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A SURVEY ON AI – BASED PLANT HEALTH MONITORING SYSTEM

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Abstract: The increasing demand for sustainable agriculture and early stress management in crops has led to the exploration of advanced technologies such as Artificial Intelligence (AI) for plant monitoring and communication. Plants continuously emit biochemical and biophysical signals in response to environmental stresses including drought, nutrient deficiency, pest attacks, and diseases. Recent advancements in AI, sensor technologies, and Internet of Things (IoT) systems enable the detection, interpretation, and translation of these signals into actionable insights for farmers.This study focuses on the development of an AI-based plant communication and stress detection system that integrates Machine Learning algorithms, sensor networks, and data analytics to monitor plant health in real time. The system captures parameters such as Volatile Organic Compounds (VOCs), leaf temperature, soil moisture, and electrical signaling patterns, which are analyzed using AI models to identify stress conditions at an early stage. By enabling plants to communicate their stress signals, this approach facilitates timely intervention, reduces crop losses, and minimizing excessive use of water, fertilizers, and pesticides.The proposed framework supports precision agriculture by improving decision-making and promoting resource-efficient farming practices. Furthermore, it contributes to sustainable crop management by enhancing resilience against climate variability and environmental challenges. The integration of AI in plant health monitoring represents a transformative step toward smart agriculture and improved global food security.

Keywords: Artificial Intelligence, Plant communication, Stress detection, Precision agriculture, IoT, Plant health.

I.INTRODUCTION

Plant stress detection has emerged as a significant challenge in modern agriculture, with crop productivity increasingly affected by environmental variability and biotic pressures. Within this technological framework, plants function as dynamic biological systems that generate subtle biochemical and biophysical signals, which serve as indicators of physiological status and stress conditions. These signals including volatile organic compounds, electrical impulses, and thermal variations often remain undetected through conventional monitoring approaches. An AI-based plant communication and stress detection system addresses this limitations by interpreting these hidden signals using advanced Machine Learning models and sensor networks. Such systems enable real-time analysis of plant responses to stresses like drought, nutrient deficiency, and pest attacks, facilitating early diagnosis and timely intervention while enhancing precision agriculture and sustainable crop management.

IMPORTANCE OF PLANT DATABASE

- **Real-Time Plant Monitoring and Early Stress Detection:** Continuous monitoring of plant physiological signals is essential for identifying stress conditions at an early stage. AI-based systems utilize sensors to capture parameters such as leaf temperature, soil moisture, and biochemical emissions, enabling accurate detection of stress factors like drought, nutrient deficiency, and pest attacks. Early diagnosis allows timely intervention, reducing crop losses and improving overall productivity.
- **Integration of AI and Smart Technologies:** The incorporation of Artificial Intelligence with IoT and sensor networks enhances the efficiency of plant communication systems. Machine Learning algorithms analyze complex datasets generated by plants and their environment, translating them into actionable insights. This integration supports automated decision-making, precision agriculture practices, and optimized resource utilization, contributing to sustainable farming systems.
- **Environmental Monitoring and Sustainable Crop Management:** AI-based plant communication systems also play a crucial role in monitoring environmental conditions such as soil health, humidity, and climate variability. By understanding plant responses to these factors, farmers can adopt eco-friendly practices that minimize excessive use of water, fertilizers, and pesticides. Continuous monitoring ensures sustainable agriculture by conserving resources, maintaining ecological balance, and enhancing crop resilience.

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II. LITERATURE REVIEW

SL NO	YEAR OF PUBLICATION	TITLE OF THE PAPER	DESCRIPTION
1	2025[1]	Lightweight EfficientNetB0 – Based Transfer Learning Model for Detection of Rice Diseases and Nutrient Deficiency	This paper was proposed for simultaneous detection of rice diseases and nutrient deficiencies using leaf images [X]. The dataset was constructed by merging two publicly available Kaggle rice leaf image datasets covering seven classes — healthy, bacterial leaf blight, blast, brown spot, nitrogen deficiency, phosphorus deficiency, and potassium deficiency. Preprocessing involved resizing images to 224×224 pixels, data augmentation through random rotation, horizontal flipping, translation, and scaling, alongside manual oversampling and inverse-frequency class weighting to address class imbalance. The EfficientNetB0 base model, pretrained on ImageNet was fine-tuned with a custom classification head comprising fully connected, dropout, and SoftMax layers, trained using the Adam optimizer for 50 epochs. The proposed model achieved a test accuracy of 97.7% and an AUC of 1.00 across all classes, outperforming existing approaches while maintaining a lightweight architecture suitable for real-time mobile deployment in precision agriculture.[1]
2	2025[2]	Monitoring Agricultural Stress Using Multi-Sensor Satellite Data and Machine Learning Techniques	This paper develops a data-driven framework integrating multi-sensor remote sensing and machine learning for monitoring agricultural stress across 34 districts of Maharashtra, India. Satellite data from Sentinel-2, MODIS, and Landsat-8 were used to derive vegetation indices including Normalized Difference Vegetation Index(NDVI), Normalized Difference Water Index(NDWI), Vegetation Condition Index (VCI), Temperature Condition Index(TCI), Vegetation Health Index(VHI), Chlorophyll Vegetation Index(CVI), Moisture Stress Index(MSI), Enhanced Vegetation Index(EVI), and Soil-Adjusted Vegetation Index(SAVI), extracted via Google Earth Engine from 2,722 observations spanning 2015 to 2023. Multiple ML models including Random Forest, XGBoost, LightGBM, Bagging Tree, Decision Tree, and a hybrid DNN-LSTM were evaluated. The study specifies the methodology including data preprocessing, feature engineering, vegetation index computation, and performance evaluation using R^2, RMSE, and Pearson correlation, while discussing challenges in spatiotemporal pattern capture. The findings demonstrate that the hybrid DNN-LSTM outperformed all models with R^2 of 0.992 and Root Mean Square Error(RMSE) of 1.415, enabling accurate early detection of drought and climate-induced stress.[2]

3	2024[3]	Drought Prediction for Farmers and Providing a Sustainable Farming Solution using IoT and Machine Learning	This paper proposes an IoT and Machine Learning-based drought prediction model for farmers in rain-fed agricultural regions. IoT sensors including weather stations, soil moisture sensors, and crop health monitors collect real-time data, which is preprocessed and fed into ML algorithms such as KNN, Decision Trees, Support Vector Machines, and Neural Networks. The system was implemented using a Raspberry Pi connected to the ThingSpeak cloud platform and a Blynk mobile application for farmer accessibility. Real-time data collected from IoT sensors undergoes preprocessing and feature extraction before being analyzed using machine learning algorithms. The framework incorporates data acquisition, feature engineering, exploratory data analysis, and performance evaluation while addressing issues related to data quality and scalability. The integration of IoT and machine learning techniques enhances drought prediction accuracy and supports sustainable agricultural practices through effective irrigation scheduling and continuous crop health monitoring [3].
4	2024[4]	Deep Learning for Stress Plant Phenotyping	This paper presents a Deep Learning-based plant phenotyping system for detecting hybrid and heat stress in barley using Convolutional Neural Networks(CNN). A Canon 2000D camera and DHT11 sensors paired with an Arduino Uno were used to collect plant images and environmental data across normal and stressed barley plants. The CNN model was developed using TensorFlow and Keras on Google Colab, trained on 1,416 augmented images across two classes. The framework employs data acquisition, image augmentation, and a CNN-based architecture consisting of convolutional, pooling, and dense layers for plant stress classification. Performance was evaluated using accuracy, precision, recall, and F-measure metrics, while considering challenges associated with field data collection. An accuracy of 99.789% and a recall of 100% were achieved for stressed plant classification, demonstrating its effectiveness as a cost-efficient and non-invasive precision agriculture solution [4]
5	2024[5]	Drought and Salinity Stress Classification in Soyabean Crops: Comparative Analysis of Machine Learning Models	This paper proposes a comparative Machine Learning study for classifying Water deficit and salt stress in soybean genotypes using six morphological parameters collected during the seedling stage. Five ML models — RFC, SVM, Gradient Boosting, KNN, and Naïve Bayes — were trained on seedling-stage features including germination, seed length, root length, total length, seed dry mass, root dry mass, and total dry mass. The approach consists of data preprocessing, GridSearchCV hyperparameter tuning, Group K-Fold cross-validation to prevent genotype data leakage, and performance evaluation using accuracy, precision, and recall, while discussing challenges in genotype-specific prediction errors. The findings demonstrate that SVM achieved

			the highest accuracy of 96.79% with precision of 96.97% and recall of 96.79%, confirming that incorporating morphological features significantly enhances stress classification reliability for sustainable soybean crop management.[5]
6	2024[6]	Comprehensive Deep Learning Approach for Identifying Plant Nutrient Deficiency, Diseases and Pests	This paper proposes a comprehensive Deep Learning framework for the simultaneous identification of plant diseases, nutrient deficiencies, and pest infestations using the OLID I dataset containing 4,749 leaf images across 57 classes from nine vegetable plant species. Four architectures — custom CNN, EfficientNetV2B0, EfficientNetV2B3, and VGG16 — were evaluated on both original and augmented datasets using TensorFlow and Keras. The process includes image resizing, data augmentation to balance class distribution to 150 images per class, model training with an 80:20 train-test split, and performance evaluation using accuracy and F1-score, while discussing challenges in simultaneous biotic and abiotic stress classification. The results indicate that EfficientNetV2B0 achieved the highest accuracy of 85.38% with an F1-score of 85.08 on augmented data, establishing it as the most effective architecture for unified multi-stress agricultural classification.[6]
7	2024[7]	Identification of Nutrient Deficiency Based on Leaf Image Data Using Machine Learning	This paper proposes a Machine Learning framework for identifying NPK nutrient deficiencies in rice plants using leaf image data and combined color-texture feature extraction. A Kaggle rice NPK deficiency dataset of 1,156 images across nitrogen, phosphorus, and potassium deficiency classes was used, with features extracted using CEDD and FCTH visual descriptors. The proposed system utilizes image preprocessing, background segmentation, combined CEDD-FCTH feature extraction, and classification using Random Forest with 10-fold cross-validation, while discussing challenges in overlapping symptoms between nutrient deficiencies and other biotic and abiotic stresses. The analysis confirms that Random Forest achieved class-wise accuracies of 94.66%, 89.63%, and 89.71% for nitrogen, phosphorus, and potassium deficiency respectively, significantly outperforming Naïve Bayes and confirming its reliability for early-stage NPK deficiency detection in rice crops.[7]

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8	2023[8]	Banana Plant Nutrient Deficiencies Identification using Deep Learning	This paper explores the ConvNeXtTiny Deep Learning model for multi-class nutrient deficiency classification in banana plants to support precision agriculture and improve crop yield management. The model was evaluated using two combined public datasets from Mendeley Data — a banana leaf dataset from Karnataka, India and the PSFD-Musa dataset — covering nine classes including healthy leaves and eight nutrient deficiencies such as boron, calcium, iron, magnesium, manganese, potassium, sulphur, and zinc, totalling 9,030 augmented images after combination. The research adopts background removal, image resizing to 256×256 pixels, data augmentation for class balancing, 70:30 train-test split, and performance evaluation using precision, recall, and F-measure across four dataset conditions, while discussing challenges in classifying underrepresented classes such as manganese deficiency with only 24 raw images. The obtained results suggest that ConvNeXtTiny achieved the highest overall accuracy of 87.89% on the augmented combined dataset with an F1-score of nearly 88%, confirming that data balancing and dataset size are critical factors for reliable nutrient deficiency classification in banana plants.[8]
9	2023[9]	Plant Nutrient Deficiency Detection and Classification – A Review	This paper reviews various Machine Learning and Deep Learning techniques used by researchers to identify NPK and other macronutrient deficiencies in plants through leaf image analysis. The review covers studies spanning multiple crop types including rice, banana, grape, maize, paddy, oilseed rape, sugar beet, and lettuce, examining models such as ResNet50, VGG16, DenseNet121, EfficientNet B4, InceptionV3, CNN-LSTM, and MobileNetV2 across diverse datasets. The framework is based on data collection, image preprocessing techniques such as segmentation, augmentation, noise reduction and color calibration, CNN-based feature extraction, and performance evaluation using accuracy, precision, recall, and F1-score, while discussing challenges such as overlapping deficiency symptoms, class imbalance, soil background interference, and model overfitting. The results reveal that DenseNet121 achieved the highest validation accuracy of 98.62% for rice nutrient deficiency classification, and that ResNet50 and VGG16 are the most widely adopted architectures due to their skip connections and transfer learning capabilities, confirming Deep Learning as a powerful tool for automated plant nutrient deficiency diagnosis in precision agriculture.[9]

10	2023[10]	Deep Learning – based Nutrient Deficiency symptoms in plant leaves using Digital Images.	In this paper a deep learning-based system was developed for identifying nutrient deficiencies in plants through digital leaf image analysis [X]. A dataset of 3,000 leaf images obtained from Kaggle was divided into train, test, and validation folders covering six categories — calcium, iron, magnesium, nitrogen, potassium deficiency, and complete nutrition. The proposed methodology involved segmenting leaf images into smaller blocks, applying a winner-take-all strategy to integrate CNN responses per block, and combining block-level predictions using a multi-layer perceptron for final classification. Four deep learning models — CNN, InceptionResNetV2, DenseNet121, and MobileNetV2 — were trained for 15 epochs using Keras and TensorFlow frameworks. InceptionResNetV2 achieved 94%, DenseNet121 achieved 95%, and MobileNetV2 delivered the highest accuracy of 97%. The study demonstrated that MobileNetV2's lightweight architecture provides superior classification performance, making it highly suitable for early-stage plant nutrient deficiency detection in precision agriculture.[10]
11	2023[11]	Detection of Plant Stress Condition with Deep Learning Based Detection Models	In this paper a comparative study applied deep learning object detection models to identify plant stress conditions in eggplant crops during the juvenile vegetative phase [X]. Plants were categorized into three classes — healthy, early stress, and severe stress — based on visual leaf conditions including yellowing, wilting, and powdery mildew symptoms. A dataset of 335 original images was expanded to 2,020 images through augmentation techniques including flipping, rotation, random noise, and shifting. Three object detection algorithms — YOLOv3, YOLOv4, and SSD MobileNetV2 — were trained using transfer learning on Google Colaboratory with TensorFlow, evaluated using mean Average Precision (mAP) and Average Recall at an IoU threshold of 0.5. YOLOv4 outperformed the other models, achieving a mAP of 83% and a detection speed of 32 milliseconds, confirming its superior precision and recall for real-time plant stress detection in precision agriculture applications.[11]

12	2020[12]	Black Gram Plant Nutrient Deficiency Classification in Combined Images Using Convolutional Neural Network	This paper explores a novel combined image approach using deep learning for classifying complete nutrient and six types of nutrient deficiency in black gram plants to improve early-stage detection and crop production quality. The dataset comprised 1,920 RGB combined images created by vertically concatenating old leaf and young leaf images of black gram plants cultivated under controlled conditions over 28 days, covering seven classes including complete nutrient, calcium, iron, potassium, magnesium, nitrogen, and phosphorus deficiency. The study specifies the methodology including offline data augmentation through horizontal flipping and scaling, image resizing to 300×400 pixels, automatic feature extraction using ResNet50 pre-trained model generating 2,048 feature vectors, and performance comparison of three classifiers — multiclass logistic regression, SVM, and multilayer perceptron — using accuracy, precision, recall, and F-measure, while discussing challenges in early-stage symptom visibility and dried leaf misclassification in later stages. The findings demonstrate that the MLP classifier achieved the highest accuracy of 88.33%, significantly outperforming the previous single-image approach accuracy of 65%, confirming that combined old and young leaf images provide richer feature information for reliable nutrient deficiency classification.[12]

III.CONCLUSION

This survey highlights the transformative potential of AI-based plant communication and stress detection systems in advancing precision agriculture and sustainable crop management. By integrating machine learning algorithms, IoT sensor networks, and deep learning models, these systems enable real-time monitoring of plant physiological signals such as volatile organic compounds, leaf temperature, soil moisture, and electrical impulses to detect stress conditions at early stages. The reviewed studies demonstrate that deep learning architectures including EfficientNetB0, YOLOv4, DenseNet121, and MobileNetV2 achieve high classification accuracies for diverse plant stress types including nutrient deficiencies, drought, and diseases. The convergence of AI with smart sensor technologies facilitates timely farmer intervention, reduces excessive use of water, fertilizers, and pesticides, and promotes resource-efficient farming practices. Future research should focus on improving model generalizability, handling overlapping stress symptoms, and deploying lightweight models on edge devices for real-world field applications, ultimately contributing to improved global food security and climate-resilient agriculture.

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