Proposed Framework for Crop Stress Detection (Wheat, Maize, Rice)

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ABSTRACT

The early detection of crop stress is essential to increase agricultural output but much of the current solution involves using a multispectral sensor or satellite-based applications that are not available to small and medium-scale farmers. This article suggests the application of a cost effective web based stress prediction system in wheat, maize and rice using images that are taken using the traditional RGB cameras. The system does not need any specialised hardware, and it is based on the analysis of visible-spectrum images and some simplified user-provided agricultural data. Images of uploaded plants are processed on the pixel level before extracting the RGB values, which are used to approximate an NDVI to determine the health of crops. Other inputs such as the type of crop, month of sowing, and location identify the growth stages and access the current weather information through external APIs. The resulting values are fed into a rule-based decision mechanism to put the degree of crop stress in a category and provide simple actionable recommendations to farmers. The results are all stored and visualised using an interactive dashboard making historical analysis and tracking easier. Empirical evidence shows that the framework is an effective, cost-effective, and resource-accessible approach to crop health tracking through efficient data analysis and visualization of stresses to detect trends in crop health.

Keywords: crop stress recognition, NDVI estimation, image processing, smart agriculture, web-based system, crop health monitoring.

I. INTRODUCTION

1.1 Context of the Problem

Agriculture supports a high percentage of the world population particularly in the developing countries whereby small and medium-scale farmers rely on crop production as a major source of livelihood. The world population has been experiencing a blistering rate of population increase and a change in food preferences, which has put a lot of pressure on food supply chains in the world. At the same time, the growing food demand, the uncertain rainfall distribution, the growth in the average temperatures, the gradual soil erosion, and the ongoing appearance of new pest species have shown a collective contribution to agricultural uncertainty.

The crop stresses related to drought, nutrient imbalance, disease and flooding or extreme temperatures suppress the chlorophyll activity and retard photosynthesis leading to high losses in yield. The early symptoms of stress are extremely subtle and cannot be detected without special measuring instruments-it takes a long time before the biochemical changes will be felt at the cellular level and even then, no external signs have taken place. When the crop starts showing visible signs of discolouration, wilting or stunted growth, very much damage has already been caused to the crop. Early and timely detection is therefore very critical to wheat, maize, and rice.

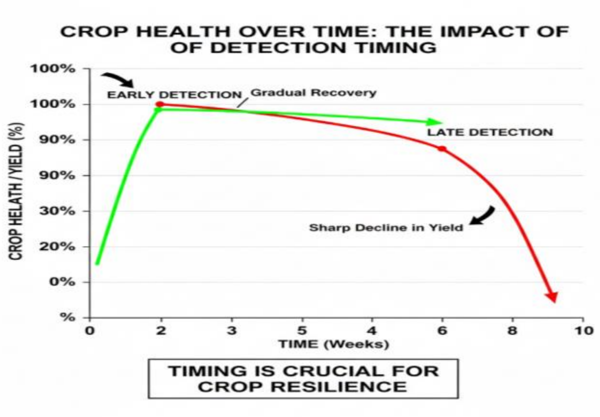

Fig. 1. Effect of early vs. late detection on crop yield.

1.2 Vegetation Reflectance and NDVI

Light reflectance behaviour gives an objective assessment of health of plants. Green plants that are healthy absorb red light (≈660 nm) to carry out photosynthesis, and reflect near-infrared (NIR) radiation. Stressed plants have lower levels of chlorophyll and lower NIR reflectance and high red reflectance. The principle is used in the Normalized Difference Vegetation Index (NDVI):

$$NDVI = (NIR - RED) / (NIR + RED)$$

The NDVI values lie between −1 and +1; values below one correspond to a stressed plant or bare soil, and higher value shows dense and healthy vegetation. The smartphone cameras do not work with NIR and, therefore, in this research, a visible red and green channel-based approximation has been used. The relative changes are intended to be used in the screening of stress and trend analysis although these are not the same as multispectral NDVI.

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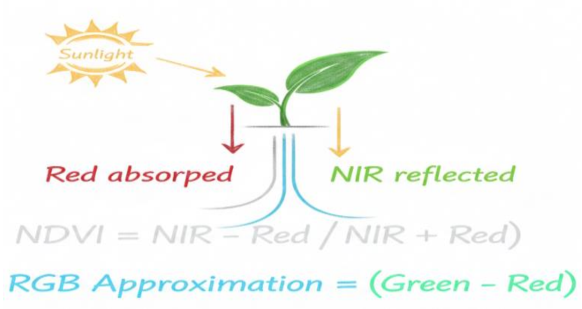

Fig. 2. Calculation of approximate NDVI from RGB channels.

1.3 Limitations of Current Technologies

Current systems of crop monitoring are not available everywhere. The amount of manual inspection is subjective and infeasible on a large scale. Lab tests are accurate and lengthy and expensive. Satellite imagery has a limitation with time and is expensive. Multispectral sensors and technical expertise of the drone/UAV systems are not available to the majority of farmers with limited resources.

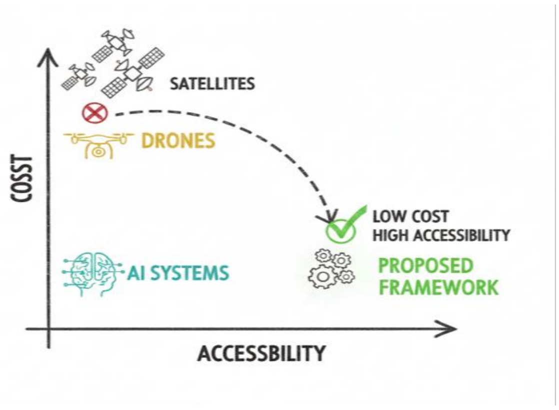

Fig. 3. Comparison of existing systems with the proposed approach.

1.4 Proposed Framework

In this paper, a slim, web-based stress detection system of wheat, maize, and rice is introduced that combines four main elements: RGB Image Processing: Extraction of pixel colour on a per pixel basis to get approximate values of NDVI.

Context-Aware Rule Engine: The type of crop, finance month, weather, and the stage of growth estimated to measure stress.

Explicit Rule matching: Human-interpretable recommendations through explicit matching.

Web-Based Deployment: Philippine-built and open API-based, low-cost, device-independent application.

1.5 Contribution and Scope

The research question: Is it possible to obtain meaningful information about crop stress using conventional RGB pictures on a basic web-based system and at the same time retain enough decision-making value? The framework is responding to the affirmative. Its design is that of a screening machine that is specialised in wheat, maize and rice and is based on the principles of affordability, transparency and accessibility.

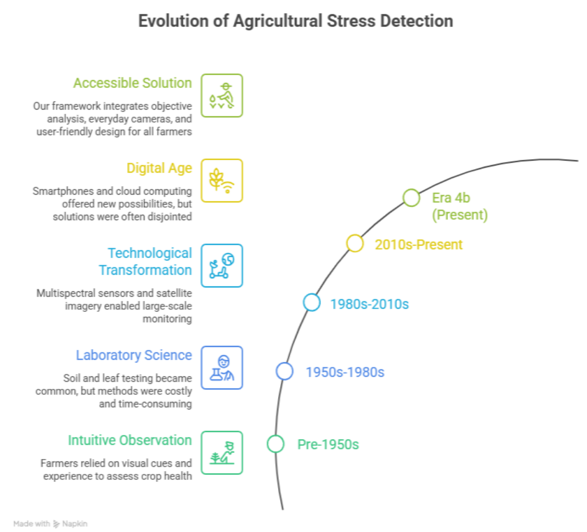

Fig. 4. Evolution of agricultural stress detection technologies.

II. LITERATURE REVIEW

An extensive and carefully organized literature review was aimed at learning the situation of research in the field of crop stress detection, plant monitoring, and artificial intelligence-based agricultural analysis. A total of 83 studies were thoroughly reviewed to find out the trends, advances in technologies, gaps in research, and deployment issues in the field of crop health monitoring.

Databases Used

To ensure credibility and academic rigor, peer-reviewed articles were collected from reputed scientific databases, including:

• IEEE Xplore Digital Library – https://ieeexplore.ieee.org SpringerLink – https://link.springer.com

• MDPI (Multidisciplinary Digital Publishing Institute) – https://www.mdpi.com

• ScienceDirect (Elsevier) – https://www.sciencedirect.com

• ResearchGate – https://www.researchgate.net

• Google Scholar – https://scholar.google.com

These platforms were selected to cover high-impact journals, conference proceedings, and recent advancements in remote sensing, machine learning, and smart agriculture. Boolean combinations of these keywords were also used to refine search results and filter relevant studies.

Foundational and Base Papers

Several highly cited and foundational research works were included to establish theoretical and technical grounding:

• AI-Based Multispectral Crop Stress Detection (2023) – IEEE Xplore

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• NDVI for Crop Health Monitoring (2020) – IEEE Xplore
• Hyperspectral Plant Stress Detection Review (2018) – ScienceDirect
• Real-Time Crop Stress Mapping (2022) – IEEE Xplore
• Vision Transformer for Agricultural Image Analysis (2023) – IEEE Xplore

These studies provided essential insights into vegetation indices, hyperspectral analysis, deep learning architectures, and real-time stress mapping systems.

Year-wise Research Growth Pattern

The evolution of research in crop stress detection demonstrates a clear technological progression:

• 2018–2019: Research primarily focused on NDVI computation and hyperspectral imaging techniques for accurate vegetation health assessment.
• 2020–2021: Increased adoption of Convolutional Neural Networks (CNNs) using RGB and multispectral imagery for plant disease detection and stress classification.
• 2022–2023: Integration of satellite data (e.g., Sentinel-2), IoT-based sensing, UAV imagery, and smartphone-based systems for multi-source data fusion.
• 2024–2025: Emerging focus on Edge AI, federated learning, lightweight deployment models, and time-series prediction for scalable and real-time agricultural monitoring.

This chronological progression highlights a shift from purely sensor-based remote sensing approaches toward intelligent, distributed, and deployment-oriented AI systems.

2.1 RGB Imaging as a Substitute for Multispectral Systems

The traditional methods of multispectral and hyperspectral sensing have been used to detect crop stress with precision based on NDVI. They are spectrally precise, but are expensive, need calibration skills and are too costly to be accessible to most smallholder farmers[6],[7]. Studies (2018-2025) show that machine learning with RGB images obtained using UAVs or smartphones has the potential to identify drought, nutrient deficiency, and disease with 90-95% [1],[11]. RGB based vegetation indices and CNN extracted features are also useful in stress classification and trend analysis, and hence RGB imaging is a practical option as a cost effective method [2],[15],[17],[18].

2.2 Deep Learning Performance and Deployment Reality

Another type of CNNs such as ResNet, EfficientNet, and YOLO variations are above 92 percent accurate on benchmark datasets [5],[6],[13],[14],[20]. The majority of models are, however, trained in controlled environments and need the infrastructure of GPUs, not available in low-resource environments. This is partially the case with recent lightweight edge-deployment architectures, however, generalisation to different crops, geographic location and agricultural procedures is still an unsolved problem.

2.3 Research Gaps: Accessibility, Transparency, Context

Three persistent limitations are identified:
• Accessibility Gap: Expensive hardware and cloud costs are barriers in low-resource environments [1],[6],[7].
• Transparency Gap: Deep learning black boxes limit interpretability critical for farmer trust [13],[14].
• Context Gap: Image-only systems rarely incorporate crop growth stage, weather, or agronomic reasoning [10],[19].

Integration of these capabilities into farmer-centric, context-aware, interpretable decision support remains largely unaddressed—directly motivating this work.

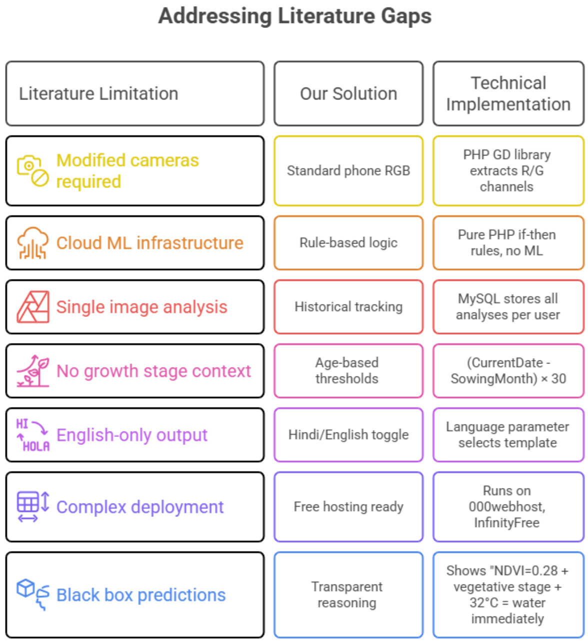

Fig. 5. Mapping of proposed work to identified literature gaps.

2.4 Research Gap

Despite the major progress that has been achieved in remote sensing and artificial intelligence in crop stress detection, there are still numerous critical areas between the technology and its application to agriculture.

To begin with, the majority of the current crop stress detectors are based on multispectral or hyperspectral imaging, on the use of UAV platforms and satellite remote sensing. Although these systems offer accurate spectral and stable vegetation indices e.g. NDVI and NDRE, they involve costly hardware, calibration skills and stable infrastructure. This poses a disparity in accessibility, especially to the small and medium-scale farmers in areas where the resources are limited as they are not able to afford these technologies.

Second, the recent trends in research focus on deep learning models like CNNs, Vision Transformers, and those based on hybrid architectures significantly to classify stress and disease. In spite of the fact that these models tend to be very accurate (over 90 percent) in controlled experimental settings, they have a number of limitations to practice: Relying on big labelled data. The

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computational intensity (training on GPUs) is high. Lessened the generalization in varied and geographical and environmental circumstances that influence the crop. Poor and lack of interpretability by black-box decision-making. This creates a transparency gap or a situation where farmers are given predictions that they do not have a clue as to how they arrived at them.

Third, a significant proportion of the image-based crop monitoring systems pay too much attention to visual representation and minimal attention to the contextual aspects of agriculture, including crop type, the time of sowing, developmental phase, and the current weather conditions. Symptoms of stress tend to change with stage of growth and environmental analysis, but the majority of known models view detection as an independent image classification problem. This poses a context integration gap to existing literature.

Fourth, although a number of studies have investigated crop monitoring using the RGB color, the majority of them attempt to optimize classification instead of creating low-cost, lightweight, and deployment-friendly networks. Very few studies revolve around web-based systems that bring together image processing, contextual processing, and clear rule-based decision supports under one available system. Thus, the major gap in research is as follows: The absence of a free, interpretable, context-sensitive, and web-deployable crop stress detection backbone, which utilizes standard RGB images and does not need multispectral cameras or computationally expensive deep learning models and systems. The study will fill these gaps by offering a lightweight-based RGB vegetation stress and estimation methods combined with growth stage modelling, weather conscious contextual decision-making and enhanced and transparent rule based expert system tailored to the practical agricultural setting.

2.5 Problem Statement

Pest and disease, loss of nutrients, crop diseases, drought, temperature and soil degradation are some of the factors that result in crop stress and thus agricultural productivity largely depends on the timely identification and control of these factors. Wheat, maize and rice crops are the ones that are quite sensitive to changes in the environment and such slight stress at the initial stages of growth can greatly decrease the yield and quality. Nevertheless, the initial stress signs are usually very difficult to detect because they cannot be determined with the naked eye by farmers.

The current approaches to crop stress detection are mostly based on multispectral sensors, hyperspectral imaging, UAV based system, or satellite remote sensing technology. Despite a high spectral resolution and quality vegetation indices (e.g., NDVI) they offer, these methods demand specific hardware, technical skills, a reliable internet connection and require substantial investment of funds.

These requirements restrict their availability and reasonable implementation among small and medium-scale farmers particularly in resource-constrained areas. In contrast, deep learning systems trained on RGB images with AI potential classification performance are usually black-box models. Large datasets with labels, high computing capabilities and they might not have the contextual knowledge about the growth stages of crops and the environment.

Moreover, the solutions that are available are usually centered on the accuracy of classification rather than on usability, affordability, and interpretability to be used in the field of agriculture. Thus, there is a severe necessity in a lightweight, inexpensive, and explainable crop stress detection architecture that: Takes common and affordable RGB smartphone pictures. No need to have costly multispectral sensors or drones. Combines situational farming information like crop type, time of planting and weather. Gives clear, superior, quicker and practical advice. Can be implemented as an easy web-based application that can be accessed by farmers. The general issue considered in this study is: Is it possible to obtain viable and trustworthy early-stage crop stress data by use of simple RGB images together with surrounding agricultural logic devoid of relying on costly sensitizing apparatus and complicated deep learning, large-scale structures? This study will be an attempt to develop and test out a viable low-cost, low-cost, and interpretable crop stress monitoring system that would suit wheat, maize, and rice production under resource-constrained agricultural settings.

2.6 Objectives of the Study

The primary objective of this research is to design and develop a lightweight, affordable, and interpretable crop stress detection framework using conventional RGB images and contextual agricultural knowledge. The specific objectives are as follows:

a. To develop an RGB-based vegetation analysis mechanism

To design an image processing method that extracts red and green pixel values from standard smartphone images and computes an approximate vegetation index for assessing crop health without requiring near-infrared sensors.

b. To implement an approximate NDVI-based stress estimation model

To formulate and validate an RGB-based NDVI approximation formula capable of identifying relative variations in vegetation health for wheat, maize, and rice crops.

c. To integrate crop-specific growth stage estimation

To develop a rule-based mechanism that determines crop growth stages (germination, vegetative, flowering, ripening) based on crop type and sowing month for context-aware stress interpretation.

d. To incorporate real-time and location, weather contextualization

To integrate external weather data (temperature, humidity) to improve interpretation of stress

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conditions, nativity of crop and reduce false-positive classifications.

e. To design a transparent rule-based expert decision system

To build an interpretable classification engine that categorizes stress levels (Normal, Moderate, High) and provides understandable reasoning and actionable recommendations instead of black-box predictions.

III. METHODOLOGY

3.1 System Design Overview

The offered framework is a web-based, lightweight crop stress detector with an ability to work only with unfiltered RGB images captured on a smartphone. The system should be able to operate without multispectral sensors, specialised equipment, commercial software or high technical skills. It combines four modules namely (i) RGB-based vegetation analysis, (ii) crop growth stage estimation, (iii) weather-sensitive contextual analysis, and (iv) an expert rule-based decision engine.

This is because the modular structure allows individual components to be maintained separately. The solution uses a normal client-server model that is available through any current web browser.

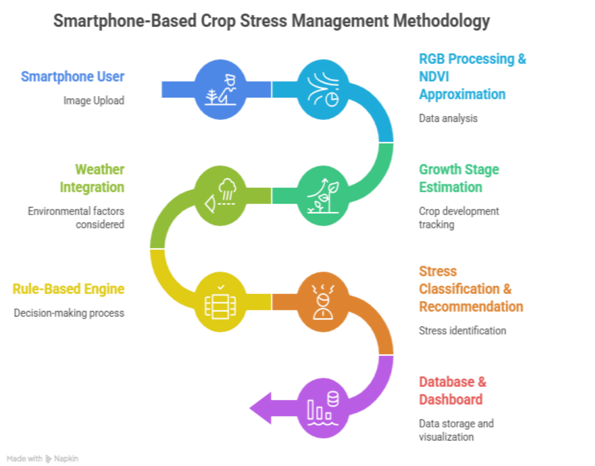

Fig. 6. Working of the proposed crop stress detection system.

3.2 RGB-Based Vegetation Stress Estimation

The smartphone cameras are not capable of recording NIR, and hence, the vegetation health is estimated through channels of the visible spectrum. The red and green pixel values are removed and a normalised ratio of vegetation is calculated:

$$NDVI\_approx = (Green - Red) / (Green + Red)$$

During active photosynthesis, green is reflected and red is absorbed by the healthy vegetation. Chlorophyll degradation under the influence of stress decreases green reflectance and raises red. The systematic pixel sampling reduces the effects of lighting variations and background distortion and creates a small variation of relative stress indicators over time and space as a result of screening and time/space changes.

3.3 Context-Aware Growth Stage and Weather Integration

The interpretation of vegetation stress is based on a biological and environmental context. The model involves two processes:

Growth Stage Estimation

The stage of growth is calculated relative to the month of sowing and type of crop by using conventional phenologic development models. The crops (wheat, maize, rice) are mapped to: Germination, Vegetative Growth, Heading/Flowering and Ripening. Stress thresholds are dynamically set on a case-by-case basis, to ensure that natural processes (i.e. chlorophyll reduction during grain filling) cause false alarms.

Weather Integration

Public meteorological APIs are used to get real-time temperature and humidity levels by using geographic co-ordinates. This classification is narrowed by these signals: low NDVI + high temperature + low humidity - water stress; low NDVI + high humidity - fungal susceptibility.

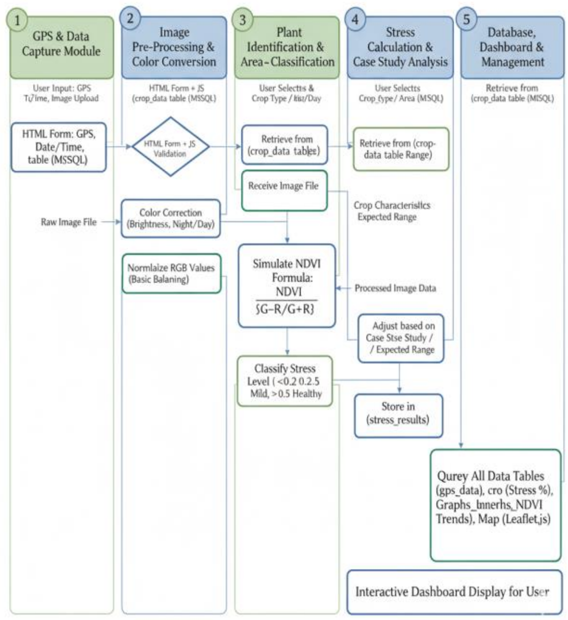

Fig. 7. Complete flowchart of system processing and decision

3.4 Expert Rule-Based Decision Engine

Its main logical element is a transparent and rule-based expert system based on the agricultural domain knowledge. Stress conditions are explicitly defined by structured, if-then rules which can be reviewed by experts and changed. The rules assess crop type, growth stage, NDVI range, and weather conditions, and provide the level of stress severity (Normal, Moderate or High), the likely cause and an actionable recommendation is generated. Its products are distributed in English and Hindi to achieve maximum access.

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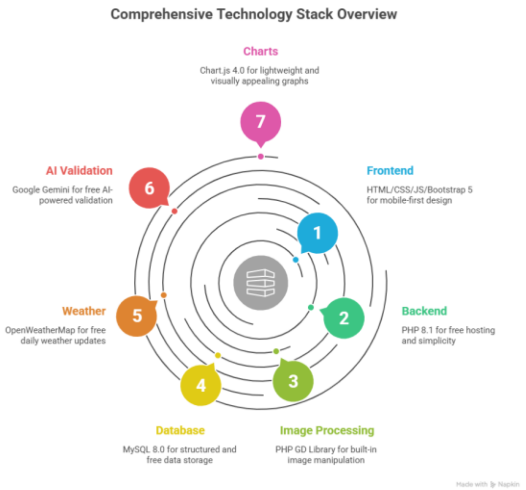

Fig. 8. Technology stack summary of the proposed system.

IV. RESULTS

Real-world plant images with smartphone and digital cameras in different lighting and background were used in the evaluation of the system [2],[15],[18]. All the images were effectively processed, giving NDVI estimates, growth stage estimates, stress categorisms and advisory outputs with low response times. Key observations:

• Constant NDVI Trends: The values were always higher when it was a green canopy and lower when it was a yellowing or bare soil; the differences between the healthy and stressed crops were constant between repeated measurements. Proper Processing: Pixel sampling allowed analysis of images in a few seconds on the regular web server.

• Stress Classification: Logical classification according to visual evaluation; healthy plants were classified in the category of Normal, weakened plant was in the category of Moderate or High stress.

• Mapping of logical Growth Stage: Logical agronomically plausible assignments were generated, with the accurate contextualisation of stress interpretations, and no false positives with natural senescence.

• Trend Monitoring: Long-term saving and dashboard visualization of slowly degrading NDVI patterns before the emergence of symptoms, the central early warning facility of interest.

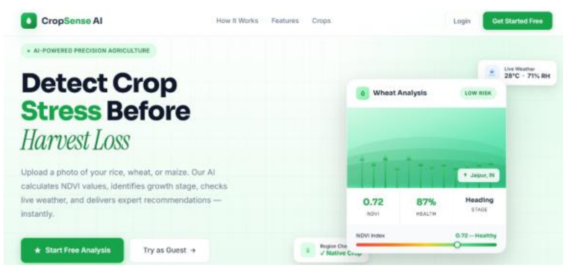

Fig. 9. System index/dashboard page.

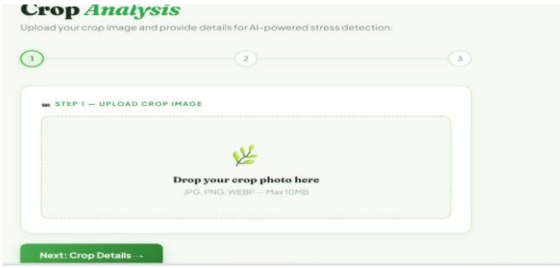

Fig. 10. Input page: crop type, sowing month, and weather access.

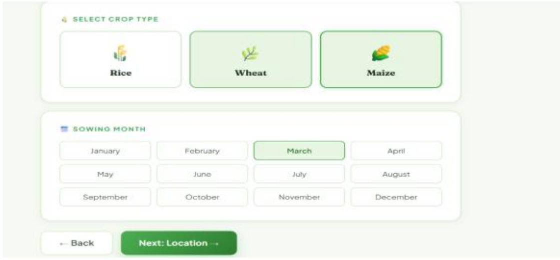

Fig. 11. Results page showing stress level and NDVI normalcy value.

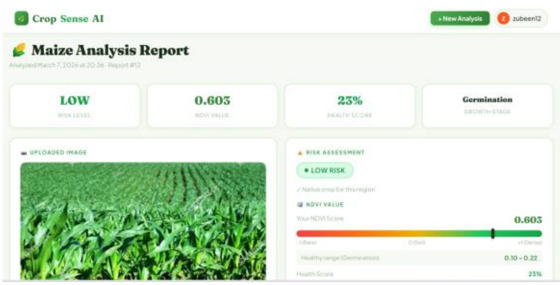

Fig. 12. Historical dashboard showing past monitoring records.

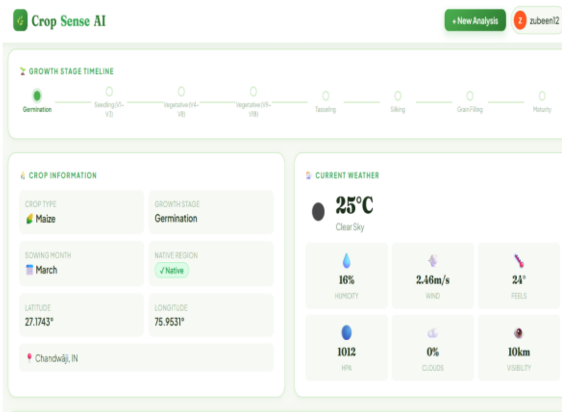

Fig. 13. Stress levels compared across monitored crop types.

Fig. 14. NDVI time-series trend for a single crop with improving stress trajectory.

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V. DISCUSSIONS

The experimental findings prove that a light application of a web-based application with composite capability of traditional RGB imaging and clear rule-based reasoning can offer practically valuable crop health data. It was observed that the RGB-channel NDVI approximation had a consistent relationship with visible vegetation state with dense green images scoring high whereas yellowing, necrosis, or bare soil scoring low as expected by the recent literature [1], [11].

Stress classification according to threshold was found to be practically working and virtually comparable to the visual evaluation by experts. Although the lack of spectral accuracy of sensors of laboratory quality, the structure can be trusted to act as a screening and early-warning instrument [13], [14], [20].

The basic growth stage mapping simplifies the complexity of the system and yields contextual information at significant cost- reduced settings of low data and connectivity- contextually sensitive but simple direction is much more useful than complex and understandable modelling.

Dashboard visualisation allows the user to differentiate temporary fluctuations and the real declining trends, which can assist in making preventive management decisions. The known disadvantages are that the RGB index is sensitive to changes in lighting, shadows and camera quality, the system can best be described as a relative screening tool, not a precise diagnostic tool.

Future directions are: calibrated imaging pipelines; an embedding of low cost multispectral sensor modules; machine learning classifiers on annotated field datasets; dynamic phenological models with real time growing degree days; predictive analytics using historical accrued records.

VI. CONCLUSION

This paper has shown that simple, web-based architecture that is anchored on traditional RGB images can in effect serve to monitor meaningful crop stress in real-time without expensive multispectral sensors and other sophisticated equipment. The platform is capable of providing interpretable and actionable crop health data at a low cost by combining RGB-based vegetation analysis, rough-NDVI computation, growth stage prediction, weather-sensitive contextual reasoning, and a rule-based expert system that is transparent and easy to understand [11].

One can use any smartphone to take photos of crop plants, give minimal metadata, and get contextually informed stress measurements within seconds. The dashboard allows us to monitor the trends and patterns of NDVI across time, and this helps us to convert single observations into meaningful, temporal intelligence [1].

Even though vegetation index approximates RGB-channel, experimental observations prove that it is a sure method of distinguishing between healthy and stressed vegetation in various imaging conditions. Although it does not yet offer the spectral accuracy of NIR-based NDVI, the system does successfully offer relative health changes and trend patterns, which is suitable as a screening platform at the early-stage where advanced sensing is too expensive or logistically impractical [6].

This piece highlights a larger idea usability and access can prove to be as effective as technical expertise. An acceptable-quality, inexpensive, and comprehensible instrument can have a wider spread and more aggregate effect than a superior, in practice, but technically out of reach version [12].

The suggested system attests to the fact that critical crop stress detection and advisory systems can be successfully implemented with low cost, image-based, web-accessible solutions- leading to more unvigilant and responsive agricultural systems.

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