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Design and Development of an Image Based Crop Water Stress Detection and Advisory System

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Abstract: *Improvement of crop water stress in agriculture is required to satisfy the requirement for rising global food production with limited water re-sources. Remote sensing of plant stress indicators has the advantages of high spatial resolutions, low cost and rapid turnaround time. This article highlights recent advances in agricultural water stress monitoring, irrigation scheduling, some of the problems encountered and future research requirements. Remote sensing systems are ready to efficiently and swiftly solve the complex and technical assessment of agricultural production, security, and crop water stress. In this paper we review the use of remote sensing systems for assessment of agricultural water stress, via an assessment of the literature, technology and data. The study looked at the relationship between relative water content (RWC), equivalent water thickness (EWT) and agricultural water stress. Remote sensing of evapotranspiration and sun-induced chlorophyll content in relation to agricultural dryness. Spectral indices, remote sensing satellites and multi-spectral sensing systems and land surface temperature measuring devices are discussed. This essential research looks at the latest approaches for monitoring agricultural water stress Agriculture is vital for maintaining human existence, but conventional farming practices face growing challenges from climate change, resource constraint, and unpredictable weather patterns. The increasing need for food and sustainable farming methods requires creative solutions that integrate technology and real-time decision-making. The combination of Artificial Intelligence (AI) and Internet of Things (IOT) in agriculture, known as Smart Agriculture, allows farmers to make data-driven decisions, providing potential progress.*

Keywords: RWC, IoT, AI, EWT, Food

I. INTRODUCTION

The project proposes an AI and IOT based Crop Advisor system that provides farmers with intelligent crop selection and cultivation advice based on real-time environmental variables. IOT sensors are used to monitor soil characteristics including moisture, pH, temperature and humidity which are important for plant growth. The acquired data is then evaluated using machine learning algorithms to select the best suited crops for a particular area or season, thus increasing agricultural output and resource efficiency. To make this system user friendly and accessible, especially for remote regions, conversational chatbot interface is implemented. Farmers may use it to ask the system questions and receive customized farming advise in plain English, without needing to be very technical [1]-[5]. The system combines sensor-based monitoring, AI-based predictions, and chatbot communication, providing a holistic solution to modernize agriculture, enhance production, and assist in decision-making in agricultural communities. the survey explores the use of deep learning technologies in smart agriculture, considering data processing and decision-making improvement the critical review addresses the integration of machine learning, remote sensing and IOT for crop yield prediction, discussing the capacity of the technologies to improve agricultural productivity [6]-[10]. I implemented an AI-based crop recommendation system based on environmental factors to improve precision agriculture. Proposed a Maharashtra-specific system for recommending crops and predicting yields using advanced machine learning methods.

Implemented machine learning algorithms such as CatBoost with feature selection and SMOTE for data balance. Implemented Long Short-Term Memory (LSTM) networks using a unique expectation-maximization algorithm [11]-[15].

II. PROPOSED SYSTEM

The integration of AI and IOT in agriculture offers a transformative approach to sustainable farming by enabling real-time monitoring and intelligent decision-making. Through the deployment of IOT sensors, key soil parameters such as moisture, pH, and nutrient concentrations tracked continuously, while AI-driven models provide accurate crop recommendations and management strategies.. The proposed system, with 92% prediction accuracy and a chatbot response time under 1.5 seconds, demonstrates its effectiveness in bridging the gap between advanced agricultural technology and farmer accessibility. By combining IOT sensing, AI-based analysis, and natural language interfaces, this system empowers farmers with personalized, timely, and practical guidance, ultimately improving crop yield, reducing resource wastage, and fostering a more sustainable and inclusive agricultural ecosystem is shown in Figure 1.

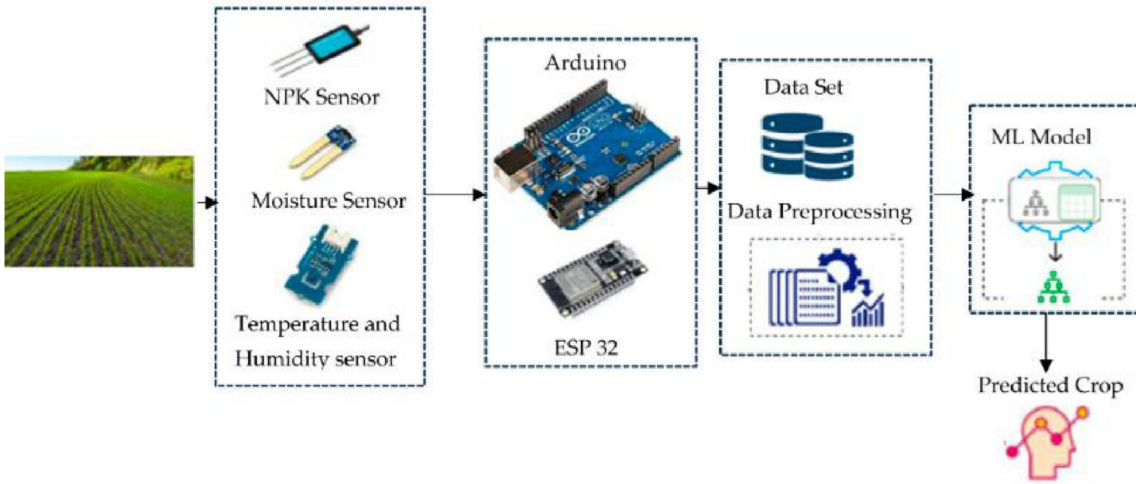

Figure.1.Block Diagram of the Proposed System

Precision irrigation scheduling requires the assessment of crop water stress, one of the elements that characterize how a crop interacts with its environment. The CWS came to be recognized as a common indicator for evaluating stress on the leaf and canopy scales. This was a better way to analyze water stress at plot and regional scales, including evapotranspiration, on a greater scale. Implementing effective irrigation scheduling tech-niques is crucial for increasing water savings and improving agricultural sustainability. Remote sensing data can reveal information on the geographical and temporal varia-tions of crops. Precision agriculture uses spectral reflectance indices from high-res-olution hyperspectral sensors on small, unmanned aircraft systems to monitor crop water status and plan irrigation. The assessment of crop water deficit using remote sensing devices was the subject of this review. The paper supplies an overview of the many remote sensing systems that can be used to find crop water stress. Optical, thermometric, land-surface temperature, multi-spectral (spaceborne and airborne), hyperspectral, and LiDAR sensing systems are exam-ined. A consensus about the use of vegetation indices (VIs) as a pre-visual indicator of water stress has not yet been reached, due to several confounding factors affecting VIs at the canopy & landscape scales. This research discusses current developments in crop wa-ter stress monitoring that may be applied to enhance vegetable crop irrigation scheduling and looks to figure out the most promising method for widespread implementation. To forecast production conditions and schedule irrigation, crop water stress needs to be de-tected during various growth seasons. It has been researched how to distinguish agricul-tural water stress using several methodologies. These techniques rely on remote sensing, measurements of soil water content, and plant responses. The study also considers the fact that different

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approaches are effectively used for different crops. Traditional methods, like measuring soil moisture, have drawbacks in terms of sensor costs, installations, and difficulty obtaining estimates. Plant-based estimates are more dependable and accurate. There are significant relationships between PRI and NDVI and attributes like LWP, stomatal conductance, crop efficiency, and stem water potential. Crop water stress evaluation is a technical and intricate process in and of itself. Our study sug-gests new techniques that bring together farmers, researchers, and tech developers. Nar-row-band optical indices could be used to plan irrigation for high-value vegetable crops in water-stressed countries. Conventional irrigation scheduling methods use measure-ments of soil moisture, weather, and physiological assessments of plant response. The method is ineffective because it is difficult to get measurements, especially for varied soil and crop canopies. Narrow-band optical indices could be used to plan irrigation for high-value vegetable crops in water-stressed countries. In context of climate change and its effects on plant physiology, maximising water use efficiency (WUE) is essential for better crop production. Among the different resources, irrigation water is recognised as a basic and necessary resource for agriculture which plays important role in food security. Insufficient irrigation water cause crop water stress at different stages of crop development. Specifically, water stress at reproductive stage of crop is very much critical. Only 20% of the world's arable land is used for irrigated agriculture, which supplies 40% of the world's food supply. Due to water scarcity, irrigation is difficult to implement in many countries. Future food and water supplies are also jeopardised as a result of growing drought situations in a major part of the world and rapid population growth. Climate change, frequent droughts, rising global water scarcity and devastating flooding pose concerns to agricultural water supply security. Plants under water stress close their stomata to conserve water, which restricts the pathway for the exchange of oxygen and carbon dioxide thus reducing overall photosynthetic potential. Reduced photosynthesis is caused mostly by a loss in leaf area as well as a decrease in PSII activity. Thus, assessment of crop water stress is important. Precision irrigation techniques are based on accurately detecting water stress in crops and understanding crop water stress. Using conventional ground-based sample techniques to measure crop water status is extremely challenging since it is a time-consuming, laborious process that is not feasible for agriculture on a larger scale. Along with it is also destructive for plants. Similarly, different evapotranspiration models assume that the reference crop in a field is a freely transpiring plant with homogeneous soil type and cover. These procedures are time-consuming and produce point data that is not representative of the state of the field as a whole.

Effective scheduling of irrigation is essential for enhancing water use efficiency as well as agricultural sustainability. Recent research has focused on the use of precision technology as an alternative to traditional field measurements of plant stress indicators since it provides information on spatial and temporal variability. Thus, in light of climate change these precision technologies such as wireless sensor networks, unmanned aircraft, remote sensing, machine learning & deep learning play a crucial role in development of sustainable goals. Spectral reflectance indices from high resolution sensors now been popular in recent years because they enable non-invasive and fast monitoring of plant water stress dynamics. This paper explored the current developments in crop water stress monitoring by precision

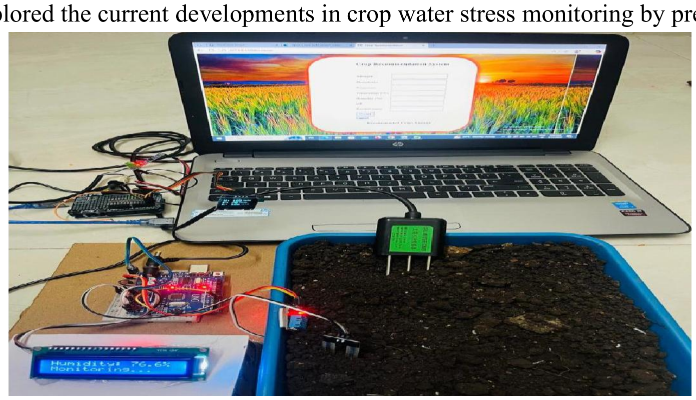

Figure.2. Hardware Model of the Proposed System

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Dense time series of multi-spectral S2 data are the input needed for both the crop type classification and water stress and water-use-efficiency calculations. Especially for the deep learning model, highest quality atmospheric corrections, including high accuracy cloud and cloud shadow masking as well as cirrus correction are necessary. This is offered by VISTA's image processing chains (VIAs), which are implemented as processors on the Food Security TEP. Starting from S2 Level 1b data, they comprise sophisticated methods on all necessary pre-processing steps (atmospheric correction incl. cirrus correction, cloud and cloud shadow masking, land cover classification for snow, water, vegetation, open soils) as well as a crop-type independent derivation of plant physiological parameters, so that time series of high-quality atmospherically corrected multispectral S2 data can be delivered for the deep learning from the Food Security TEP. Finally, the atmospherically corrected images are preprocessed to generate a Time Series (TS) of 12 monthly composites per tile. Hence, TS acquired over different tiles are made up of images acquired on different dates and have different lengths (different temporal sampling). Moreover, they are noisy due to the presence of clouds at irregular intervals. To achieve accurate and consistent crop type mapping at large-scale, we consider a pixel composite approach that collapses the optical images acquired within each month down to a single image.

III. CONCLUSION

Using both short term and mid-season weather forecasts, also predictive analyses of water stress can be calculated. In combination with water availability calculations (integrating the hydrological cycle of the catchments) the water demand calculations will lead to being able to give irrigation policy advice, suitable on local to regional level. EO derived crop information has proven its potential to support and improve crop and water related challenges in future farming and food security management. This is done by a statistic-based approach that computes the median value for each pixel, thus providing a harmonized TS from the temporal and radiometric view point across tiles. To successfully train a deep learning model, very large training datasets are required. From the operational viewpoint this goal is not trivial, since the collection of field data or manually annotated samples is demanding at large scale. To solve this problem, we consider the publicly available 2018 Austrian crop type map, which is based on farmer's declarations collected by surveys within the subsidy application process in the context of the Common Agricultural Policy. An automatic Machine Learning (ML)-based procedure has been defined to identify pure spectral pixels having the highest probability to be correctly associated to their labels in an automatic and unsupervised way. The obtained dataset is made up of more than 1 million of labelled units and presents a detailed classification scheme of 16 crop categories. A stratified random sampling strategy is applied to select labelled units per crop type proportional to the number of fields present in the study area. Please note that while the 2018 Austrian crop type map can be used to perform experiments at country scale for one specific year, the deep learning model trained with the extracted training set can be used to classify a study area larger than the Austrian country and for multiple years.

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