Optimized crop management using AI and deep learning based approaches.

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Abstract

Farmers have the opportunity to make their dreams of up to 4-5 times more farm output per acre a reality by incorporating and utilizing upcoming smart technologies in farming methods, maximizing the potential of each acre. It is an impressive figure by all accounts. Today, more than ever, technology is enabling farmers to make significant progress, greatly enhancing their quality of life. Seen through the eyes of a farmer, it is a significant miracle occurring on their modest farm land. Using IoT-based sensors and devices, farmers can monitor and regulate environmental parameters like soil moisture, humidity, and temperature, resulting in more accurate and productive agricultural methods. In order to evaluate data and improve farming techniques, IoT-based rooftop farming models can include AI and machine learning algorithms. We may anticipate the development of even more sophisticated algorithms in the future, which will enable farming to become more productive and efficient.

Keywords-Smart farming,IOT,AI,Machine learning.

Introduction

PF(Precise farming) integrates various technologies instead of adopting a singular strategy, enabling the effective management of resources and the achievement of economic benefits through site-specific management (SSM). Grasping and enhancing comprehension of the natural fluctuations present on a farm are crucial elements of PF.

Precision agriculture has become a game-changing technique that is transforming conventional farming methods. The Internet of Things (IoT) and artificial intelligence (AI) are two modern technologies that are seamlessly integrated and at the center of this transformation.

The convergence of artificial intelligence (AI) and the Internet of Things (IoT) has made precision agriculture possible, ushering in a new era of farming.

Amidst increasingly complex circumstances such as population growth, unpredictable weather patterns, and limited resources, precision agriculture presents itself as a tactical advantage. The convergence of IoT and AI is essential for handling these challenging scenarios, offering a flexible framework that maximizes practical resource management and improves fundamental farm productivity.

The emergence of IoT in agriculture has led to an abundance of sensor technologies that collect data on crop energy, weather, and soil fitness. These sensors, which may be anything from sophisticated drones to soil moisture detectors, form a dynamic and interconnected network that gives farmers a comprehensive perspective of their fields. AI algorithms, meanwhile, are essential in transforming these data into insights that can be put to use. AI provides a degree of sophistication and performance to agriculture that was previously unattainable, from the development of choice assistance systems to predictive modeling for crop production estimation.

Literature support

Machine learning and data analytics enables us to extract the most significant insights from the extensive data gathered from the agricultural fields. It exposes the latent patterns, concealed connections between the factors influencing horticulture such as humidity, temperature, and soil salinity, etc. The majority of utilized and associated machine learning methods for crop forecasting When weather data is analyzed, diseases and pests are artificial SVM, Logistic, and Neural Network (ANN) regression neural network-based recognition technology, Support Vector fuzzy technology for recognition (SVM) (Singh and Gupta, 2016).

Predictive modeling and prescriptive recommendations are made possible by the smooth integration of AI algorithms with IoT-generated records, enabling enhanced analytics (López et al., 2017; Tanwar et al., 2020). This cooperation is essential to building a comprehensive and intelligent farming ecology.performance in agriculture that was previously unattainable.

The implementation of precision farming technology includes significant upfront costs, such as purchasing IoT devices, AI systems, and necessary infrastructure. Farmers might be reluctant to invest without a good understanding of the long-term economic advantages and a realistic ROI timeline (Barbieri et al., 2021).

In Oberti et al. (2016) various approaches like automatic chemigation and vehicle spray, those are mainly used under precision agriculture to treat diseases of crop.

Hamad et al. (2018) stressed the value of smart phones for learning agronomic facts about various elements, such as temperature, humidity, and soil moisture. The advantages of smartphones for agriculture are discussed in the same article. In order to find out what the roughly 230 farmers, the authors surveyed them using questionnaires and interviews. The author conclude that farmers are interested in using smartphones to obtain information on current farm data after completing the process.

In Ayaz et al. (2019) precision agriculture has been discussed broadly. They gave the detailed overview of how IoT is playing a role in precision agriculture by making the fields talk. With the help of IoT they gave the idea how to increase the agricultural yield to meet the needs of the bulky population by using the limited available arable land for cultivation, fresh water for irrigation etc. by giving the precise and required quantities of fertilizers, insecticides, water, etc.

Using the integration of WSN, cloud, and IoT, Foughali et al. (2018) develop a unique decision support system (DSS) for the prevention of late blight. The concept worked well in preventing the illness known as potato late blight. DSS was able to calculate the exact amount of fungicide that needed to be used. In addition, weather-related IoT sensors were installed to gather data in real time, which was subsequently sent to a cloud-based IoT framework for analysis. For the purpose of predicting late blight, the forecast model used historical data with weather-related information from weather stations. For the farmers, the technique proved very cost-effective and efficient.

A method for classifying apple illnesses using machine learning classification algorithms was presented by Singh and Gupta (2018). The two illnesses that they categorize as utilizing the apple tree's leaf photos as input, apple scab and marsonina coronaria were identified. On the same set of data, the classification techniques Naïve Bayes, K Nearest Neighbor, Support Vector Machine, and Decision Tree were applied. The suggested system's simulation was conducted using Matlab 2016. They demonstrated that the K nearset neighbor has a 99.4% accuracy rate in classifying the disorders. The system was created in Uttarkhand's Himachal Pradesh state.

The crop water stress index (CWSI), which was created in (Zhang et al., 2018; Irrigation & water utilization, 2020) based on IoT, can be utilized to boost the efficiency of harvest. The necessary sensors are deployed in the necessary fields in the CWSI system, and data is collected and sent to the central processor. We also gather information from weather stations and satellite photos at the central node, and we use this information to determine whether or not to irrigate the area.

In summary, we can claim that by implementing new technology, we can keep crops at the necessary moisture content, which will preserve freshwater resources.

Kim et al.(2018) and Venkatesan et al. (2018), work highlighted techniuqes to halt misuse of these insecticides. Current IoT-driven pest control using real-time environmental monitoring, it offers illness predictions, modeling, etc., leading to more efficient outcomes.

Device capture attacks are most common target for IoT system as mentioned in the work of varga et al.2017;Newel et al.,2014,Denial of service attacks mostly tagert higher layers as mentioned by Elijah et al.,2018.

In Geetha (2015), the authors predicted the occurrence of late blight disease in potatoes using IoT technology and machine learning approaches. Temperature and humidity levels were recorded, among other environmental factors.By the employment of sensor devices placed across the agricultural fields and sending data to the central gateway. The information gathered aids in determining the severity and danger of blight. With a 94% accuracy rate, the authors of Geetha (2015) concentrated on a moderately vulnerable potato crop and deployed a back-propagation network.

In Xia et al. (2011) environment monitoring system has been designed and deployed for precision agriculture using WSN. The system was tested in a red bayberry greenhouse situated on a hillside by collecting the following parameters; temperature, voltage, humidity etc. The system proved to be scalable, stable, and accurate and can provide real time data for precision agriculture. Data Analytics and Machine Learning techniques are playing an important role in the agrarian sector in order to handle the increasing challenges due to the weather and climatic changes like temperature, rain, humidity etc which are causing serious damage in crop production.

The key to successful precision agriculture lies in farmers' ability to identify and effectively utilize advanced technologies. The digital gap in rural regions, combined with the necessity for educational tools, presents a challenge in ensuring that farmers can utilize their resources effectively.

Methodology

Precision agriculture's Internet of Things component includes a variety of sensor technologies for data collection, from drones to weather stations and soil moisture monitors. By enabling real-time monitoring of crop health and environmental factors, these gadgets build an ecosystem rich in data. The massive amount of agricultural data is processed and stored using cloud-based platforms, and wi-fi communication protocols ensure smooth connectivity between several devices. In India the production of wheat about 341.57 lakh ha area coverage during 2024 has been reported compared to 339.20 lakh ha during the corresponding period of last year 2023. Thus 2.37 lakh ha more area has been covered compared to last year during the corresponding period.

Precision agriculture model composed of three elements as a part of the architecture

1. IOT nodes to monitor condition of the plant
2. Collection of precise data and store in the nearest node for further forward to cloud database.
3. The status of the crop field identification with the support of analytics.

PA can be achieved by recording data at the appropriate scale and frequency, interpreting and analyzing it properly, and finally producing operational management decisions for implementation at scale and right time.

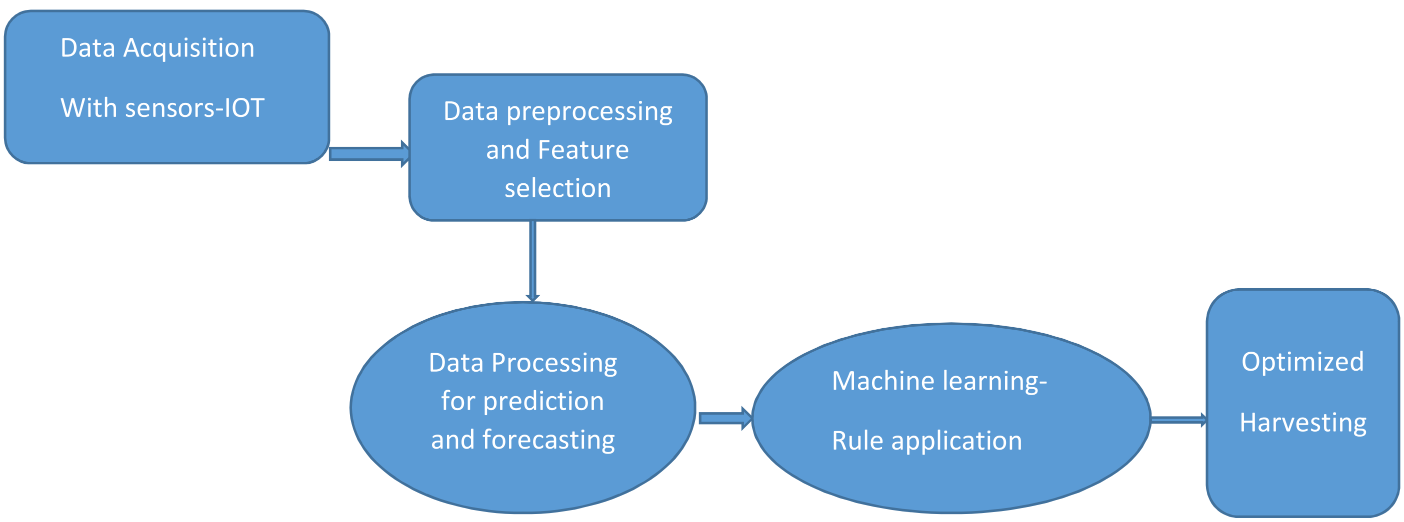

Figure 1.Machine learning based Precision Agriculture Model

Wheat stripe rust disease, or WRD, poses a serious threat to the health of wheat crops and has a significant negative impact on crop yield, raising the possibility of food insecurity. The amount of damage to wheat fields and the spread of the disease are inspected manually by skilled workers. However, due to the vast expanse of wheat plantations, this is very laborious, time-consuming, and inefficient. Deep learning (DL) and artificial intelligence (AI) provide precise and effective answers to these kinds of real-world issues. Artificial intelligence (AI) algorithms can detect patterns in vast amounts of data that are hard for humans to notice, which makes early disease detection and prevention possible. Deep learning models, however, rely heavily on data, and one of the biggest challenges in creating models is the dearth of information about particular crop diseases.

A segmentation dataset specific to wheat stripe rust disease was created by gathering, preprocessing, and manually annotating multi leaf images from wheat fields with complex backgrounds and varying lighting conditions. The literature has found solutions for the problem of classifying wheat leaf disease (WRD) into various types and categories. However, the task of semantic segmentation of wheat crops to identify the individual plant and leaf areas affected by the disease is still unresolved. Because of this, our goal in this work is to estimate the extent of disease spread in wheat fields using semantic segmentation of WRD.

One openly accessible classification dataset is the Kaggle research dataset. There is only one leaf per image in this dataset, which presents data in close view. The Kaggle Wheat Leaf Dataset is a classification dataset for wheat diseases that includes images categorized as "healthy," "leaf rust," "powdery mildew," or "scab." There are several leaves in each image in the CGIAR crop disease dataset, which is a WRD dataset. But this classification dataset divides diseased wheat leaves into two categories: stem rust and leaf rust.

The controlled and diseased rust leaf images for classification into healthy and diseased images are included in the wheat nitrogen deficiency and leaf rust dataset. The study's wheat crop disease dataset is an unprecedented multi leaf, publicly-available segmentation dataset of wheat rust disease, gathered from crop fields in Islamabad, Pakistan. A single wheat crop season, which began in November 2021 and ended in May 2022, was used to gather the data. When rust-friendly conditions are met, the illness begins to appear in February and spreads throughout March and April. The data were progressively obtained during this season in the morning and afternoon.

It is a real-world dataset made up of excellent, high-resolution pictures of rust disease. It was taken in a natural setting with the weather and field conditions that accurately depict the difficult and real-world aspects of the diseased crop fields.It is a heavily annotated dataset that shows different rust disease stages (in terms of the disease's spread). Multiple diseased rust leaves can be found in a single image in the dataset's densely annotated images.

Using the same set of data, we applied machine learning to forecast the condition and need for early illness treatment using a straightforward linear regression model. After analyzing the collected data, It is discovered that the prediction model fit the data. Three variables applied in the linear regression prediction model. The variables T, W, and I stand for temperature, leaf wetness duration, and pathogen incubation period, respectively. After analyzing the data that was gathered, identification of a prediction model that fit the data is done. As such, model consists of three variables. The initial factors are the temperature (T), followed by the length of wetness (W), and the infection-causing pathogen's incubation period (I).

Significant biotic factors of wheat, a major source of carbohydrates for the world, include bacterial pathogens. According to reports, the diseases brought on by these pathogens can cause annual wheat production to drop by 10% to 40%, with severe infections that strike early in the growth period. The symptoms, distribution, identification, and taxonomy of important bacterial pathogens of wheat are covered in this chapter, with special attention to the seed-borne bacterium Xanthomonas translucens pv. undulosa, which is the cause of black chaff and leaf streak diseases.

A single response measurement for each observation in a basic linear regression model is correlated with a single predictor (covariate, regressor) X. The model's fundamental premise is that the conditional mean function is linear, as demonstrated by Eq. 1:

E=aX ----------------(1)

There may be several predictor variables available in the majority of problems. As a result, the "multiple-regression" mean function that follows is displayed in eq(.2):

E-a+b1x1+b2x2+…….(2)

where b represents the slopes or coefficients of the X variables and a is referred to as the intercept. Each coefficient estimates the change in the mean response per unit increase in X, holding the other predictors constant.

Equation (3) displays the equation we discovered:

I= 36:774 - 0:3128T - 0:876W--------(3)

Using a linear regression model reveals that the temperature and wetting period values predict the incubation period.

The inverse relationship between the wetting duration and temperature and the incubation period is indicated by the negative coefficients. Put differently, we can state that there is an increase in the value of I with a decrease in the temperature and wetting period.

Coefficient	Estimated Value	Standard Error	True value
Wetting duration	-0.876W	0.1665	-4.463
Intercept	36.774	9.23	4.043
Average Temperature	-0.3128	0.131	-2.45

The equation 3 is obtained using the above-mentioned linear regression model shows that the temperature value and the wetting period value are predictive of the incubation period. The value of incubation I increases as the values of temperature T and wetting period W decrease.

Conclusion

By integrating AI, precision agriculture can assist farmers in producing higher yields with less input. AI in agriculture merges the optimal practices for soil management, the use of technology that adjusts inputs based on variability, and the best methods for handling data to increase production while reducing costs. Precision agriculture has an extremely bright future. Driven by developing AI algorithms and future technologies, we may expect increasing automation in chores like planting and harvesting, better pest management, and increased accuracy in disease prediction.

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