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Smart Irrigation for Crop Management Using IoT

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ABSTRACT: Agricultural production involves cultivating plants and raising domesticated animals to produce food and feed for humans and other animals. Agriculture or farming as it is also called is a complex activity, and each aspect of it impacts the overall crop production. Farmers need to manage all segments of crop production to achieve success. Farmers make strenuous efforts to produce good quality crops but they face challenging issues of monitoring and maintaining it around the clock. The problems in the agriculture domain largely affect the food production and supply chain. This project includes the proposal of an integrated crop management system to maintain the health of crops by supplying the required amount of water and nutrients to them. One aim is to reduce the amount of water lost to unnecessary evaporation, a concern in the 21st century. As a result, other factors, such as cost, time, and effective care are also benefited. This is why, after the soil preparation and planting are completed, the growth phase of the plant also requires special attention. The paper discusses a process for detecting and solving plant health issues using an intelligent automated system.

KEYWORDS: Plant Disease detection; Machine learning; Automated Irrigation; Raspberry Pi.

1. INTRODUCTION

Agriculture is the main source of income in India. Initially, farming needs human interaction. The yield depends upon the way a farmer takes care of his field. But if the land is far from his residence, it is difficult to monitor. While in case the crops turn out to be diseased farmers to spend more time and money on curing them [1]. For salt-affected soils and saline water to be safely utilized, primarily salt-tolerant crops have to be grown, seedbeds have to be managed, and fields have to be graded.

It is necessary to minimize local concentrations of salt, improve irrigation efficiency, and monitor soil, water, and salinity to gauge drainage and leaching requirements. This has led to the development of autonomous, robotic vehicles, such as those used in mechanical weeding. It is now possible to calculate biomass development and fertilization by using aircraft equipped with a hyperspectral snapshot camera that uses lightweight powerful and autonomous flight control systems. These cameras are being developed to aid in unmanned aerial vehicles' application of fertilizer and harvesting of fruits. A decision-tree model based on optical information allows discerning between plant diseases based on crop status. In addition, today's technology farms reed crop histories to provide sophisticated farm management advice [2]. In addition, decision tree models are now available, allowing farmers to differentiate between crop diseases using visual information. Taken together, these technical improvements represent a technical revolution that will lead to disruptive changes in agricultural practice. This trend has for agriculture not only in developed countries but also in developing countries. At the same time, the demand for food is growing and the supply side faces constraints in terms of land and agricultural inputs [2]. The worworldpulation is on track to reach 9.7 billion by 2050, requiring a corresponding 70% increasing calories available for consumption even as the cost of inputs required to produce those calories increases. By 2030, water supply will be 40% below global water needs,d raising energy, labor, and nutrient cost are already putting pressure on profit margins. About a quarter of farmland is degraded and requires extensive restoration before it is once again suitable for large-scale cultivation. Climate change is irreversible, and agriculture is a highly affected industry. Unexpected weather and sometimes bad weather is a serious problems to be solved [3]. Proper timing of fertilizer application increases yields, reduces nutrient losses, and prevents environmental damage. Bad weather and unpredictable weather can cause fertilizer damage and damage the crop. Information is needed on how to apply fertilizer [4]. Weather forecasts can help farmers determine when and where to use them. Both resources and money can be wasted if fertilizer application is done incorrectly so proper information and forecasting are required. The land is an important resource for agriculture. Soil and chemical conditions play a major role in the production cycle. One of the most important tools for farmers to improve their crop production is soil analysis. In this regard, soil testing plays an important role in plant growth. Farmers can add organic or non-living nutrients to the soil in appropriate amounts. Yield growth depends largely on the nutrients in the soil: nitrogen (N), phosphorous (P), and potassium (K). Excessive distribution of fertilizer can significantly reduce production and quality 1.

2. LITERATURE SURVEY

Paper [1] recommends drip irrigation performance when water is supplied to plants where the required weather forecasting and crop diagnostics are performed with ugh MCP 3008. This paper proposes a cheap and efficient and effective irrigation system. CNN is responsible for the separation and accuracy of the high voting number and the state of full connection. This paper [1] proposes drip irrigation efficiency when water is supplied to plants were necessary to predict the weather and crop diagnostics are performed with MCP 3008. The degree of yellowing of leaves in plant cracks and on earth is determined by CNN calculations. And based on the data of the clouds using raspberry pi will determine whether to spray water and its value.

Paper [2] provides an advance in the field of in-depth research technology in the field of leaf spot disease in recent years. In this paper, the diagnosis of plant leaf disease is based on an in-depth study, and as long as sufficient information is available for training, in-depth study methods can detect plant leaf disease with high accuracy and advanced photography techniques learned. The comparative study in [3] was conducted, focusing on developing and comparing several Machine Learning (ML) models, assessing the various conditions and horizons of time, and predicting rain using two types of methods. The forecast model uses four different ML algorithms, namely Bayesian Linear Regression (BLR), Boosted Decision Tree Regression (BDTR), Decision Forest Regression (DFR), and Neural Network Regression (NNR). Rainfall was predicted at different times using different ML algorithm that methods used to predict rain using Autocorrelation Function (ACF) based on rain history data and Rainfall Forecasting Using Predicted Error based on historical and predictable rainfall data. This paper concludes with the use of two different methods with different conditions and different horizons of time, and ACF shows higher accuracy than predicting Rainfall Using Forecast Error using BDTR modeling. Paper [4] focuses on various agricultural and crop diseases. The paper has reviewed the Inception-ResNet-v2 model developed using in-depth learning theory and neural network technology. Tests show that the model can successfully diagnose a set of data and the accuracy of overall recognition which is why it can be used effectively in diagnosing and diagnosing plant and insect diseases. Paper [5] proposes an effective way to systematically classify the symptoms of plant diseases using neural convolution networks. This program is trained and tested on two plant disease databases namely plant data and pepper data sets. Learning the slow transmission helped to reduce CNNS meeting time. The accuracy of training and validation is measured in three tests with MonileNet_V3_Large for transfer learning with and without the Plant district data set compared to VGG-16 and transfer learning. Paper [6] suggests how to diagnose cardamom plant disease using the effective NETV2 model. A complete set of tests was performed to determine the effectiveness of the method and to compare it with other models such as NET which works well with Convolutional Neural networks. Paper [7] operates and compares Markov's predicted modern performance with rain forecast and other six alumni learning algorithms, namely: Gene Programming, Support Vector Regression, Radial Basis Neural Networks, Rules for M5, MS. Model Trees, and k-Close Neighbors. This paper also focuses on finding the correlation between different weather conditions and the accuracy of forecasts. paper [8] provides research on artificial neural network (ANN) that contains multiple layers and back-propagation to enable computer literacy in determining the indirect combination. A convolutional neural network (CNN) is generally regarded as an improved version of ANN called a deep learning neural network. This method uses a multilayer perceptron system designed for reduced processing needs. CNN contains the output layer, the hidden layer, the most flexible layers, the integration layers, the fully connected layers, and the default layers to automatically extract the shallow and deep input features. 2D-CNN and 3D-CNN have been used to output spatial-spectral presentations of hyperspectral images. Based on this paper [9] the basis of a network-based disease module, a recurring clustering algorithm was adopted to classify 299 diseases into different categories. The optical clustering scheme is based on the networks and functions of disease-related genes, which can provide functional phases for each disease as well, with more goals or KEGG methods identified and validated. This paper proposes several computational methods to reveal functional differences between different diseases such as group disease identification and classification, the functional relationship between diseases shared by the same group, and the important function associated with the classification of diseases. This paper [10] proposes a diagnostic method for the diagnosis of asymptotic non-local means (ANLM) image algorithm and integration of parallel convolution neural network (PCNN) and advanced reading machine (ELM) with improved linear particle swarm optimization (IPSO). PCNN-IPELM-based peach image detection i.e. neural network parallel convolution, IPSO-based high-resolution machine learning, and precision particle efficiency The paper propose an NLM-based audio output algorithm for peach images. The Parallel convolution neural network model is used to process data after audio output. This paper [11] suggests early diagnosis and complementary measures can be taken at the onset of plant disease. They are trained in specific types such as AlexNet DenseNet-121, ResNet-50, VGG-16, and Xception and it is shown that almost all of the above types cannot provide satisfactory results. X-reception can achieve only 80%. The proposed approach focuses on leaf dot features, which include an advanced R-CNN object acquisition algorithm and a background production platform, two Db and Daux stereotypes are presented to judge the generated or non-realistic image and to determine whether the generated image contains space.This paper [12] proposes an in-depth study approach based on the development of convolution of neural networks (CNNs) for the real-time diagnosis of apple leaf disease. Introducing a new apple leaf diagnostic model using the original GoogLeNet structure and Rainbow Concatenation. This paper proposed a new model of deep neural convolution network, i.e., INAR-SSD was designed by introducing the GoogLeNet launch module and integrating Rainbow integration to improve diagnostic and diagnostic function. This paper [13] suggests nutritional recommendations using an advanced genetic algorithm (IGA) that uses time-series sensor data and recommends various plant settings. Through the proposed model, crop production increased and enabled the determination of the right combination of different types of resources available. N-P-K automation helps to avoid manual manipulation. The method is also improved if a large amount of data for a variety of crops can be achieved and the target will be to produce values that are correctly calculated by soil type and location. This study [14] provides a comparative analysis using simulated rainfall models based on conventional machine learning algorithms and in-depth study structures that work well in sub-river operating systems. This study aims to compare the performance of rain forecast models based on the LSTM-Networks architecture and modern Mechanical Learning algorithms. Weather data from 2000 to 2020 was used in five major cities in the United Kingdom. This paper suggests that LSTM-Networks-based models with a few hidden layers work better in this approach, demonstrating its potential for use as a smart rain forecast forecasting app. This paper concludes that it is appropriate to consider the analysis of the significance of the features and the inclusion of other climatic factors to achieve better performance of rain forecast models. This paper [15] introduces a fast-paced FCM-KM and Faster R-CNN fusion detection system to address a wide range of problems with rice disease photography, such as noise, blurred vision, severe background disturbances, and low detection accuracy. . The Faster 2DOtsu algorithm mentioned in this paper has achieved excellent results in the use of image classification of rice. This paper suggests that this method is more effective in detecting rice diseases and improves the diagnostic accuracy of the Faster R-CNN algorithm while reducing the required diagnostic time. The paper concludes that there is a need to integrate smart internet resources such as the Internet of Things agricultural and terminal processor processors to real-time monitoring and pest identification in grain storage facilities, ready to promote modernization and agricultural industry ingenuity. This paper [16] focuses on promoting effective humidity control based on the Modern Irrigation System (MIS) using the Arduino Nano with various modifications in the planting area. The main objective of this project is to reduce excess water consumption, thereby saving crops from damage. The proposed system can be applied to a variety of plants, as those plants have different humidity conditions for their growth. This article [17] introduces various recent strategies related to intelligent irrigation systems in agriculture using the IoT and intelligence surveillance systems. In this introductory article, various components of smart irrigation, the functions of each layer in smart irrigation, and modern irrigation systems are introduced. System [18] is a sensor that measures soil moisture and adjusts the relay that controls the solenoid valve according to the requirement. The model shown provided the expected results at different humidity levels. The system can be enabled with the help of a solar panel; a solar controller can be used that controls the power of the system. This paper [19] introduces an image classification algorithm used for the automatic detection and classification of plant leaf diseases. It also compiles a study on a variety of disease-specific methods that can be used to diagnose plant leaf diseases. Image classification, which is an important factor in the diagnosis of plant leaf disease, is performed using a genetic algorithm. This paper demonstrates the effectiveness of the proposed algorithm in detecting and classifying leaf diseases. Another advantage of using this method is that plant diseases may appear early or in the early stages. In this paper [20] they developed a self-defense measure based on ground moisture and salt sensitivity, an electrophoretic sensor for measuring ions/nutrients in the soil, a nano-patterned plasmonic-resonance, and light-based sensors based on resonance-based optical mode. in the plant, flexible organic compounds are extracted. In this, they used the input impedance of the metamaterial-inspired pool embedded in the soil sample as a measurable area, known to be directly related to the permit, and proposed a method of determining ion-ion saturation mixture using Impendence spectroscopy. Using a multi-frequency impudence measurement method, a method of measuring the concentration of in-suit nitrate in the soil by analyzing dielectric mixture models over a mixture of Debye-type elements is developed. In this paper [21] the trapezoid method is widely used in SM recognition based on pixel distribution within the thermal remote vision and optical sensing. The SM recovery algorithm that combines a common method with learning methods that integrate with packaging technology is proposed. The accuracy of the predictions tested against the in situ, RMSE, MAE, and group return correlations was performed. This paper a potential application for remote sensing data measuring SM in TP using integrated learning methods. The SM retrieval algorithm that combines a common method (trapezoid method) with integrated learning methods with packaging technology is suggested. In this paper [22] SMMI (soil moisture monitoring index), MSMMI (soil moisture monitoring index), PDI (perpendicular drought index indicator), and MPDI (modified perpendicular drought index) for moisture measurement of land (SM) on farms. Here

Spectral indicators and plants that are important in distinguishing the earth cover species mainly include Sentinel-2 bands of SWIR1, SWIR2, Red, Green, Red edge1, blue, and plant extracts such as MNDWI, NDMI, TCARI, I S2REP (Sentinel-2 REPI), REPI, MRENDVI, red-edge vegetation index32, and MRESR. MSMMI is not dependent on the soil line and can more accurately establish a standard SM regional testing model for farms. Sentinel-2 satellites with red belts and SWIR can create an SM map of 0–5 cm depth of 10–20 m of landscaping and provide a solid foundation for agricultural waste management. Repeating farmers' financial profits until 2022-23 from the 2016-16 primary year requires an annual improvement of 10.42 percent on the farmer's income. In this paper [23], they evaluated each function separately based on the performance of a built-in robot. the grid structure is used for pomegranate plants. 5 pairs of transmitters and receivers are used to locate the white line in a dark area with the help of an IR-based line. The visual sensor is made by connecting the light transmission setting with the right-angle detection setting. The distance between the LED and the photodiode varies using the test and error method to obtain maximum transducer sensitivity. Plant growth depends on several factors such as NPK, soil characteristics, soil pH, soil moisture, temperature, climate, and light. To manage all the necessary information and complexity of crop growth system, based on IoT technology, can measure, analyze, and take action. It is an accurate agricultural context. acts as a key parameter sensor. The paper introduces an IoT-based system and innovative strategies that improve soil yield through which it is a new way to feed this population growth. this paper proposes [24] a solution that integrates IoT to monitor agriculture more accurately. This paper is primarily aimed at improving the visual system [25] of nitrogen, phosphorus, and potassium-containing the optic nerve. It uses a transfer system and a recovery system. This paper shows the built-in NPK optical sensor for ground detection, which includes light transmission and detection system. An integrated optical sensor war can detect the NPK element on the ground. the clear container is high, about 80%. Based on the test results, there was a significant interaction between the light samples and the NPK samples taken at different locations which caused the light intensity to decrease as the voltage was reduced. Output responses to high NPK were obtained from 32.0 volts of Nitrogen, 4.6 V of Phosphorus, and 19.8 V of Potassium. This paper [26] introduces an agricultural precision recognition system using Wireless Sensor Networks, which enables remote monitoring of soil fertility and other parameters namely soil moisture, pH, and temperature. The proposed Internet of Things (IoT) software system is smart enough to recommend water and fertilizer improvements that improve soil quality and ensure good crop growth. This program helps to reduce the use of excess fertilizer thus increasing the yield. To estimate the amount of nitrogen, phosphorus, and potassium present in the soil, soil fertility tests are used. Data from the sensor is sent to the AWS cloud, and a mobile app is developed that provides information about various soil features by using this information, the farmer will make the right decision on growing the right crop. For the plant to grow continuously above macronutrients (such as N, P, and K), trace elements such as copper, iron, manganese, molybdenum, and zinc are also required to affect yields. The system can be expanded to measure these features with appropriate integration of additional components and precision specifications. The main purpose of this paper [27] is to
incorporate an integrated irrigation network and to measure the amount of three major macronutrients, nitrogen (N), phosphorus (P), and potassium (K), in the soil, respectively. Saving farmers time, money, and energy. Comparing the solution in the color scheme determines the value of N, P, and K in the soil sample. It will define the upper, middle, and lower levels of N, P, and K. This paper introduces an intelligent system that will detect and analyze the NPK level of the soil and will determine the moisture content of the soil, and then based on these values, automatically. watering will take place. Like the tiny Microcontroller system used here to make the device less expensive and instead of the pH meter here it used the TCS230 color sensor to determine the pH level of the soil or NPK, this sensor detects the color of the soil sample solution. A tiny Microcontroller performs sensory measurements about NPK objects.

3. PROPOSED SYSTEM

The proposed solution ensures monitoring the health of a plant during its entire lifecycle by using various sensors and taking required actions based on data collected. RaspberryPi is the controller of the setup. We also develop an AI model to take necessary decisions depending on the condition of the plants and the weather. It collects data from sensors and, cameras, and based on the suggestion of AI models it controls the irrigation network [1]. The sensors used are soil NPK and moisture. The water tank consists of a water level sensor to monitor the water level. The main water tank is connected to four containers consistent with nutrients and medicines concerning the plants. The camera and sensors constantly check the plants, once it detects any disease or malnutrition. Then the AI model suggests the required nutrition or fertilizers be supplied to the plants [2]. This enforces the RaspberryPi to open the valve of that container containing the nutrient. The nutrient gets mixed up with the water coming from the tank [13] and is made to flow to the plants. Once the required water is supplied, the valves get closed. The amount of water and nutrients left is noted and if it is very minimal, then an alert message will be sent to the user to refill the container and tan

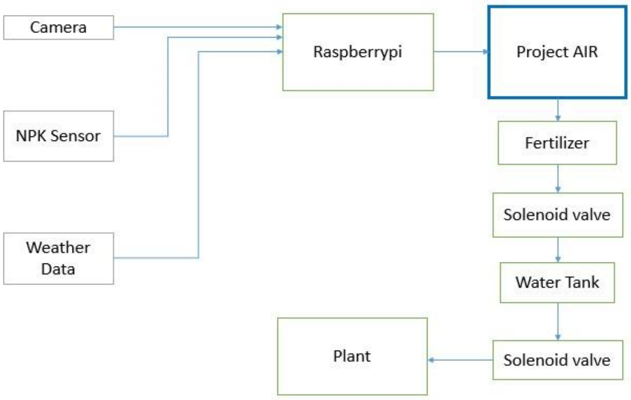

Fig.1 Work Flow

The solution also aims at applying real-time data on weather conditions relevant to the current location and season to take care of soil and crops and manage all weather-related risks. It gets data such as rainfall [14], temperature, humidity, and wind from reliable sources and takes appropriate measures to conserve water, plan smart irrigation, and predict crop yields. If the rainfall is very less in that particular season [3], then the amount of water used is regulated, and plans to wisely use it. This combined solution promises to improvise crop maintenance and yields good quality crops.

4. RESULTS AND DISCUSSION

The ML model is tested and verified for different crop diseases and the results obtained are highly satisfactory. The success rate of the Convolution Neural Network model for all the diseases is almost similar. To optimize the results of detection and prediction, the number of epochs can be increased. The data collected from these devices is sent to the project's AIR app and analyzed. The pipeline created in the AIR app receives the data and filters the required parameter (Image and Integer from camera and NPK sensor respectively will be collected). Once filtered, the rules section will monitor the NPK values and, depending on that, it sends notifications and commands to the valves to turn-On/Off.

Fig.2 Prototype Setup

Fig.3 Water outlet to plants

Fig.4 Plant disease detection

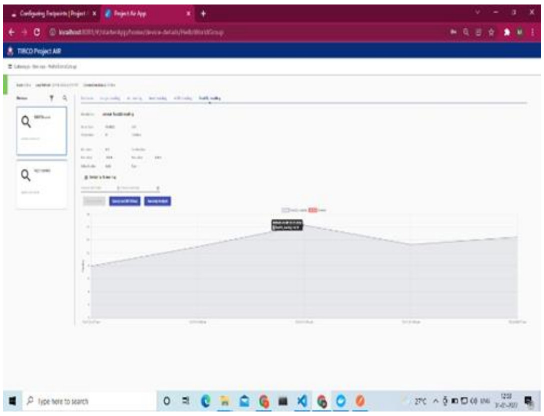

Fig.5 Analysis of NPK data

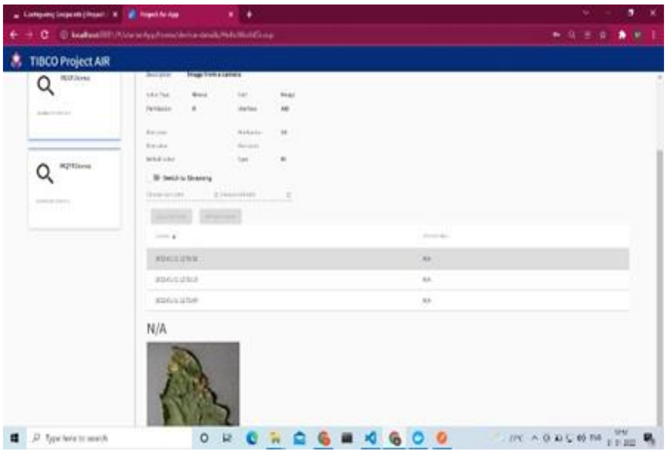

Fig. 6 Analysis of image data

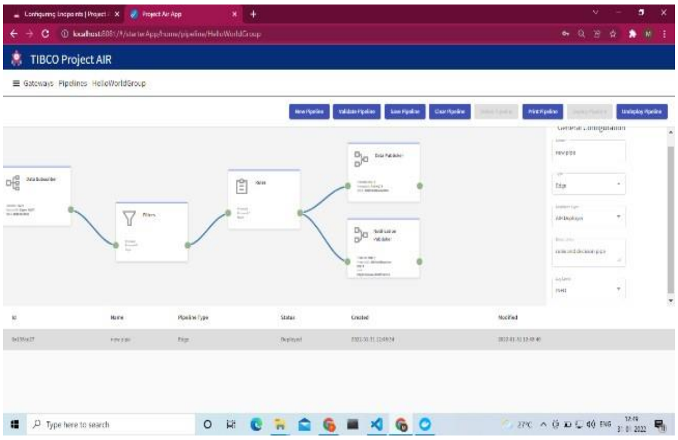

Fig.7 Decision pipeline

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5. CONCLUSION

Smart farming using IoT is a significant answer for different health-related issues of plants. With the traditional methods, it is difficult to assess plant diseases and suggest remedies for them. The proposed system enhances the irrigation system using new-age technologies like AI, ML, and edge computing. The system keeps track of plant health status and automates the process of supplying fertilizers. This path-breaking solution promises to handle these issues more systematically with minimal effort. This takes into consideration versatile and prominent answers for a significant issue influencing many million individuals across the globe.

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