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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 past few years. Deep

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learning has become a shining example of innovation in agriculture since conventional approaches are overwhelmed by the ever-changing threats from environmental conditions and new infections. This analysis aims to comprehend the complexities of how deep learning approaches interact with agricultural disease control. Our goal is to offer 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. When it comes to farming, crop health assessment is crucial. It entails finding and controlling pests, diseases, and environmental stresses that can impact crop growth and yield. In order to safeguard their crops, increase productivity, and guarantee food security, farmers can benefit from early detection of stress factors like nutrient deficiency, pest infestation, and drought [1]. So, farmers require reliable and fast ways of assessing crop health that can furnish them with pertinent data.

Automated crop health evaluation using stress detection and classification algorithms is a new and promising method.

In order to detect and categorize crop stresses, these models employ image processing and machine learning algorithms to examine a variety of data types, including thermal imaging, spectral reflectance, and hyperspectral imaging [2]. Improved precision, velocity, and efficiency in crop monitoring are a few ways in which stress detection and classification models assist farmers in making better decisions about how to manage their crops.

An exhaustive review of the state of the art in crop health assessment stress detection and classification models is the primary contribution of this study. 2) A detailed examination of many models, including information on their datasets and metrics 3) Models for Assessing the Severity of Crop Stress 4) We have found research gaps in the current models. The paper is structured into six sections. In the first section, you should outline the review's goals and parameters. The topic's relevance to the field and its importance should be emphasized. Give some context and background. The second section details the methodology used to compile the literature for this study. It details the methodology and criteria used to choose the databases, keywords, and filters used in the literature review. Third and fourth portions covers crops disease detection and classification models in detail along with their comparative analysis, their strengths and limitations. Fifth portion discusses crop disease severity quantification models along with obstacles. Last part highlights and discusses research gaps that has been found along with the study topics in which future research work may be carried out. Specifically, we will focus on the strengths and limitations of different models, compare their performance metrics and benchmarks, and discuss the problems and future research paths in this subject. This review article aims to help academics, practitioners, and stakeholders in the agricultural sector improve crop health assessment by offering insights and recommendations. The goal is to make it more effective and efficient.

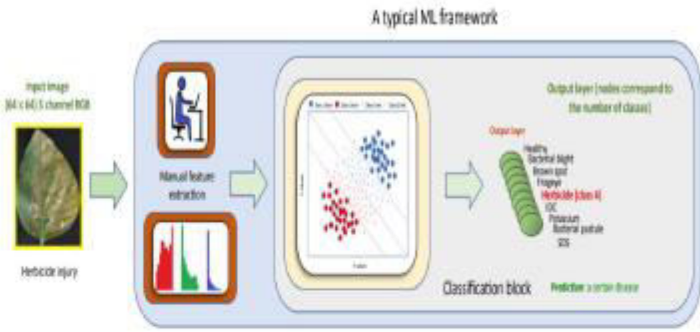

Fig. 1. A typical ML Framework.

II. LITERARUTE REVIEW

Section A: Methods and Criteria for Finding Relevant Literature We systematically reviewed the literature on stress detection and classification models as they pertain to evaluating the health of crops. Electronic databases, conference proceedings, and scholarly publications were all part of our search technique. Google Scholar, Scopus, IEEE Xplore, and the Web of Science were among the databases that were searched. We employed a mix of terms associated with strain identification, categorization, crops, farming, and ML algorithms. Our search was restricted to papers published in English between 2010 and 2023. Databases, keywords, and filters utilized are described in B. For this search, we used the following terms: (stress OR health) AND (detection OR classification) AND (crop OR agricultural) AND (machine learning OR image processing). To get appropriate search results, we combined these phrases using Boolean operators (AND, OR). To further refine our search, we used filters for publication date and language. 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. Research that was either duplicated, irrelevant, or inaccessible was not included. D. Method for extracting and synthesizing data: We used a standardized data extraction form to obtain data from the chosen studies. 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 study to create a data synthesis. Additionally, we looked for patterns and gaps in the research by comparing and contrasting the outcomes of different studies.

III. STRESS DETECTION MODELS

A. Description of feature extraction techniques and algorithmsused:

Texture analysis, color analysis, shape analysis, and deep learning techniques like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are among the feature extraction

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algorithms and approaches that have been utilized for stress detection [3] in crops. In order to extract texture information from crop photos, texture analysis techniques like GLCM and LBP have been extensively utilized. Color characteristics have been extracted using color analysis methods including color moments and color histograms. In order to extract form characteristics, shape analysis approaches including shape context and Fourier descriptors have been utilized. The use of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to automatically train and extract characteristics from crop pictures for disease diagnosis has been covered in [4]. Barbados [5] and Lee et al. [6] discussed the idea of focusing on individual lesions and patches rather than the entire leaf because every disease location is different. This method's advantages include the ability to detect the presence of many diseases on a single leaf and the fact that it can increase data quality by dividing the original leaf picture into multiple smaller photographs. To identify apple leaf disease, Liu et al. [7] proposed a new convolutional neural network (CNN) structure. In order to construct the network, a cascade of an Inception network and an AlexNet precursor network was used. By substituting the Inception network for the fully connected layers of the traditional AlexNet model, we were able to significantly reduce 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. Using SVM, BP, AlexNet, GoogLeNet, ResNet20, and VGG16 as benchmarks, this network's performance was assessed. Examining the benefits and drawbacks of each model:
There are advantages and disadvantages to every feature extraction method and algorithm. For example, texture analysis algorithms tend to be sensitive to noise and illumination fluctuations, but they are efficient and may catch small changes in crop photos. Despite their robustness and ability to record color variations, color analysis systems could miss subtle changes. When it comes to color and texture, form analysis tools could miss subtle changes, but when it comes to shape, they're on the money. Though they may be computationally costly and data intensive, deep learning methods like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) may automatically learn complicated characteristics.

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

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

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IV. STRESS CLASSIFICATION MODELS

A. A rundown of the models and methods used for classification: In order to categorize stresses in crop health assessments, many algorithms and models have been employed. The use of convolutional neural networks (CNNs) to train models on massive labelled picture datasets is a popular method [8]. Many examples are Multi-Layer Perceptron (MLP), Decision Trees (DT), Random Forest (RF), and Support Vector Machines (SVM). Spectral, image, and sensor data may all be used to train these models, which can then be used to recognize stress factors including nutrient insufficiency, drought, and insect infestation [9]. Based on ResNet18, Wang et al. [10] proposed an improved multi-scale residual (Multi-scale ResNet) model that drastically reduced model parameters, storage space, and computing overhead by adding a multi-scale feature extraction module. This changed the residual layer connection method, decomposed the large convolution kernel, and performed group convolution operations. In the self-collected dataset of seven actual environmental illnesses, the accuracy percentage was 93.15%, whereas in the PlantVillage dataset, it was 94.95%. The model encountered minimal issues with picture shadows, occlusions, and fluctuations in light intensity. A model called Deconvolution-Guided VGGNet (DGVGGNet) was built by Ren et al. [11] and others. It can detect plant leaf diseases and segment disease spots. For the 10 different tomato leaf diseases included in the Plant Village dataset, our model achieved a recognition accuracy of 99.19%. Segmentation of illness spots had an average intersection ratio of 75.36 percent and a pixel accuracy of 94.666 percent. It was also quite resilient in conditions of obstruction and poor light. One of the most used algorithms for agricultural disease classification is Support Vector Machine, according to a review publication [12]. A deep convolutional neural network (CNN) with eight layers—three fully connected and five convolutional—was presented by the authors as the AlexNet architecture. Capturing intricate hierarchical elements from photos was made possible by this deep architecture [13]. Using the K-means clustering method, Dubey and Jalal [14] were able to segment the regions of lesions. They then employed a combination of global color histogram (GCH), color coherence vector (CCV), local binary pattern (LBP), and completed local binary pattern (CLBP) to extract color and texture features of apple spots. By utilizing this information, three different apple diseases could be detected and identified using improved support vector machine (SVM), and the classification accuracy reached 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. The discriminant model was built and the distinctive parameters were extracted using principal component analysis and other discriminant approaches. Both approaches achieved respectable levels of accuracy—94.71% and 98.32%, respectively. In order to detect and categorize eight different types of soybean stress, the authors of this study[16] used a machine learning system. In addition, we offer an explanatory mechanism that makes use of top-K high resolution feature maps to create predictions based on visual symptoms. The visual symptoms may be identified (as a form of foliar stress) and classified (as low, medium, or high stress) without the need for thorough expert annotation thanks to the quantitative measure of stress intensity supplied by the unsupervised detection of symptoms. One issue that was discovered while reviewing the paper's literature is the presence of shadows and dark areas in the photograph. 2) Shooting a picture while blurry or imbalanced 3)No conclusion Using a dataset of 100 photos recorded with a Samsung mobile model GT-S3770 digital camera, Shrivastava and Hooda (2014)[17] proposed a digital image processing strategy that focuses on the identification and classification of two plant diseases, brown spot and frog eye. In order to isolate the diseased areas from the pictures, the authors used morphological procedures and thresholding to remove the leaf portion. A K-Nearest Neighbor (KNN) classifier was trained using the form characteristics of the affected areas to differentiate between brown spot and frog eye disorders. Nevertheless, the following restrictions apply to this model. Brown spot and frog eye are the only disorders that this technique takes into account. In the realm of plant disease diagnosis, where precision is paramount for efficient disease management, the stated identification rates of 70% for brown spot and 80% for frog eye might not be good enough for practical uses.

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 identifiction	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

B. A comparison of the models' advantages and disadvantages: There are advantages and disadvantages to every model and classification method. When it comes to evaluating the health of crops, support vector machines (SVMs) have shown to be successful because to their famed capacity to deal with high-dimensional data. To attain good performance, multi-layer perceptron (MLP) models [18] may necessitate additional computing resources and training data, but they are versatile and can manage non-linear correlations among variables. Due to their simplicity of implementation and ability to handle noisy data, KNN models have also found usage in crop

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stress classification, especially for spectral data [19]. Another popular method for agricultural stress classification is random forests or decision trees, which offer a clear and understandable approach to stress factor categorization [20]. In order to categorize maize leaves with varying degrees of nitrogen stress, [21] used an SVM model and attained a 91.6% accuracy rate.

V. INTEGRATION OF STRESS DETECTION ANDCLASSIFICATION MODELS

A. Description of ensemble methods and fusion techniquesused:

When it comes to evaluating the health of crops, integrated models often include ensemble approaches and fusion techniques. To make an ensemble technique more accurate and resilient, it combines the output of several models. A more comprehensive view of crop health may be obtained by combining data from several sources using fusion methods. The three most common types of fusion methods are feature-level, decision-level, and classifier-level fusion. The use of stress detection and classification algorithms for the evaluation of crop health has been effectively carried out in several research. 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 demonstrated 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. In a separate research, Liu et al. (2021) created a deep learning model that could detect maize illness signs with a 94.8 percent accuracy rate. Previous research has shown that support vector machines (SVMs) can accurately identify various crop kinds when used for agricultural classification tasks [24]. In[25], the authors created a model that uses machine learning and multispectral imagery to detect water stress in grapevines early on. 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. The unique use case must also be carefully considered while deciding on the best ensemble or fusion approach. Section VI: Models for Quantifying the Severity of Crop Diseases Several writers have made an effort to measure the extent to which a stressed or sick crop is affected by several criteria, such as GCI, NDVI, and remote sensing data. In order to control diseases and make informed decisions, farmers rely on precise and timely measurements of disease severity. A number of

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techniques for measuring the severity of agricultural diseases have been the subject of several research articles, which have detailed these approaches and discussed their advantages, disadvantages, strengths, and possible future developments.

VII. FUTURE RESEARCH DIRECTIONS AND CHALLENGES

Improving the accuracy and efficiency of feature extraction algorithms and methodologies should be the primary goal of future work on stress detection models for agricultural health assessment. Building models that can manage increasingly complicated situations, including several stressors or interactions between them, may be the subject of stress categorization models for crop health evaluation. 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 can be employed. Improving models for stress detection and classification might involve creating more complex ensemble and fusion methods, adding new data sources including soil and weather data, and combining machine learning models with human expertise. Problems in this area include gathering big, high-quality datasets, creating models that can withstand changes in the environment, and making these models available to farmers and other interested parties through 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. Each approach has its

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own set of advantages and disadvantages, but taken together they help push crop disease severity estimation forward. Data accessibility, model generalizability, environmental variability, and incorporation into useful decision support systems for agronomists and farmers should be the primary foci 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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