Nature Environment and Pollution Technology
An International Quarterly Scientific Journal
p-ISSN: 0972-6268
(Print copies up to 2016)
e-ISSN: 2395-3454
Vol. 22 | No. 3 | pp. 1387-1399 | 2023
Review Research Paper
https://doi.org/10.46488/NEPT.2023.v22i03.025
Open Access Journal

Computer Vision Based Machine Learning and Deep Learning Approaches for Identification of Nutrient Deficiency in Crops: A Survey

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Nat. Env. & Poll. Tech.
Website: www.neptjournal.com

Received: 04-01-2023
Revised: 18-01-2023
Accepted: 08-03-2023

Key Words:
Crop stress
Nutrient deficiency
Sensors
Precision agriculture
Machine vision,
Deep learning

ABSTRACT

Agriculture is a significant industry that plays a major role in a country's sustainable environment and economic development. The global population demands increased food production with minimal losses. Nutrient deficiency is one of the major and crucial factors influencing crop production significantly. Common techniques for determining crop nutrition status are the diagnosis of plant morphology, Enzymology, chemical effects, fertilization, etc. However, the above techniques are invasive and time-consuming or infeasible while considering varied production practices in different locations, environments and climatic conditions. Computer Vision is an area of Computer Science that deals with creating Artificial Intelligence based vision systems that can use image data, process, and analyze as humans perform. Early Detection of Crop Nutrient deficiencies favors the farmers to monitor the affected crops and plan for the manure or fertilizer application, which supports to regain of the crop's efficiency for attaining its maximum yield. Modern computer vision systems rely on Machine Learning (ML), Remote sensing, Satellite imagery, unmanned aerial vehicles (UAVs), Internet of things (IoT) based sensor devices, and Deep Learning (DL) models that use algorithms to extract required features from data. The objective of this work is to provide an overview of recent research and identify the scope of computer vision-based technologies used for identifying crop nutrient content and deficiency, find research challenges in predicting nutrient imbalance in comparison with plant diseases that show certain similar characteristics, thereby to improve crop health and production.

INTRODUCTION

The agriculture sector has witnessed numerous changes for improving crop production. Several standards have been set to promote agricultural businesses, helping farmers improve their operational efficiency, reduce cost, provide quality food, and ensure their food hygiene and safety. Soil productivity closely depends on the available nutrients that result in a good yield of crops. The availability of nutrients in the soil is monitored using a specific system to determine the fertility of that specific area. An analysis is done to decide on fertilizer recommendations to strengthen it. Due to the adoption of synthetic or chemical-based fertilizers by most farmers in the twentieth century, there had been a 50% increase in the overall yield from the field. Still, it has led to the major issue of Soil infertility or unavailability of major natural elements (Kilic et al. 2020). The climatic effects and environmental conditions should not degrade the yield. Farmers require data-driven or service-based techniques to enhance crop yield with the available field and other resources to meet all these needs. In this regard, precision agriculture has evolved with several tools and techniques that are being formulated, including automated harvesters, robot-weeders, Smartphone-based monitoring, UAVs, computer vision, pervasive computing, wireless ad-hoc sensor networks, Radio Frequency Identifier (RFID), cloud computing based data storage, ML models, IoT based devices combined with DL, satellite monitoring, remote sensing, context-aware computing, etc., which are becoming increasingly popular and beneficial to the farmers for monitoring the crop stress which limits the output. With regard to precision agriculture, many areas of scope or use case models shall be explored. They are as follows:

- Crop health monitoring for deficiencies and diseases
- Soil Nutrient management
- Monitoring of climate conditions
- Farm land monitoring and mapping for predictive analytics

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- Greenhouse automation
- Automated irrigation scheduling and optimization
- Production and yield management
- Livestock monitoring
- Farm Inventory management systems
- Crop security

Motivation

In the current scenario, there are four major challenges in agriculture. (I) The availability of groundwater, which cannot be produced artificially, is scarce. (II) Limited agricultural lands as the world population grows. (III) The soil became infertile to produce enough food. (IV) The agriculture production or the output is inefficient. Farmers apply manures and fertilizers to their crops to boost their production. However, over usage or under usage of these applications may harm the crop, soil, humans, and animals. It is important to consider the nutritional values and food quality by understanding the crop's nature during growth, the reasons for low quality and yield, and identifying the crop inefficiencies. Common techniques for determining crop nutrition status are the diagnosis of plant morphology, Enzymology, chemical effects, fertilization, etc. Computer Vision Technologies play a major role in identifying and monitoring crop deficiencies that prevent the prescribed output. It is concerned with building artificial systems or models that make sense out of images through training and processing at a pixel level in the image for extracting application-specific information. These intelligent systems retrieve the visual data and interpret the results using designed software or applications. This domain is widely used in the medical field, industrial manufacturing process, military applications, agriculture or field robots, phenotyping, grading and sorting, livestock monitoring, identification of diseases, and nutrition deficiency in plants/crops.

Significance of Nutrients for Crops

Plant growth requires various minerals and nutrients to grow and complete their life cycles. The application of appropriate nutrients is required to attain maximum sustainable yield. Deficiency of these nutrients results in different symptoms like stunted growth, poor yield, and the poor quality of food output from crops. The Nutrient deficiency should be identified at the earlier growth stage, and necessary actions are to be taken to regain and improve yield. Primary nutrients or macronutrients are required in larger amounts, including nitrogen, phosphorus, and potassium (Espiritu 2017, Haifa Group 2020, CGIAR Platform 2020). The secondary nutrients or micronutrients such as Sulphur, Magnesium, and Calcium are needed in certain quantities depending upon the plant species for its germination, resistance to pathogenic disease, and reproduction that ensures the healthy growth of plants. Calcium provides vital structural support for the plant cell. Magnesium is required for photosynthesis as it activates the enzymes required for plant growth. Sulfur is also required in moderate quantities that help the plants develop chlorophyll and protein synthesis. Feeding the crops with optimum levels of nutrients under experimental conditions becomes very difficult. The absorption of nutrients by plants is not assured by the mere availability of nutrients in the soil due to various factors such as moisture content and temperature of the soil, water pH level, toxic elements, and low salts. Hence, adequate levels of diagnosis are an important process to detect abnormalities and find effective solutions to improve the productivity of crops.

Fig. 1 depicts the identification of crop health using various dimensions of leaf symptoms.

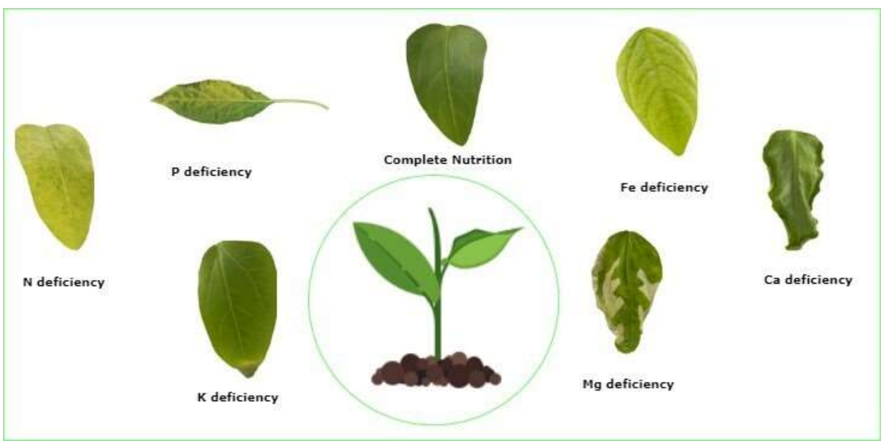

Fig. 1: Examples of Various Dimensions of crop health.

Paper Organization

This survey article enables the readers to get an overview of Computer vision-based advancements in the identification and classification of crop nutrient deficiency, understand the existing shortcomings, and improve the technology by means of further research. The article is framed by studying various articles related to computer vision technologies for predicting crop nutrient deficiencies from 2010. However, most of the papers range between 2018-2022. About 60 articles related to agriculture and crop nutrients were studied, among which 30 papers were selected for this survey as a perspective on computer vision and nutrient deficiency. The study focused on the evolution of computer vision, such as from Image processing to ML or DL, and a combination of recent models or advancements. The subsequent content of this survey paper is structured as follows. The second section explores the factors related to crop stress causing nutrient deficiency and its associated specific works for detection. The third section constitutes various sources and data collection methodologies for stress prediction. The fourth section identifies the outcomes, potential challenges, and future scope. Finally, section five concludes this survey paper.

Factors of Crop Stress Causing Nutrient Deficiency

Nutrient deficiency is visible through different specific symptoms of crop health, which may be visual or internal characteristics. For example, the leaf shape is deformed due to calcium deficiency. Nitrogen deficiency causes the change of color in leaves to light green and yellow at the top and bottom of the plant, respectively. Manganese deficiency causes holes, whereas copper deficiency causes pale pink between the leaves' veins (Karthika et al. 2018). In view of smart agriculture, different robotic machines are developed to improve crop yields, such as the popular FarmBot and Agribots, to determine various crop-dependent factors such as soil depth for effective seeding processes, soil salinity, soil organic carbon (SOC), etc. The major reasons for crop stress are (1) Soil Quality and Nutrient Supply Imbalance (Electric Conductivity and Mobility of Nutrients), (2) Fertilizers, (3) weather conditions, (4) pests, (5) irrigation and pH levels.

Soil Quality and Nutrient Supply Imbalance

In general, soil analysis is performed to measure the nutrient content in the soil. The influence of biological, chemical, and physical processes in the soil plays a major role in plant growth and development. A variety of tools and technologies have been implemented through research findings in terms of monitoring and predicting the soil nutrient distribution, including conditions of moisture, temperature, pH value, level of water holding, and humidity of the air, such as the Geographic Information Systems (GIS), Global Positioning Systems (GPS), Variable Rate Technology (VRT), thereby estimating the present level of nutrients and recommend the required quantity of fertilizers or manures across the field. (Raza et al. 2014) Proposed an automatic Gaussian process classifier with support vector machine algorithm for determining the soil-moisture stress using visible and thermal images of spinach canopies captured remotely, in which the efficiency of using combinational methods was explored. Lavanya et al. (2020) designed an IoT-based NPK sensor system that includes LDR and LED. The colorimetric principle was used for monitoring and analysis of the soil nutrients. The sensed data of NPK sensors from various fields are uploaded to the Google Cloud database to quickly retrieve information, and the fuzzy logic concept was applied to data. Yu et al. (2021) compared the usage of UAV multi-spectral imagery and Planet Scope satellite imagery to predict the nitrogen weight of wheat fields using plant height, leaf area index, soil moisture, and field topographic metrics. Here, Random Forest and support vector machine-based regression models were applied to predict nitrogen weight.

Fertilizers

Fertilization in crops is location-specific and depends upon soil nutrient concentration level, including soil absorption, fertility rate, crop size, and other associated factors. Overusing fertilizers causes unpredictable negative impacts on soil, crops, the atmosphere, and human health. Leaf nitrogen content is an indicator of nitrogen status based on which the required nutrient for crops at regular intervals or during unexpected environmental effects are identified. Appropriate fertilization measures are taken through strategies in smart agriculture. But, parameters such as leaf area index, chlorophyll, amount of protein content, and biomass value are not proportionate to the amount of nitrogen content. The normalized vegetation index (NDVI) is computed to predict the vegetative health status of the soil. Chen et al. (2010) used the NDVI index to determine the nitrogen content of rice crops at the jointing stage. They constructed a nitrogen top dressing regulation model that estimated the accurate level of required fertilizer (Agarwal et al. 2018). The leaf chlorophyll content of spinach seedlings was assessed to distinguish between the healthy and stressed using multivariate data analysis tools. Haider et al. (2021) Devised a computer vision algorithm that extracts the similarity feature and pattern from the leaf image while comparing it with the given reference. The green color value (GCV) index was computed to identify nitrogen content. It could be further used for distinguishing other deficiencies with the diseases.

Weather Conditions

Smart sensors placed across the farm acquire data from the surrounding environment regarding parameters such as humidity, temperature, moisture, precipitation, and dew detection and send them for analyzing or processing through various application-specific tools. Jangam et al. (2018) stated that the sensor data could be used to map the climatic conditions or patterns for selecting appropriate precise methods to improve specific crop productivity. Moreover, the results of accurate measurement and analysis of agro-meteorological factors provide a tool for farmers to predict or enhance crop yield. It also assists in the selection of pesticides and fertilizers. Diedrichs et al. (2018) designed an IoT-based frost prediction system using ML algorithms evaluated by training classification and regression models. The Random Forest algorithms outperform other models in terms of sensitivity, precision, and F1 score. Many smart decision-support User Interface systems have been developed through research to inform farmers about crop management activities. Nabi et al. (2022) quoted that these smart farming techniques also helped the farmers by lowering the investment cost and getting higher yields from their farms. The Global Positioning System coordinates acquired using IoT play a vital role in the event of spatial object topographic analysis by providing low-cost solutions to various areas like field traversal, including ground truth values, recording of weather parameters, and observations. Also, besides providing better accuracy and high consistency using rapid communication protocols, smartphones can provide diverse adaptability to run high-end applications.

Pest Control in Crops

Crop production is severely affected by the occurrence of pests and development of diseases. The pests hide behind the leaves to avoid the thermal heat during the day and start appearing in the evening or at night. Hence, it creates a major issue of observing the pests physically during the daytime, leaving the crops with bacterial infections resulting in large-scale diseases. Wang et al. (2013) created an environmental monitoring system for recording the status of apple orchards using many sensors with YOLO v3 Dense models, which was effective for identifying anthrax and anthracnose on the surface of apples. Chandy (2019) developed a drone-based pest identification system embedded with NVIDIA Tegra System on Chip (SoC), which captures the images in coconut farms and processes using DL algorithms for determining pest-affected or unhealthy trees. The algorithm developed was also suited for unstructured images, and the information being transferred to the farmer's smartphone helped for early pest identification or unhealthy trees. Gladence et al. (2020) highlighted the application of human-robot interaction by combining sensed environmental data with DL tools or algorithms, which helped farmers to prevent pests and monitor crops, particularly at earlier growth stages. Chen et al. (2020) designed a smart pest identification system using a drone-based YOLO V3 DL model. The designed system provided better control over Tessaratoma papillosa (insect), improving crop yield and quality. Some drawbacks were discussed, such as leaf occlusions, drone stabilization between the trees, Illumination conditions, and improving pest recognition performance using various angles. It tends to be the future scope of research. Image pattern recognition technology is a non-invasive strategy for identifying pest damage and thus helps improve crop production. The recent advances of YOLO v4 DL models are used to monitor pests and crop environmental conditions.

Irrigation and pH

Irrigation in agriculture has evolved with various smart techniques to manage crop loss due to water scarcity. These irrigation systems help estimate water requirements for a specific crop, soil type, moisture, and climate. A precise soil moisture control system using wireless sensor networks and many other advanced tools developed, such as an IoT-based framework measuring crop water stress index, could be used to optimize irrigation to improve crop health and productivity. The pH level below the soil plays a key role in optimizing various factors responsible for nutrient cycling and soil remediation, as it affects the entire crop's interaction with the environmental system. But the pH requirement and sustainability differ from crop to crop. Certain crops, such as lime, can tolerate the soil's acidity, but very few survive in moderately alkaline soils due to the limited mobility of nutrients. Soil with high organic matter has a pH level of 5.0 to 5.5. Liu et al. (2020) created a comprehensive interactive model for dynamic tracking of alfalfa growth by regulating water and fertilizer. The model is added with a simulation platform that closely monitors crop growth by measuring the physical environments parameters such as leaf area and soil water level. Wu (2021) proposed an LSTM-based smart agricultural system using IoT sensors and devices that monitors environmental conditions like soil moisture, sunlight, temperature, and weather forecast information. Depending upon the data collected with respect to the factors considered, the irrigation is done to balance the soil's pH level, hence enriching the yield. Boursianis et al. (2021) explore a smart irrigation system, AREThOU5A, which includes ML algorithms and an IoT platform with inbuilt sensors for sensing the relative surrounding physical environment. Depending on the parametric values, precise irrigation is performed. The system has 5G network capabilities.

MATERIALS AND METHODS

Prediction of Stress

As technology advances, crop stress prediction is performed using various methods and combinations of tools to improve performance factors like accuracy and quality. Agricultural field data monitoring and collection involves the communication of different devices between each other, sensors that provide information about soil, crop health conditions, and other associated factors. This enables us to determine the specific crop variety concerning its location. Several algorithms and models are developed to determine crop efficiency by means of matching crop vegetative index parameters with a particular color: green means no stress, yellow for medium stress, orange with high stress, and red means it has very high stress. Table 1 summarizes the specific works using computer vision with ML, and Table 2 summarizes the specific works using DL to detect nutrient deficiency. This section summarizes some specific works related to data collection methodologies involved with Computer Vision based identification of Nutrient deficiencies using Remote Sensing, ML, DL, and IoT-based UAV Monitoring. The following figure (Fig. 2) depicts the workflow of a typical computer vision model.

Computer Vision-Based Remote Sensing

Remote sensing is utilized for crop nutrient control and enhancing productivity by developing various advanced tools in decision-making systems. A set of IoT-based sensors placed along agricultural fields continuously monitors the environmental conditions. The collected data is transferred to an analytical tool, after which the farmers can track the field and crops through the user interface dashboard. Necessary actions for crops are taken based on the data insights. Remote sensing could be deployed in many agriculture-related applications such as soil versus yield monitoring, stress management of soil to crops, schedule irrigation, crop disease detection, residue estimation, and crop maturity. Liu et al. (2017) proposed a multi-spectral remote sensing technology based on the UAV application of LNC. Diagnosis of other deficiencies other than nitrogen is rarely reported using Remote sensing. Zhang et al. (2018) used a UAV equipped with a digital camera to monitor the nutrition of the maize canopy during summer in terms of nitrogen. By analyzing the dynamic normalized color coefficient values, the diagnosis is performed efficiently and quickly compared to the conventional methods of obtaining those management parameters. With the development of Hyperspectral remote sensing, the spectral information of crops is obtained, and

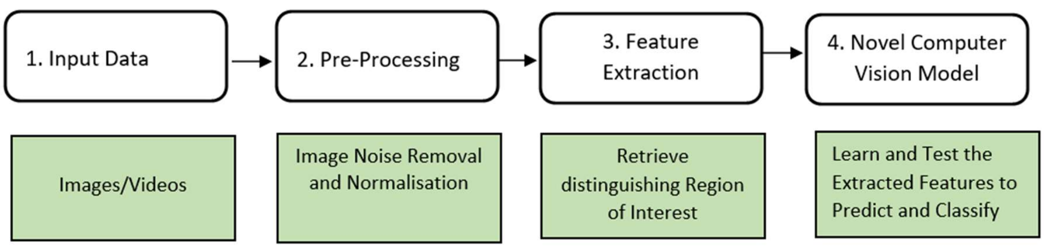

Fig. 2: Workflow of a Typical Computer Vision Model.

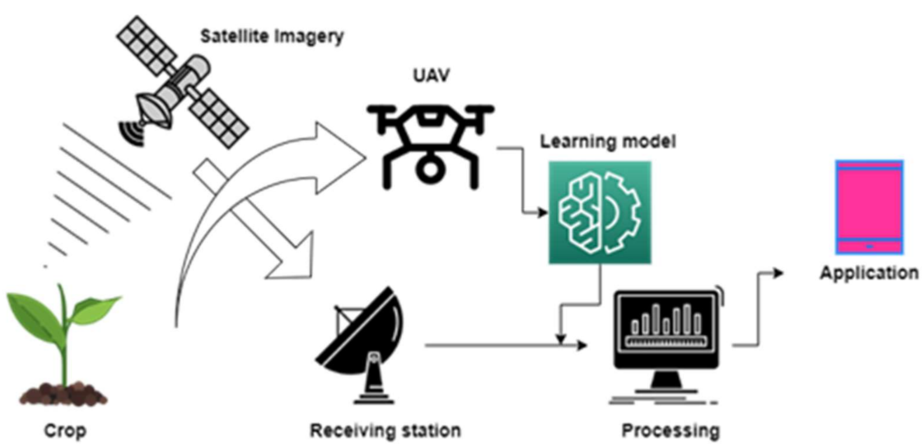

Fig. 3: Remote Sensing and UAV in Agriculture.

the nutrition diagnosis is made using a computer (Feng et al. 2020). Shendryk et al. (2020) compared the performance parameters of prediction models based on multi-spectral predictors or LiDAR. A benchmark evaluation for the Vegetative Index standard on varied geographical areas is challenging. The Figure (Fig. 3) overviews computer vision-based remote sensing and UAV. Future research could focus on ensembling multi-spectral imaging with LiDAR predictors.

Computer Vision-Based Drones and IOT-Based Crop Monitoring

In recent years, drone technology has become very popular with its built-in camera and autonomous flying capabilities enabling it to be used for various applications. Depending on the flight requirement and application, ground or aerial-based drones are used in agriculture. The drones help assess crop health information using the overall aerial view of agricultural land and geo-sensing data. Computer vision models, in combination with IoT-based devices and DL tools, are trained using captured images by the camera and other sensors being mounted on UAV to know the soil conditions, segment crops, classify crops, identify vegetation, detect disease and weeds, and monitor crop nutrient content. Drones can be remotely controlled or by using specially designed software in synchronization with sensors and GPS, thus creating an Embedded system-based flight. Therefore, UAVs are suitable for various activities ranging from counting and yield prediction enabling smart farm monitoring. As agriculture is related to highly variable environmental conditions and factors, an automated real-time monitoring system is in need. IoT applications in agriculture aim to solve the above issues and equalize the population's food demands with reduced loss (Jesus 2019). Torres-Sanchez et al. (2015) proposed a ground-breaking method for measuring and mapping. The result provided a relation between the factors related to field geometry, its resources, and tree growth. The following Table 1 lists some important activities in agriculture that involves IoT technology.

Table 1: Major activities in agriculture involving IoT technology.

Tasks	Sub Activities
Crop Monitoring	Environmental sensing, Detect crop stress, Pests, weeds, Ripening
Crop Practices	Smart farming, Automation, and precision mapping activities
Services	Education, Crop Models, Financial Management, Information Systems, Accountability, Paying agency (PA), Resource usage
Market operations	Quality and certification, Traceability, Seeds, machinery, Labor

Szewczyk et al. (2018) established a crop monitoring system using UAVs for assessing the impact of fertilizer elements on crop health with the help of captured spectral properties. Niu et al. (2019) found that the height of a UAV flight can affect the detection accuracy of different image spectral bands for irrigation systems of Onion crops using neural networks. The author showed that the RGB combined with the near-infrared (NIR) image band gave the best accuracy. The following are some features of UAVs mentioned in their article. The Agdrone could cover 600 to 800 acres in one hour at an altitude of 400 ft. The DJI Matric100 has a double battery that facilitates an extra 40 minutes of flight time and is an added feature of the GPS system. The advanced Agras MG-1-DJI had a unique feature to carry 10 KG of liquid and spray over an area of 4000 to 6000 sq. meters in about 10 minutes, comparatively 70 times faster than manual spray. The DJI T600 captures the environment with 4K video resolution. The EBEE SQ drone is used for monitoring crop growth at various stages. The Lancaster, 5 precision Hawk, was used to collect atmospheric temperature and the environment's humidity level surrounding the agricultural area. The SOLO AGCO drone with advanced cameras mounted had high resolution and accurate image recording capabilities.

Computer Vision Related to Machine Learning and Deep Learning

Modern Computer vision development models focus on tools based on ML or DL, sensors, and devices that support real-time monitoring of agricultural fields, such as UAV, IoT sensing devices, satellite imagery, etc. (Stokes 2019, Eastern Peak Technology Consulting 2020, Scnsoft 2022, Crop In 2022). The Learning Models and algorithms are pattern recognition based that find the patterns and label the objects on those images. A typical ML architecture consists of feature extraction and classification modules. Watchareeruetai et al. (2018) proposed a Novel method for identifying and analyzing plant nutrient deficiencies using Image segmentation and CNN. The results are validated with a real-time nutrient-controlled environment. Shah et al. (2018) proposed an automated system for nutrient deficiency analysis. A digital camera dataset was created for color feature extraction, edge detection, texture detection, etc. The detection of exact nutrient-deficient and healthy plants was performed using supervised ML algorithms, and necessary care was taken to improve the yield. Ghosal et al. (2018) Implemented a deep convolutional neural network for identifying soybean stress from RGB leaf images. With regard to the plant stress identification model or phenotyping, four stages, namely identification, classification, quantification, and prediction, termed ICQP, were evaluated. This approach provided a relatively quantitative measure for each modeling stage, such as identifying stress type, classification of stress levels, and severity of stress. The below figure (Fig. 4) gives an architecture of a classification model that differentiates the characteristics between specific crop nutrient deficiency and crop disease.

Learning models with more than 25,000 images classify several biotic and abiotic stress. This methodology allows for accurate stress management in real-world situations providing high reliability and adaptability to certain illumination levels. Wulandhari et al. (2019) developed a deep convolutional neural network to manage health conditions using crop images. Here, a hybrid network with a transfer learning approach, namely Inception-Resnet architecture, was trained using the ImageNet dataset. It was then experimented with fine tuning of hyperparameters such as learning rate and number of epochs. The authors achieved 96% and 86% accuracy during training and testing, respectively. A comparative graph depicting the number of authors who worked to identify a nutrient deficiency in crops using machine learning and deep learning is shown in Fig. 5 & Fig. 6, respectively.

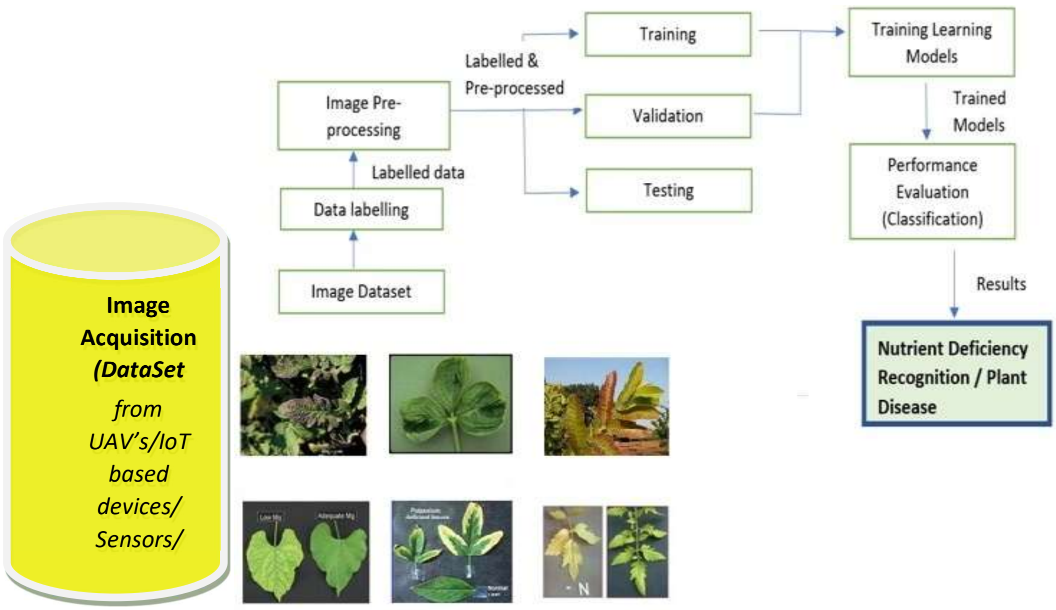

Fig. 4: Architecture of a typical classification model that differentiates the characteristics between specific crop nutrient deficiency and crop disease.

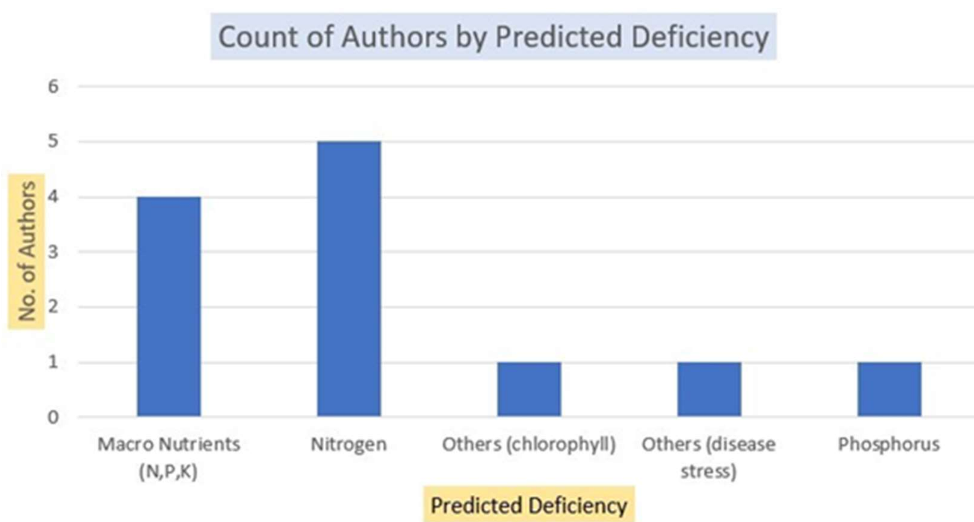

Fig. 5: Machine learning-based prediction of nutrient deficiencies.

Xu et al. (2020) used deep convolution networks (DCNN) to recognize the symptoms of nutrient deficiencies in rice crops using their leaf color and shape. Among the different DCNNs, the DenseNet121 outperformed with the best validation and test accuracy of 98.62 ± 0.57% and 97.44 ±0.57%, respectively. Anami et al. (2020) designed a Deep CNN-based framework that classifies about 12 classes of Biotic and Abiotic stress of the Paddy field using VGG-16. The authors collected about 30,000 images of five different paddy varieties during their growth and compared them with BPCNN (Backpropagation) models. The proposed framework had better classification performance. Sethy et al. (2020) compared Six DL models such as AlexNet, VGG-16, GoogleNet, ResNet-18, ResNet-50, and VGG-19, combining SVM learning to predict nitrogen deficiency using leaf images. Among these architectures, ResNet-50 with SVM outperformed. A Classification Model for handling increased datasets could be upgraded with an updated Leaf color chart (LCC). Sathyavani et al. (2021) designed a DL-based classification model, DenseNet-BC, which utilizes IoT devices for data acquisition. The simulation results of the proposed model showed an improved classification accuracy and F-measure value compared to other models. Karthickmanoj et al. (2021) implemented a stress modeling system that detects the health status of the crop by using leaf images. The captured features in the crop images are sent from the field to an agricultural consultant through the cloud. The classification uses an SVM classifier to determine unhealthy and healthy leaves.

Joshi et al. (2022) proposed a DL-based handheld device, RiceBioS, for detecting the biotic stress in rice crops. The device acts like an Edge-as-a-Service (EaaS) for classifying images into healthy and stressed. The inferences from this work are that the quantification and classification could be improvised with respect to specific crops. Sharma. et al. (2022) designed an ensembled learning framework that uses a transfer learning approach to address rice plant nutrient deficiencies. The authors used two public datasets from Mendeley and Kaggle. The results from Inception ResNet V2 were 90% and Xception of 95.83%. The future scope of this work shall be to design a complete deficiency diagnosis support system for farmers by means of IoT-enabled systems. It may be concentrated on specific conditions affecting yield potential versus yield stress.

Fig. 6: Deep learning-based prediction of nutrient deficiencies.

Moreover, the severity of crop stress should be identified by designing more efficient models with minimized errors. Also, the nutrient deficiency symptoms differ from crop to crop and within a particular variety of crops. Hence, appropriate models should be developed and integrated to identify diversified stress. The related works for identifying Crop Nutrient deficiencies using Machine Learning and Deep Learning are depicted in Tables 2 and 3, respectively.

RESULTS AND DISCUSSION

This survey article shows that most research uses ML and DL for crop stress management. Such approaches have been modeled for analyzing plant stress from identification, classification, prediction, and quantification perspectives. The AI techniques for modeling plant stress responses, such as the Random Forest, Support Vector Machine, Artificial Neural Networks, and Convolutional Neural Networks, were predominantly used for classifying nutrient deficiencies and other stress symptoms from the image datasets.

Research Gaps Contributing to Future Research Scope

Current challenges include food demand satisfying the growing population using limited agricultural lands, identification of specific factors like limited manpower, changes in environmental conditions, identification of crop deficiencies in different illuminations and geographic locations, weed differentiation, leaf occlusions, etc., causing total yield loss. The future scope with regard to the development of computer vision classification models is related to the above-mentioned research challenges and other specific factors such as the following:

- Limited Datasets specific to secondary and micro nutrients
- Predictive analysis and smart monitoring for improving classification accuracy of deficiencies
- Nutrition imbalance quantification
- Stress due to residues of pesticide application and pest damage or other external factors
- Micro-nutrients identification

Table 2: Summary of Computer Vision works related to Machine learning.

Author& year	Methodology/Equipment Used	Crop	Dataset	Predicted Deficiency
Yu et al. (2021)	Machine Learning - LAI2200C Plant Canopy Analyzer, Da-Jiang Innovations UAV, and DJI Phantom 4 RTK UAV	Wheat	UAVand satellite-Based imagery	nitrogen weight
Agarwal et al. 2018	Machine Vision - PCA and AHCA/SPAD-502Plus chlorophyll meter	Spinach seedlings	Own dataset	High and low chlorophyll content
Haider. et al. (2021)	Machine Vision – GCV index	Spinach	Smartphone camera images	Nitrogen content
Shendryk et. al. (2020)	UAV Light Detection and Ranging (LiDAR) and multi-spectral imaging	Sugarcane	Raw images from UAV and sensors	Nitrogen
Shah et al. (2018)	Machin Vision-RGB color feature extraction	Neem	Own dataset	Nitrogen, Phosphorous and Potassium
Sharif et al. (2018)	Machine Learning – Multi class-SVM – optimized weighted segmentation and feature selection methods.	Citrus plants	Plant Village and own Citrus Images Database	Classification of diseases
Leena & Saju (2019)	Artificial Neural Networks (ANN) and Multiclass Support Vector Machines (SVM) - MATLAB 2015	Maize	Own dataset of 100 sample leaf images	Macronutrients-Nitrogen, Phosphorous, and Potassium
Shidnal et al. (2019)	Machine Learning Algorithms and Google Tensor Flow Library	Paddy	Random Images simulating cropland	Nitrogen, Potassium, Phosphorous
Marin et al. (2021)	Machine Learning – Random Forest	Coffee	Raw images from Remote Piloted Aircraft (RPA)	Spatial variability of Nitrogen content
Zermas et al. (2021)	Machine vision- UAV-assisted RGB sensor and Deep Learning for Training data	Maize, Corn	Field data images	Nitrogen deficiencies
Costa et al. (2021)	Unmanned aerial vehicle (UAV) multi-spectral imagery and AI	Citrus orchards	Raw images from UAV and sensors	Macronutrients (N, P, K, magnesium, calcium and sulfur
Shi et al. (2021)	Hyperspectral Imaging and classification models	Cucumber	Own dataset	Phosphorus

Table 3: Summary of Computer Vision works related to Deep learning.

Author & year	Methodology/Equipment Used	Crop	Dataset	Predicted Deficiency
Chandy (2019)	Deep Learning - Drone interfaced with NVIDIA Tegra System	Coconut	Own dataset	unhealthy and pest-affected trees
Watcha- reeruetai et al. (2018)	Image Segmentation and CNN	Black gram	Own dataset	Ca, Fe, K, Mg, and N deficiencies
Ghosal et al. (2018)	Deep CNN Model framework	Soybean	Own dataset	Multiple stress, herbicide injury, and potassium deficiency
Wulandhari et al. (2019)	Deep CNN- Inception ResNet architecture with Transfer Learning	Okra	Imagenet dataset	Macronutrients (N, P, K, Ca, Fe, Mg)
Sethy et al. (2020)	CNN, pre-eminent classifier -SVM	Rice	Own dataset	Nitrogen
Sathyavani et al. (2021)	IoT-based Nutrient Sensor, CNN Model	Black gram, coriander, pepper, chili, Tomato	Own dataset	Macronutrients (nitrogen, phosphorus, potassium, magnesium, calcium, and sulfur
Joshi et al. (2022)	CNN and using Edge as a service	Rice	Own dataset	Biotic stress
Sharma et al. (2022)	Computer vision, Ensembling of various Transfer Learning (TL) architectures	Rice	public datasets from Mendeley and Kaggle	Multiple deficiencies
Anami et al. 2020	Deep CNN with pre-trained VGG 16	Paddy	Own dataset	Various classes of Biotic and Abiotic stress
Manoharan et al. (2020)	CNN, RCNN	Guava, Groundnut and citrus plant	Own dataset	Nitrogen, phosphorous, and potassium,
Yi et al. (2020)	CNN using RGB images	Sugar beet	(DND-SB) Dataset	N,P,K, Calcium and fertilization status
Song et al. (2020	BP-ANN and K-nearest neighbors (KNN) - stepwise-based ridge regression (SBRR)	Wheat	Own dataset	Chlorophyll content
Azimi et al. (2021)	Multilayered Deep Learning	Sorghum Plant	Public Dataset -Donald Danforth Plant Science Centre	Nitrogen
Kusanur and Chakravarthi (2021)	Pre-trained deep learning model	Tomato	Own dataset	Calcium and Magnesium
Ahsan et al. (2021)	Deep Learning architectures	Hydroponically Grown Lettuce Cultivars	Own dataset	Nitrogen
Ponce et al. (2021)	CNN based classifier + Artificial Hydrocarbon Network (AHN)	Tomato	Github Repository Dataset (ccevallo/ Monitoreo Jitomate)	nitrogen, phosphorus, potassium
Chang et al. (2021)	Deep Learning Models – CNN, BPNN, DCNN, LSTM	Muskmelon	Own dataset of greenhouse-grown plants	Nitrogen
Sathyavani et al. (2021)	CNN- Densenet-BC, IoT for data acquisition	Rice	Plant village dataset	Multiple deficiencies

- Optimizing the performance parameters in a neural network model for best fit
- Identification of a computer vision model for automated monitoring of crop nutrient cycle
- Most research is based on Static Image Models and pattern recognition

The developed model using IoT devices like sensors for determining the unavailable nutrients and recommendation system is another area that could be focused to get better real-time monitoring datasets for validation. The agricultural industry would evolve as a highly progressive sector when these kinds of systems and tools or techniques are used for various management strategies, such as sowing to yield forecasting. The other advanced management strategies and approaches needed to be concentrated are the implementations of greenhouses, hydroponics, aquaponics, and vertical farming.

CONCLUSION

This survey provides an overview of the crop stress, and related works performed using Remote sensing, ML, and DL to identify crop nutrient deficiency and the data collection methods. The use of different technological aspects in agriculture enlightens the role of connected farming, particularly computer vision combined with advanced DL models and IoT-based sensing devices, to meet future expectations. This survey would be useful for researchers in this area to discover the advances of computer vision of Crop Stress Identification and establish the research towards fine-tuning the performance hyper-parameters. The integrated system architecture will constitute several agricultural equipment, robots, UAVs, computer vision-based DL models, and IoT enabling various real-time agricultural process management from soil preparation to harvesting. By adopting these smart and precise approaches, farmers will be able to understand the problems that limit production, thereby improving their agricultural resources in terms of yield and quality, leading to sustainable agriculture.

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