Feasibility and accessibility for disease quantification	Accessibility	Requires validation, integration with existing systems needed	Validation, integration with existing systems

B. Weighing the pros and cons of integration strategies: Improved accuracy and the capacity to detect several stressors concurrently are two of the many benefits offered by integrated models compared to standalone stress detection or classification models. On the other hand, compared to standalone models, integrated ones might be more resource-intensive and complicated. It is important to carefully analyze the unique use case while picking the proper ensemble or fusion approach. section six: models for quantifying crop disease severity Using criteria such as remote sensing data, normalized difference vegetation index (NDVI), green crop index (GCI), and others, several writers have attempted to measure the severity of the stressed or sick crop. The management of diseases and the decision-making processes for farmers are greatly impacted by the timely and correct assessment of disease severity.

VII. FUTURE RESEARCH DIRECTIONS AND CHALLENGES

The development of more efficient and reliable feature extraction algorithms and methodologies should be the focus of future research in stress detection models for crop health assessment. The development of stress categorization models for crop health assessment might center on tackling increasingly complex situations, including dealing with numerous stressors or interactions between them. Deep convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two examples of deep learning approaches that researchers may look into using to make stress categorization models more accurate and easier to understand. To further increase models' generalizability and create more training data, data augmentation approaches may be used. More sophisticated ensemble and fusion methods, new data sources including soil and meteorological data, and the combination of expert knowledge with machine learning models are all potential components of stress detection and classification algorithms. Problems in this area include gathering big, high-quality information, creating models that can withstand changes in the environment, and making these models available to farmers and other interested parties via intuitive interfaces. An essential part of good disease control systems is the ability to quantify the severity of crop diseases. Spectral indices derived from remote sensing data, machine learning-based picture analysis, smartphone apps, and deep learning-based analysis of UAV pictures are just a few of the methods highlighted in the evaluated research articles. The area of agricultural disease severity quantification has progressed thanks to the combined efforts of several methods, each of which has its own advantages and disadvantages. Integrating into practical decision support systems for farmers and agronomists, tackling issues with data availability, model generalization, and environmental variability should be the focus of future study.

TABLE IV
IDENTIFIED RESEARCH GAPS

Title	*Identified Research Gap*
Inversion of chlorophyll content under the stress of leaf mite for jujube based on model PSO-ELM method[35]	Chlorophyll content inversion due to leaf mite is studied but correlation between Chlorophyll content and stress is not studied
Crop Disease Recognition Based on Modified Light-Weight CNN With Attention Mechanism[36]	Dataset (consisting of Images of crop plants leaf and their Chlorophyll content values as metadata) is not available from local area.
A novel method for the estimation of soybean chlorophyll content using a smartphone and image analysis[37]	Only Chlorophyll estimation using image processing is discussed but impact of crop stress on it's chlorophyll contents or vice-versa is not discussed.
CROPCARE: An Intelligent Real-Time Sustainable IoT System for Crop Disease Detection Using Mobile Vision[38]	Has used Plant Village dataset and has stressed on disease detection using CNN and no other parameter is taken into consideration.

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