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sCrop: A Novel Device for Sustainable Automatic Disease Prediction, Crop Selection, and Irrigation in Internet-of-Agro-Things for Smart Agriculture

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***Abstract*—Agriculture Cyber-Physical System (A-CPS) is becoming increasingly important in enhancing crop quality and productivity by utilizing minimum cropland. This paper introduces the innovative idea of the Internet-of-Agro-Things (IoAT) with an explanation of the automatic detection of plant disease for the development of ACPS. Majority of the crops were infected by microbial diseases in conventional agriculture. Also, the constantly mutating pathogens cannot be known to the knowledge of the farmer, due to which, there arises a demand to develop a disease prediction system. To prevent this, we use a trained Convolutional Neural Network (CNN) model to perform an analysis of the crop image captured by a health maintenance system. The image capturing along with continuous sensing and intelligent automation is performed by the solar sensor node. The sensor node houses a developed soil moisture sensor which has a high longevity compared to its peers. A real time implementation of the proposed system is demonstrated using a solar sensor node with a camera module, a microcontroller and a smartphone application using which a farmer can monitor the field. The prototype was deployed for three months and has achieved a robust performance by remaining rust-free and sustaining the varied weather conditions. An accuracy of 99.24% is achieved by the proposed plant disease prediction framework.**

***Index Terms*—Smart Agriculture, Agriculture Cyber-Physical System (A-CPS), Internet-of-Agro-Things (IoAT), Solar Energy, Sensor Node, Automatic Crop Disease Prediction, Machine Learning, Convolutional Neural Network (CNN)**

I. INTRODUCTION

Food is one of the quintessential assets in life, needed by each and everyone alike for survival. Although, not everyone is entitled to having a sumptuous meal daily. The World Health Organisation estimates that two-thirds of the world population is starving. The technologically advanced solution to this age-old problem is Smart Agriculture, which helps in maximizing the output of farmland using minimal resources. The recent developments in Information and Communication Technologies (ICT) have led to the development of robust ACPS. Whilst focussing on maximizing food production, heed must be paid to the loss of crops to various diseases. Around 137 different pathogens and pests cause a loss of 10 to 40 percent in the staple crops, which cater to around 50% of the calorie intake of the human population. And the constantly mutating pathogens cannot be known to the knowledge of the farmer, due to which, there arises a demand to develop a disease prediction system. The crop disease prediction system assists the farmer in timely detection of the crop diseases.

With the significant population growth around the world and reduction of amount of farmland available, the Precision Farming (PF) or Precision Agriculture (PA) is becoming important to increase crop output and farm efficiency while reducing the misapplication of products [1], [2]. Precision agriculture is an innovative and resourceful method of continuous real-time observation of the agricultural fields and thereby providing efficient management methods to respond to the variations that prevail among the crops. The adoption of these techniques has increased the net benefit of up to $75/hectare and is expected to increase the contribution of agriculture in the world GDP by 8% [3]. The significant advantages of precision agriculture are yield monitoring [4], remote sensing, and obtaining data in real-time for better management decisions. The advantages mentioned above can be achieved by employing the use of a solar-powered device, i.e., the sensor node [5].

Smart Farming (SF) or Smart Agriculture (SA) is the use of information and communication technologies (ICT) for optimization of complex farming/agriculture systems [2], [6]. Smart agriculture makes use of an aggregation of data from sensors to monitor various parameters of agriculture/farming including the varying environmental conditions, crop health and soil moisture to understand the intra- and inter-field variations [7]. Smart agriculture helps in devising a cost-effective, energy efficient [8] automated system for various agricultural appliances, such as water pumps for irrigation, and thereby reducing the workload of the farmer. The bigger umbrella concept of Agriculture Cyber-Physical System (A-CPS) thus can evolve just similar to healthcare Cyber-Physical System (H-CPS), transportation Cyber-Physical System (T-CPS) and energy Cyber-Physical System (E-CPS) making the system of systems smart city [9], [10].

The Agriculture Cyber-Physical System (A-CPS) is in essence driven by the Internet of Things (IoT) which is the interconnected network of various computing devices embedded in daily life appliances to the Internet, thus enabling them to communicate with each other [11], [12]. Due to the popularity and advantages of IoT, it has even penetrated the field of agriculture. The percentage contribution of agriculture in the

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world Gross Domestic Product (GDP) as of 2016 is 3.7% [13]. Thus research in smart farming or smart agriculture made by using A-CPS based on IoT is the need of the hour.

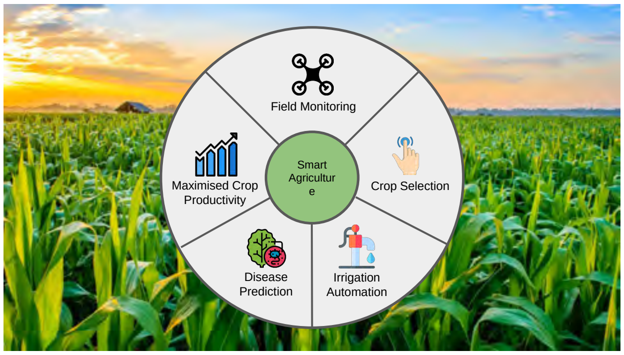


Fig. 1: Selected Challenges of Smart Agriculture.

The major challenges of smart agriculture include continuous monitoring, energy harvesting, automatic irrigation, and disease prediction (See Fig. 1) [14]. An important issue that arises in farming is the loss of crops to various diseases. Around 80% of the crops get destroyed by various agents such as bacteria, viruses, weather conditions, etc. in spite of the farmer toiling hard throughout the year. Thanks to the modern analysis systems and deep learning techniques, we can identify the chances of a plant being infected and thus notify the farmer in advance. Thus, crop disease prediction will be in line with the end goal of smart agriculture i.e. achieving maximum output by utilizing the least amount of resources.

Henceforth, the paper is organized as follows: Novel contributions of the current paper is summarized in Section II. IoT based A-CPS architecture is described in Section III. Section IV discusses the related prior research. The proposed methodology is briefly explained in Section V. The proposed novel CNN model for automatic plant disease prediction and solar-power end-device for IoAT are explained in Section VI and Section VII. The proposed sCrop device is solar powered device description is given in VIII. Later in Section IX, the result analysis of the proposed method is presented. Finally, Section X concludes the paper with discussions on future directions.

II. Contributions of the Current Paper

Existing works in smart agriculture works are primarily on optimization of food production. Plant growth is the key detrimental factor for obtaining adequate fodder, however, it is also the primary obstacle for increasing productivity. The growth of the plant is affected by various factors such as biotic stress, excessive irrigation, soil salinization, and diseases. Biotic stress is seen in the plants due to less availability of moisture in the soil. Thus, a robust solution for indispensable autonomous irrigation systems is the need of the hour. Adding on to it, a disease prediction system would help increase the food productivity.

A. Problems Addressed in the Current Paper

The literature survey points out that the existing solutions make use of non-renewable sources of energy to power the sensors. Also, most of the existing solutions look at the problem of automated irrigation and crop disease prediction as two different areas of research. The prototype presented in this paper unifies the afore-mentioned to develop a robust smart agriculture system. Our solution aims at solving the problem of corrosion in the existing soil moisture sensors. The longevity of the commercially-off-the-shelf available soil moisture sensors is limited as they are made up of either iron or copper which are highly corrosive. The available moisture sensor's probes are short in length, which restricts their usage for trees with bigger roots. Also, shorter sensory probes lead to lesser accurate moisture readings. In general, the sensor nodes are powered using a battery which gets exhausted as time progresses. This leads to the problem of repetitive replacement of the battery, which in turn, causes an increase in the cost of the solution. Further, most of the disease prediction systems require the application to be connected to the Internet, which might not be available at the disposal of a farmer. Thus, having an on-system computation is ideal for the farmer.

B. The Challenges in Solving the Problem

Developing a robust, cost-efficient and cutting-edge system keeping in mind the economic and technical considerations of a farmer is a challenging task. The initial problem that was encountered was the calibration of the developed soil moisture sensor was a gritty task as the aim was to for sure reach the current baseline, if not perform better than the existing soil moisture sensor. The power conversion from the solar cell to the sensor node must be performed with utmost care as the sensors in the node operate at a much lower voltage compared to the solar cell output. Once the embedding system circuitry was taken care of, emphasis was laid on training an efficient deep learning model for plant disease classification keeping in mind the curse of dimensionality.

C. Novel Solutions Proposed in the Current Paper

This paper proposes a novel concept of Internet-of-Agro-Things (IoAT) to build agriculture cyber-physical systems (A-CPS). The proposed system efficiently mitigates the mentioned challenges. **The major contributions of the current paper** are the following:

- To develop a novel cyber-physical system for the agricultural domain coupled with a deep learning model for recognizing plant diseases.
- The deep learning model is fine tuned by adding additional fully connected layers to facilitate better feature mapping and class label assignment.
- An energy-efficient and accurate IoT enabled A-CPS system, which houses the durable soil moisture sensor and camera module is developed.
- The A-CPS system, equipped with Edge Device Layer and Cloud Layer Services help in sensor data analysis, helping obtain actionable insights leading to intelligent automated irrigation.
- Finally, the IoAT based solar powered automatic irrigation system and the CNN model integrated plant disease

detection is successfully developed and validated in different extreme conditions in the result analysis.

III. Internet-of-Agro-Things based Agriculture Cyber-Physical System (A-CPS) - Our Vision

IoAT involves developing futuristic applications for smart agriculture. Prominence is given to farmer-friendly and energy-efficient solutions. An IoAT system includes an end-to-end prototype that can arrive at meaningful predictions by assimilating the spatial and temporal sensed values. This leads to a cyber-physical system (CPS) being the crux of an IoAT solution. A CPS encompasses a blend of enormous computational hardware, software, and physical sensory components. The constituents of a CPS communicate with each other seamlessly and help in the real-time monitoring of the environmental variables. The paper presents a cyber-physical system for the agricultural domain, i.e. A-CPS. The breakdown of the proposed A-CPS as seen in Fig. 2 is as follows:

- **sCrop Device Layer:** The device layer comprises the solar sensor node and the mobile application. The solar sensor node is the core component of the A-CPS, which consists of an interconnected network of sensors, coordinating with each other to sense real-time environmental changes. The sCrop device communicates with the upper layers in wireless. The actionable insights, for automating irrigation, are executed in the agriculture device layer. Further, the sCrop application acts as an interface for the farmer to visualize the disease predictions and irrigation timeline of the IoAT prototype.
- **sCrop Edge Layer:** The sensor data is relayed to the edge nodes for immediate analysis. The communication between various devices in the edge device layer takes place with the help of state-of-the-art technologies such as 5G, WiFi, etc. These technologies help the edge device layer to perform computations with reduced latency. The layer can be used to train low computation machine learning models, often being of low accuracy. This improves generating insights for achieving irrigation automation in our developed prototype.
- **sCrop Cloud Layer:** The cloud acts as a database for the sensory data coming from the device layers. Additionally, the cloud is also a host for serving the computation-intensive Machine learning models. It has high-end computational resources at its disposal to process the incoming sensor data. The meaningful insights obtained from the analysis are sent to the sCrop mobile application with the help of the gateway.

Thus, A-CPS goes hand in hand with deep learning models to develop a robust IoAT system. An IoAT system in its entirety helps the farmer in getting additional information, which is obtained by analyzing the temporal sensor data from A-CPS.

IV. Related Prior Research

Technology in smart agriculture is mainly focused on making agriculture efficient and easy for farmers. The technology of smart agriculture mainly focuses on Automatic smart irrigation as stated in [15]–[19]. The sensors used to collect different environmental parameters for achieving smart agriculture are stated in [15], [17]–[21]. The need for an efficient energy source is proposed in [22]. The use of efficient routing protocols for wireless communication of data packets from the sensor nodes to the server is discussed in [23]. A disease prediction solution emphasizes on the size of the dataset used [19], [24], [25] i.e number of disease being predicted and the accuracy achieved [26]–[28]. Considering their drawbacks, sCrop, a hybrid solution is proposed. To the author's knowledge, smart agriculture systems presented in the existing literature have not been using solar based sensor nodes for reliability. The disease prediction system presented in the existing literature has not achieved a higher accuracy over 38 different diseases among various crops. The summary of the comparison of sCrop with the existing solution is given in Table I.

V. Proposed Architecture of Novel IoAT

A. Proposed Novel Internet-of-Agro-Things (IoAT) for Sustainable Disease Prediction

This section discusses the proposed three stage pipeline for novel sCrop Architecture for Sustainable Crop Disease Prediction, as shown in Fig.3. The different stages in the pipeline is explained below:

- **Sensory Block:** This block is used for data sensing and communication. It consists of a sensor node, powering module, and solar sensor node data hub. The sensor node is powered using the powering module, which is used to measure various parameters sensed by the data hub and send the data to the Storage and Data Analysis block. The powering module consists of a solar panel and a battery to power the node at the time with zero or no solar energy. The data hub consists of a camera module that constantly clicks the crop images and a moisture sensor is used to measure the soil moisture content of the field.
- **Storage and Data Analysis Block:** This block is entrusted with data storage and edge computing. It consists of two modules. The Cloud Storage and Analytics module is used to store the data received from sensory blocks, in a cloud database and get actionable insight from the data. The Edge Computing and Intelligent Access Module automates the process of irrigation based on crops selected by the farmer and helps in preventing Biotic Stress Control in crops.
- **End-User Block:**This block consists of Crop Disease Prediction Module which is used to predict eh crop disease based on the image stored in cloud. And a sCrop User Interface which is used to notify farmers about the infected crop and also for farmers to select the cultivating crop and live track irrigation.

B. Novel sCrop Thing for Sustainable Crop Disease Prediction in IoAT

A solar sensor node is a collection of different sensors interfaced to tackle a specific problem and is connected to the internet. They are compact devices that can be easily deployed over a wide area, forming a connected network and

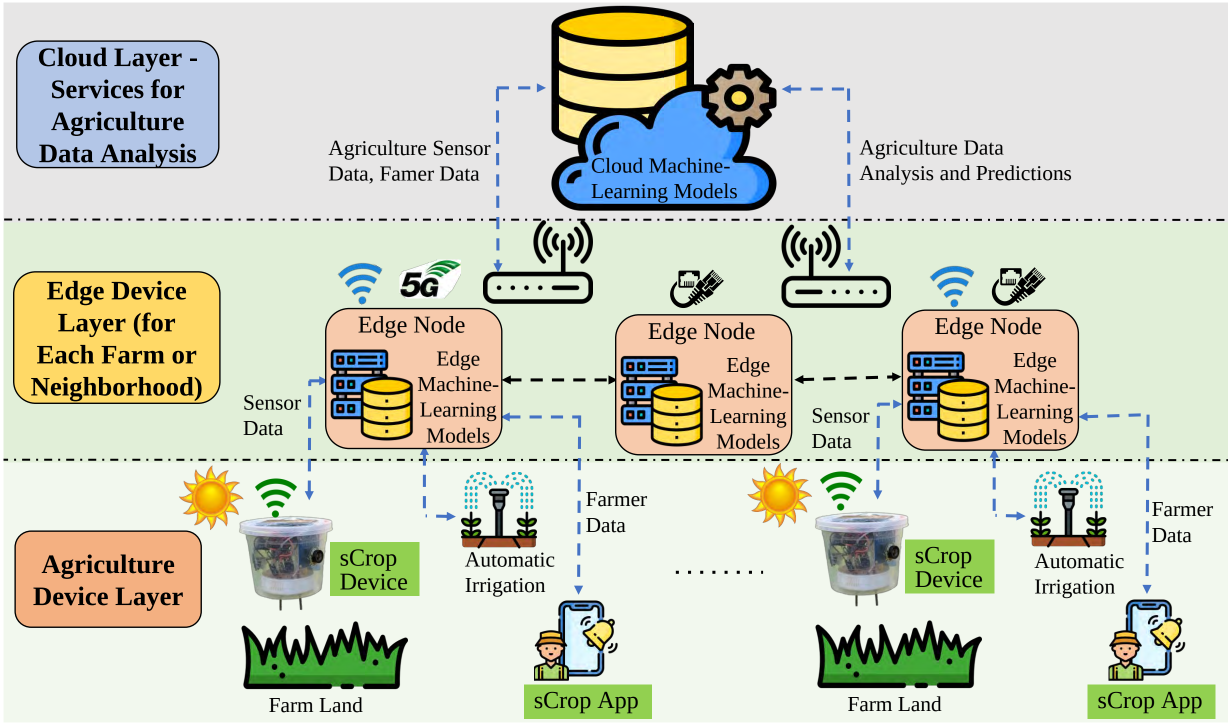


Fig. 2: Internet-of-Agro-Things (IoAT) based Agriculture Cyber-Physical System (A-CPS) - Our Vision.

TABLE I: Comparison of Existing Solutions with IoAT.

Smart Agriculture Works	**Soil Moisture Sensor**	**Solar Powered**	**Approaches Used**	**Device Cost**
Soil Crop-field Monitoring [15]	No	No	NA	High
Smart Irrigation [16]	No	No	NA	High
Toward Making the Field Talk [18]	No	No	NA	Moderate
Agriculture Intelligent System [21]	No	No	NA	High
Ricetalk: Rice Blast Detection [19]	No	No	AI Technologies	Very High
Semi Automatic Leaf Disease [27]	NA	NA	SVM	Negligible
Leaf Rust Disease Detection [24]	NA	NA	Regression Algorithms	Negligible
Prediction of Potato Disease [25]	NA	NA	Deep CNN	Negligible
Early Disease Detection [28]	NA	NA	KNN, LR, RF	Negligible
Current paper: sCrop	**Yes**	**Yes**	**CNN**	**Low**

coordinating with each other, and help in the monitoring and controlling of that area. Due to the above advantages, the solar sensor nodes are ideal for the Smart Agriculture System. The proposed method makes use of a solar powered sensor node, overcoming the drawbacks of using a battery causing temporary termination of the system and decreasing the maintenance cost. The solar powered node makes use of the abundantly available solar power and ensures the continuous working of the node.

The solar sensor node also helps in automating the irrigation process based on the soil moisture content of the soil. To measure soil moisture values, a developed soil moisture sensor is used. The developed sensor uses stainless steel probes to overcome the drawbacks of existing off-the-shelf sensors which are prone to corrosion and are not durable and inaccurate for the long run. To monitor and predict the infected crop, we have proposed a disease prediction system. The system monitors the crop, by predicting the disease over the images captured over regular intervals. The cameras attached to the solar node feed in images of the crops to the Deep Learning (DL) model to predict the plant diseases, if any [29]. Deep Learning neural networks are used due to their compression strategy that leads to highly accurate and efficient models [30]. To provide an easy interface for the farmer to monitor his field, an app, IoAT is designed.

VI. Proposed Novel CNN Model for Automatic Plant Disease Prediction

This section outlines the approach behind development of the crop disease prediction model using deep learning techniques. Details about the dataset used and the preprocessing

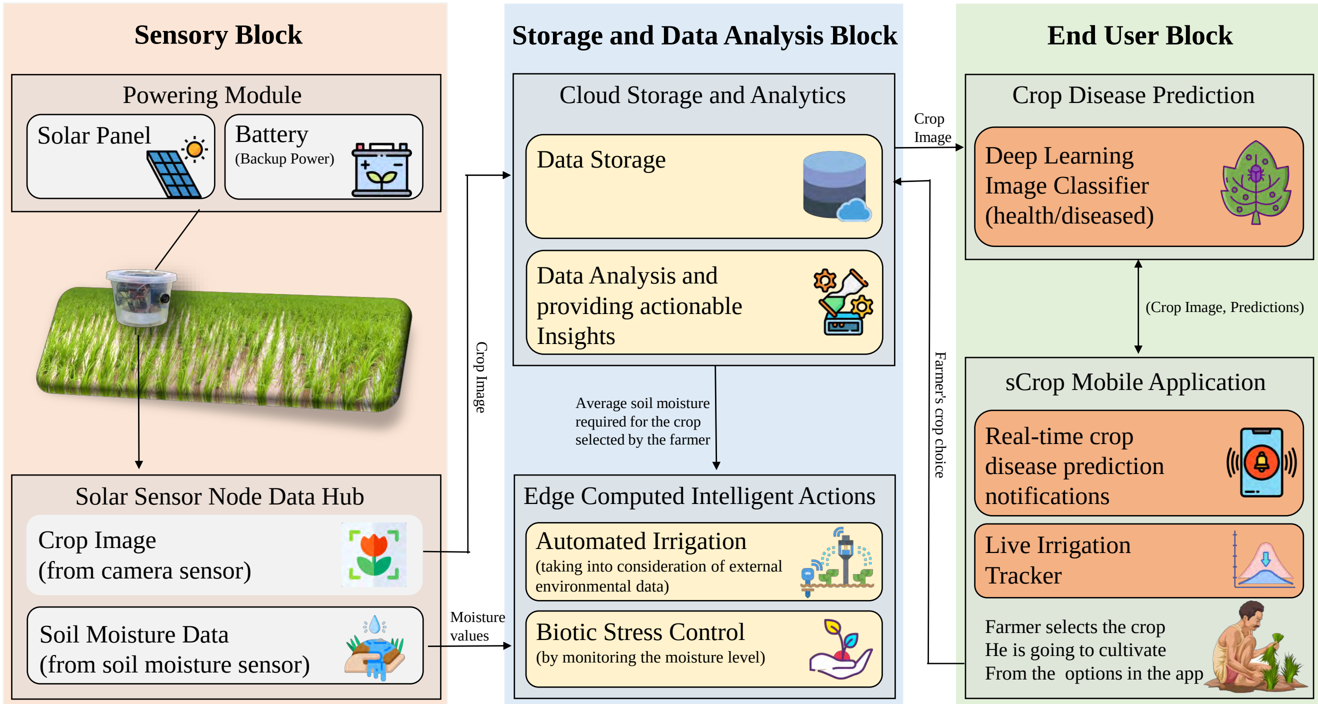


Fig. 3: System Level Working Flow of the Proposed IoAT.

techniques are elaborated. Furthermore, the process of training the CNN model with its associated analysis is discussed.

A. *Method for Automatic Disease Prediction*

The CNN model based automatic disease prediction approach is shown in Fig.4. The captured leaf images are given as input to the trained model for disease identification and the output of the model is sent to the farmer user interface.

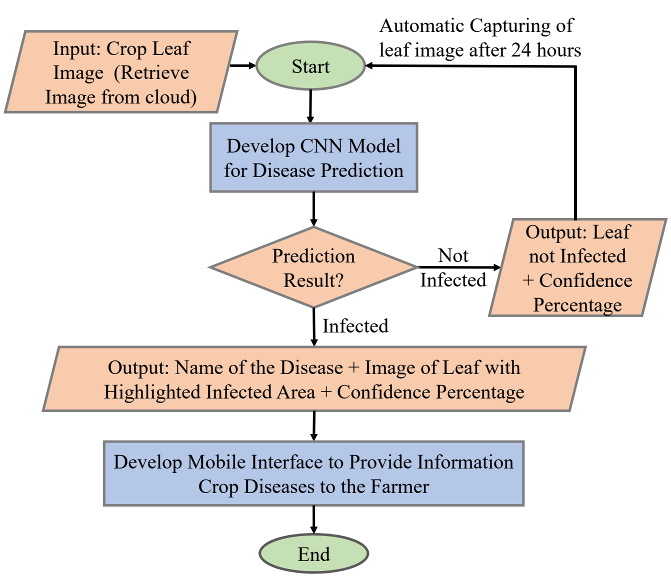


Fig. 4: Proposed Method for Disease Prediction in IoAT.

B. *Dataset used*

Dataset is the most critical factor which affects the performance of the DL model. The Plant Village dataset [31] consists of 54,306 healthy and unhealthy crop's leaf images, which can identify 38 different diseases. The training set consists of examples from the dataset which are used for learning to fit the parameters for training the image classifier model. The validation set is used to fine-tune the parameter of the classifier being trained. For testing the trained model, we use image sets of both healthy and diseased crop diseases.

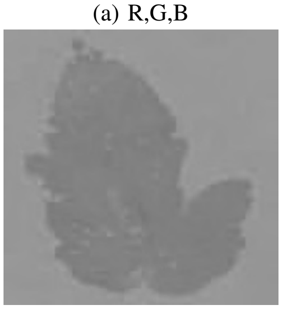
C. *Image Preprocessing and Augmentation*

The real world scenario of capturing leaf images is loaded with obstacles/noise. Thus, preprocessing techniques are employed to gain consistency and achieve better feature extraction. The preprocessing that the images undergo is the color gamette conversion from (R,G,B) as shown in Fig. 5a to the L channel i.e. the Lab color space. Under the Lab color space the L represents the image in grayscale, a represents the image in green-red color spectrum and b represents the image in blue-yellow color spectrum as shown in Fig. 5b, Fig. 5c, and Fig. 5d respectively. By obtaining images in the L channel, the depth calculation to distinguish the boundary of leaves from the background is potent. Once the preprocessing techniques are applied to extract superior features, the task at hand is data augmentation.

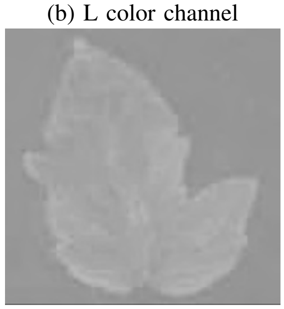
The exclusive objective of using augmentation techniques is to notably increase the heterogeneity of the data available for training the model, without going through the gruesome process of collecting new data. Furthermore, the distortions to the images help in reducing overfitting. The augmentation techniques performed on the images Fig. 6a include perspective transformations Fig. 6b affine transformations Fig.6c and rotations Fig. 6d. Perspective transformation helps in achieving a birds-eye view of an image. A 3x3 and 2x3 matrices are required for perspective and affine transformations simultaneously. Besides this, rotations of the images on different axes by varying the degrees is considered as well for data augmentation.

(a) R,G,B

(b) L color channel



(c) a color channel



(d) b color channel

Fig. 5: Preprocessing images

(a) original image

(b) Perspective Transformation

(c) Affine Transformation

(d) Rotation

Fig. 6: Image Transformations

D. Proposed CNN Model Training

There are several well-known state-of-the-art architectures such as AlexNet, EfficientNet, RestNets, and many others. For the proposed disease prediction, we have chosen three state-of-the-art architectures that require fewer computations and are suitable for both deployment and research. The steps for proposed disease prediction is described in Algorithm 1. Better performance has been achieved with ResNet 50. The basic building block of ResNet 50 is the convolution block and identity block. It allows skipping connections, which helps in designing deeper CNN (up to 150 layers) and uses batch normalization. The comparison of the performance of models is discussed in Section VII (E).

Algorithm 1: The Proposed Algorithm for Disease Prediction

Requires: *Crop's Leaf Image input from cloud*
Ensures: *Disease prediction result*
Notions: CI: Crop Image, OUTPUT_CI: Crop image from previous layer processing, **: Data flow is happening between the cloud database.
while *TRUE* **do**
  ReadFromCameraModule(CI)**;
  SendCloud(CI)**;
  ReadCloudtoMobileApp(CI)**;
  IntializeInputLayer(Pre-Processed(CI));
  Input(OUTPUT_CI, conv block);
  Input(OUTPUT_CI, max pool);
  PredictionStatusUpdate(OUTPUT, Infected/Healthy)
end

To further add on to the advantages of ResNet 50 and increase the prediction accuracy of IoAT, an additional three fully connected layers with a softmax activation function is added. When we give the crop image as input to the ResNet 50, where it passes throught batch normalisation, and conv and identity blocks. After which it act as input to the fully connected layers, after which by using the Softmax Activation layer it is classified as Healthy / Infected or Diseased crop, along with the name of the disease. Therefore, ResNet 50 architecture is used transfer learning and the architecture designed for IoAT is given in Fig. 7.

The choice of using CNN for training and the advantage of using transfer learning is briefed about. The model has been trained using Google Cloud Services. The specification of which are TPUv2-8, 8 cores and 64 GB processing memory. The different layers of a CNN and their output shape is shown in Table II. The Convolutional layers are the most essential building block of CNN. Each convolutional layer has I maps of equal size, I_x and I_y, and a kernel of size KL_x and KL_y, if shifted over a certain region of the input image. The skipping factors F_x and F_y define how many pixels the filter/kernel skip in X and Y direction between subsequent convolutions. The

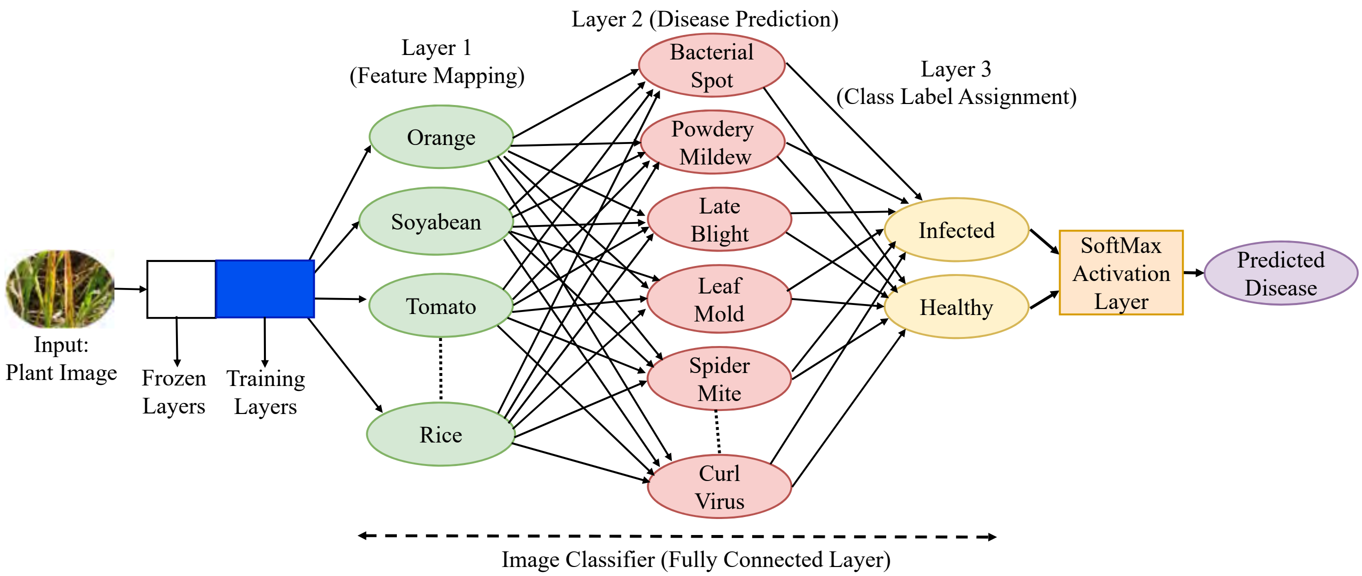


Fig. 7: Proposed CNN Model for disease prediction.

size of the output map is defined in the following expression:

$$I_x^n = \frac{I_x^{n-1} - KL_x^n}{F_x^n + 1} + 1 \quad (1)$$

$$I_y^n = \frac{I_y^{n-1} - KL_y^n}{F_y^n + 1} + 1. \quad (2)$$

In the above expression, n indicates the layer. Each map in the layer C^n is connected to most I^{n-1} maps in layer C^{n-1}.

TABLE II: Different layers of a CNN and its output.

Layer	Output Shape
Conv2d_1	(None, 256, 256,32)
Activation_1	(None, 256, 256,32)
BatchNormalization_1	(None, 256, 256,32)
MaxPooling2D_1	(None, 85, 85,32)
Dropout_1	(None, 85, 85,32)
Conv2D_2	(None, 85, 85, 64)
Activation_2	(None, 85, 85, 64)
BatchNormalization_2	(None, 85, 85, 64)
Conv2D_3	(None, 85, 85, 64)
Activation_3	(None, 85, 85, 64)
BatchNormalization_3	(None, 85, 85, 64)
FullyConnectedLayer_1	(None, 85, 85, 64)
FullyConnectedLayer_2	(None, 85, 85, 64)
FullyConnectedLayer_3	(None, 85, 85, 64)
SoftmaxLayer_1	(None, 1, 2, 19)

In spite of a plethora of classification techniques being available, CNN is best suited for image classification because:

- The capability of capturing and learning relevant features efficiently from the image is a major advantage of CNN, which is calculated by the following expressions:

$$G[m,n] = (f * h)[m,n] \quad (3)$$
$$= \sum_j \sum_k h[j,k]\, f[m-j, n-k]. \quad (4)$$

In the above expressions, the input image is denoted by f, and the kernel or filter (small matrix of numbers) is denoted by h. The indexes of rows and columns of the result matrix are denoted by m and n.

- The final features obtained from CNN are invariant to occlusions. This is achieved because the system does feature extraction by convoluting the image and filters to generate invariant features which are passed into the next layer.
- CNN is found to perform better with unstructured data such as images in comparison with other classifiers such as Support Vector Machine (SVM).
- The advantage of training the model for a specific application on top of an existing pre-trained model is adding to the current knowledge. This is known as Transfer Learning and CNN makes use of it to make the model more intelligent. The network is represented using the following expressions:

$$H(x) = F(x) + x \quad (5)$$
$$F(x) = W2 * relu(W1 * x + b1) + b2. \quad (6)$$

In the above expressions, $H(x)$ is a mapping function, $F(x)$ and x simultaneously represent the stacked non-linear layers and the identity function. $W2$ and $W1$ represent the weight matrices, and $b1$ and $b2$ are the bias terms.

Based on the above features of CNN, the proposed architecture was implemented. The model validation and error analysis of the proposed framework is discussed in the next section.

E. Model Validation and Error Analysis

This section briefs about the performance measures of the trained image classifier. The deep learning model is trained using three different architectures to compare and select the best performing architecture. The accuracy produced by using each of the three architectures, i.e., sCrop, ResNet 34, and AlexNet, is described in Table III.

TABLE III: Comparison of accuracy's of model architectures.

Architecture	Accuracy for epochs = 4
ResNet 34	94.97%
AlexNet	90.63%
Current Paper (IoAT-sCrop)	99.24%

During our experiment we have trained the model with higher epochs, such as 8, 9 and 10. However, the change in the accuracy from epochs 4 to 10 is 0.01 and size of model was increasing by an average of 12 MB. Thus, considering the memory and accuracy tradeoffs, we have considered 4 epochs in sCrop. As sCrop provides the best accuracy, it has been chosen as the pre-trained model architecture for production. Since the accuracy achieved is taxing, there arises a demand for performing a check on the overfitting of data. To accomplish this analysis, the dataset is split into varying percentages of training and validation, which is presented in Table IV.

TABLE IV: Test for overfitting of data.

Train Split(%)	Validation Split(%)	Accuracy for epochs = 4
80%	20%	99.24%
60%	40%	96.19%
40%	60%	95.27%
20%	80%	93.37%

As the accuracy is consistently above 90% even when the train split is just 20%, it can be concluded that there has been no overfitting. Along with that we have also compared out findings with variopus other models, such as Siamese Network gives an accuracy of 96.16 % when trained over the same dataset. Along with that we attanined an accuracy of 96.34% with Vanilla CNN and 97.63% with keras layers and adam optimized. The confusion matrix, as shown in Fig. 8, is used as an evaluation metric for the performance of the trained model on the test data. It is calculated between the different class labels of the actual and predicted values of the test dataset. The number of misclassifications in predicting the actual class label for various diseases images can be seen in red circles in Fig. 8. From the figure, a total of 72 images among the complete dataset are found to have been misclassified, whereas a total of 7580 images have been tested and classified correctly. A total of 200 images of 38 different diseases belonging to 14 different crops is tested using the developed IoAT mobile app. Out of 200 images, 197 images were identified correctly with the developed IoAT mobile app.

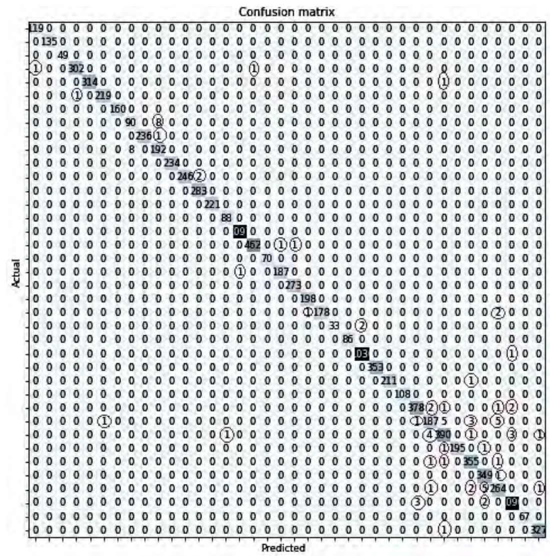


Fig. 8: Confusion Matrix for the trained model.

The experimental prediction results of the crop's leaf image sent by the OV7670 Camera module is shown in Fig. 9. An example of the identification of a healthy tomato image is shown in Fig. 9a, whereas the affected portion in the Fig. 9b is highlighted with a bounding box and identified as an infected image.

(a) healthytomato (b) infectedtomato

Fig. 9: Prediction results of crop leaf images.

VII. Proposed Methods for Automatic Crop Selection and Live Irrigation Tracking

A. Proposed Method for Crop Selection

This is the most important module of the developed IoAT app. It enables the farmer to choose the crop which is being cultivated in the field, from the already available list of crops. The selected crop details are sent to the cloud storage. This module updates all the threshold values used in the system for the best growth of the cultivated crop. Fig. 10 shows the method of crop selection used in IoAT.

B. Proposed Method for Live Irrigation Tracking

It enables the farmer to view live irrigation updates on all the parts of the field. Tracking allows the farmer to monitor

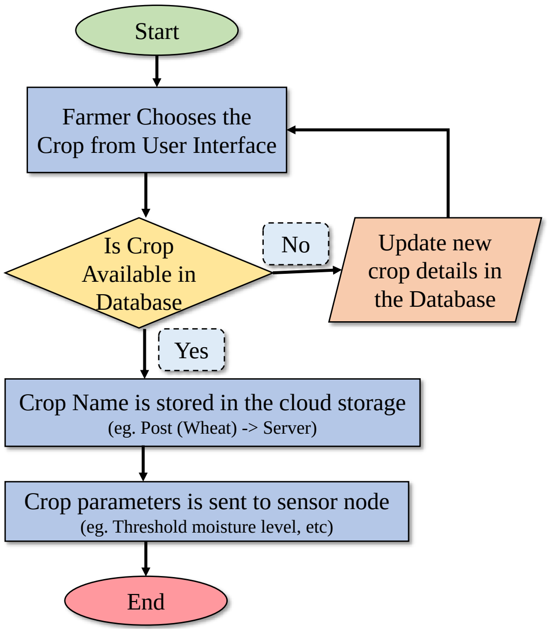


Fig. 10: The Proposed Method for Crop Section.

the accuracy of the irrigation. The live irrigation data shown is requested from the Thing-Speak cloud. The data so received by the cloud is updated in the application in graphical format. Data is updated in the cloud storage with a latency of 15 seconds and is retrieved from the cloud to the app with a complete latency of 30 seconds $(15\ seconds \hookrightarrow\ cloud + 15\ seconds \hookrightarrow\ mobile\ app)$. Algorithm 2 describes the data flow for the process of automatic irrigation.

Algorithm 2: The Proposed Algorithm for Irrigation Automation

Requires: *Sensor Input and Data from Cloud*
Ensures: *Relay ON/OFF*
Notions: TEMP: DHT11 Temperature Data, SM: Soil Moisture Value DATE_TIME_S: Date and Time Stamp.
(val)*: 1 - ON; 0 - OFF
**: Data is being sent to a different cloud database
while *TRUE* **do**
    ReadFromSensor(var CurrentTEMP,var CurrentSM);
    ReadFromCloud(var ThresholdSM);
    if *var CurrentSM <= var ThresholdSM* **then**
        WaterPump = (1)*;
        SendToCloud(DATE_TIME_S)**;
    else
        if *var SM > var RSM* **then**
            WaterPump = (0)*;
            SendToCloud(DATE_TIME_S)**;
        end
    end
    delay(9000(ms));
end

The aforementioned algorithm is implemented using a solar powered sensor node. The details of the energy module and calibration of the sensor node is discussed in the succeeding section.

VIII. Proposed Novel sCrop Thing for IoAT

The proposed sCrop device is a solar-powered consumer electronics as presented in Fig. 11. Use of solar energy harvester for sustainable IoT in which sensor node powers itself is envisioned. The solar-powered energy module of IoAT consists of various sensors for achieving real-time monitoring of the environmental and crop variables, powering units, memory control slots, and the security module connected to the microcontroller bus. The advanced microcontroller bus architecture (AMBA) facilitates communication between various constituent components of the IoAT energy module. The sensor security module predominantly helps in protecting the programme theft in the microcontroller. Hamming weights are assigned to the suspicious penetrated code and a simple string match is performed with the reference implementation to prevent malicious code modification.

We leverage that idea in our current sCrop work. The sensor node is powered using an efficient and robust powering module. The power module consists of a solar cell and a battery for backup power. Photons from the sun strike the silicon atoms in the crystal structure, which transfers enough energy to silicon electrons to escape from the parent atom. The electrons move and flow from n-type to p-type electrodes, converting solar energy to electrical power. The voltage generated from the solar panel varies based on the change in the amount of sunlight, as shown in Table V. The voltage generated from the solar panel is used to power the solar sensor node using a voltage regulator. It is also used to charge the battery using a junction rectifier diode, which will be used to power the node in the night and gloomy days. The powering core which houses a solar panel and rechargeable battery feeds the unregulated voltage as an input to the series pass element in the voltage regulator core. The amplifying circuit present in the voltage regulator core outputs regulated voltage required to power the microcontroller and various sensors.

We propose a novel soil moisture sensor for the sCrop device introduce in the current paper. The soil moisture sensor overcomes the drawbacks of the existing sensors, such as corroding of rods, faulty values, shorter probe length and robustness. The probes of the developed sensor are made of Stainless Steel (iron + ($>$ 10.5 %). Chromium is a very active element that reacts with oxygen in the air and forms a protective layer of Cr2O3 (Chromium oxide), which prevents corrosion. The rods are placed in the holes, which are 1 inch apart from each other on an insulator. The length of the sensor varies according to the range of the roots of the crop plant.

The powered microcontroller is interfaced with a camera module and a self-made robust soil moisture sensor. The camera module is used to capture the image of the leaf and send it to cloud storage. It is a cheap camera module which can be easily interfaced with the microcontroller using a DEMUX and is capable of capturing an image in VideoGraphicsArray (VGA) format. It also comes with a FIFO buffer, which

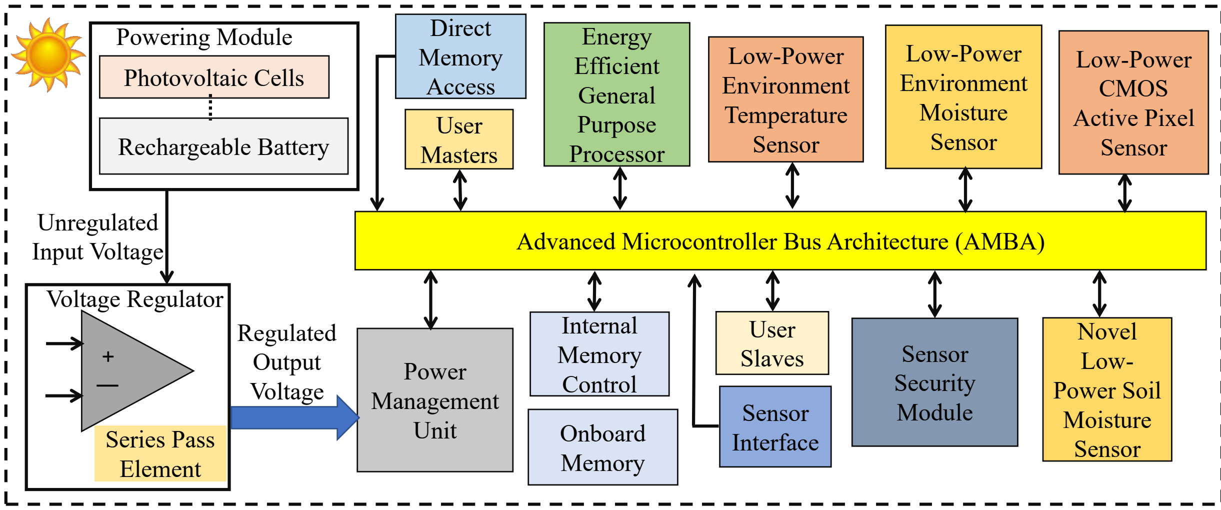


Fig. 11: The Proposed Solar Energy Module of the Sensor of IoAT.

TABLE V: Variation in output Voltage value.

Conditions	Output Voltage (in Volts)
Sunny	16.3
Moderately Sunny	14.4
Overcast	8.33
Shady/Dark	0.89

enables the oldest entry to be processed further in the data buffer.

The time interval between measuring soil moisture of the field is kept high enough to avoid faulty values because of the time delay in processing and sending the values to the cloud storage. The two probes are given 5 V and gnd respectively, because of which after dipping the probes in the soil, the medium between them(soil) will be conductive, and probes receive some electron. To measure the moisture level of the soil, we calculate the resistance between the two probes using the concept of dielectric permittivity. The 10kohm resistor between the pins A0 and gnd creates a reference resistance for us to calculate the resistance between the probes. For calibrating the soil moisture sensor, 100 grams(gm) soil was mixed with 100 milliliters (ml) of water, and the moisture content of the soil was calculated using the following expressions

$$Sm = \left(\frac{WW - DW}{DW}\right), \quad (7)$$

$$Smp = 100 \times Sm. \quad (8)$$

In the above expressions, Sm refers to the soil moisture level, Smp is the percentage of soil moisture content, WW is the weight of the wet soil, DW is the weight of the dry soil. The soil moisture sensor calculates the % moisture content using the following expression:

$$Smps = k^2(0.008985 \times MV + 0.207762), \quad (9)$$

where $Smps$ is the percentage of soil moisture content, $k = 2.718282$, and MV is the analog reading of the soil moisture sensor from the microcontroller. The calibration values of the soil moisture sensor are, given in Table VI. The Table shows the same change in the values of the soil moisture sensor and calculates soil moisture values, which shows the efficiency of the sensor.

TABLE VI: Comparison of self-made and existing soil moisture sensor values.

Parameters	Self-Made Values	Sensor	Calculated Values
Inside Dry Soil	1		1023
	2		1022
	4		1021
Inside Water	250		673
	260		650
	260		623
Inside Wet Soil	537		534
	482		489

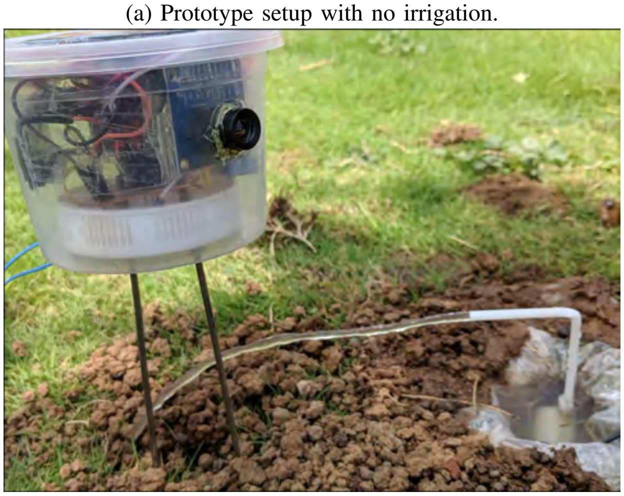
The proposed solar-power module can be integrated with hardware-assisted security feature as presented in our work called "Eternal-Thing" [5] that combined security and energy harvesting. We can also integrate our proposed solar-power module with our intelligent battery modules that improve battery life to further improve sustainability [32].

IX. Experimental Prototyping and Validation

A. *Experimental Prototyping of IoAT Using*

This section describes about the hardware and software requirements necessary for the proposed system design. The prototype of IoAT device is shown in Fig. 12. The experimental prototype of sCrop is given in Fig. 12a showing no irrigation, as the soil moisture level measured is greater than the threshold soil moisture content. Whereas, in Fig. 12b, the irrigation is actuated as soon as it detects a soil moisture level less than the threshold.

(a) Prototype setup with no irrigation.



(b) Less soil moisture level, prototype setup with irrigation.

Fig. 12: IoAT Experimental Prototype.

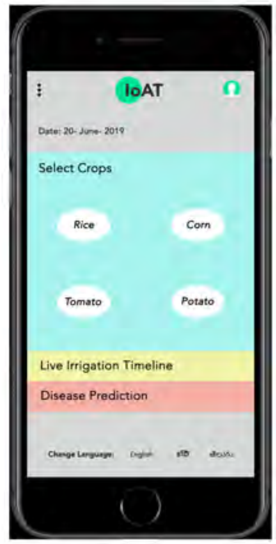


Fig. 13: Proposed sCrop App for User Interface.

The hardware constituents of the prototype include ESP-8266 as the micro-controller [33], interfaced with the soil moisture, temperature, humidity, and camera sensors [34]. The developed soil moisture is durable, accurate and cost-effective when compared with its peers. The sensory probes of the soil moisture sensor are made of stainless steel and variable length, to prevent corrosion and be adaptable to any root length. The software requirements include Arduino Integrated Development Environment (IDE), ThingSpeak cloud database, and Python IDE.

The IoAT mobile application, as shown in Fig. 13 , provides various options for selecting the crop, track live irrigation status and crop disease predictions. The requirements for the development of the application are Android Studio, PyTorch and Keras. PyTorch and Keras helps in deploying the trained CNN model in the mobile application.

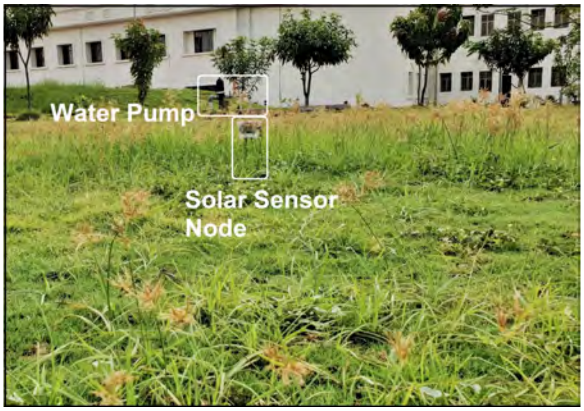
B. Experimental Validation

For experimental purposes, the proposed system is deployed with one solar sensor node and two functionalities of the prototype are validated, i.e.automatic irrigation using solar sensor node and disease prediction. The experiment is performed by deploying the prototype in a real agricultural field as shown in the Fig.14. During the experiment, we found the peak power comsumption by our node to be 20 mA. As we have made sure of using a the sensors with low power consumption, we can run a fully charged 1000mAH battery for about 48-55 hours fully functional. Even with a high enviornment temperature, the circuit temperature didn't cross the threshold temperature of the node. The first functionality is tested in three scenarios for a period of three months: Morning / Evening Hours, Noon / Peak Hours, and Dusk / Night Hours. Following which, the disease prediction is discussed. The experiment is carried out in the field of size $50X50\ m^2$.

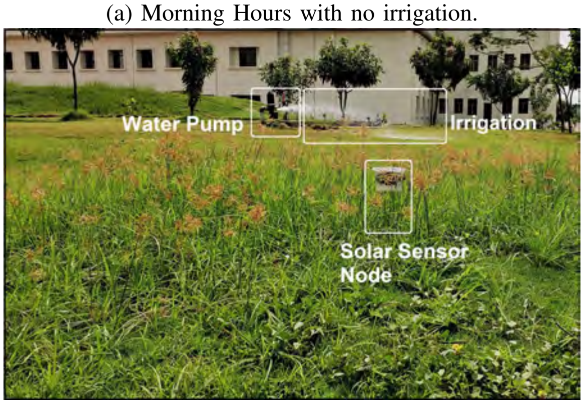
1) Morning/ Evening Hours: This experiment is carried out in two time slots, i.e., Slot 1 (5 AM - 7 AM and 3 PM - 5 PM) and Slot 2 (7 AM - 11 AM and 5 PM - 6:30 PM). Slot 1 consists of an overcast sky that powers the solar panel, which generates a total of 8.33 V, stepped down to 3.3 V to power the node. Similarly, Slot 2 generates a total of 14.4 V. Once the soil moisture reading is less than the threshold Fig. 14a, the water pump is turned on for 45 minutes Fig. 14b. The sensor node data along with a time stamp is sent to the cloud. A similar pattern is observed in the change of moisture value during the Slot 2 experiment.

2) Noon / Peak Hours: This experiment is carried out in the time slot of 11 AM - 3 PM during which the sunlight is at its maximum luminosity. The solar panel generates a total of 16.3 V, out of which, 3.3 V is used to power the microcontroller and 12.9 V is used to recharge the backup battery. The solar sensor node senses the value of the soil moisture content to be more than the threshold value. The experimental setup for the condition described above is represented in Fig. 15. The significance of this experiment is to notify the farmer as this time-slot doesn't require irrigation and thus he needn't be at the field. He can monitor all other changes via the app.

3) Dusk / Night Hours: This scenario, shown in Fig. 16, is considered for the time duration 7 PM - 4 AM during which there is no sunlight. The solar panel generates a total of 0.89



(a) Morning Hours with no irrigation.



(b) Less soil moisture level, morning hours with irrigation.

Fig. 14: Experimental setup (Morning Hours).

Fig. 15: Experimental Setup (Noon Hours).

V, hence, the backup battery power is used to control the microcontroller. The solar sensor node senses the value of the soil moisture content to be more than the threshold. All the environmental variables along with the time-stamp are updated in the cloud. The experiment has been carried out during night time and hence, the quality of the image appears dark.

Fig. 17 shows optimised soil moisture values when automation is used instead of traditional irrigation approach. The x-axis denotes the duration and the y-axis denotes the soil moisture content. From the comparison, it is visible that without automation there is an excess in the irrigation which might lead to biotic stress and diseases. However, the IoAT

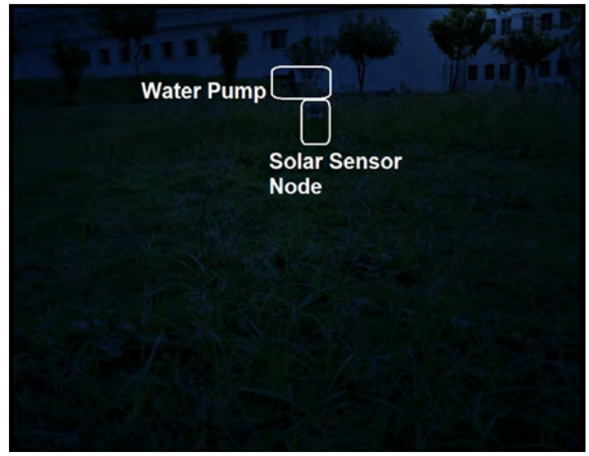


Fig. 16: Experimental Setup (Night Hours).

system being equipped with disease prediction provides real-time protection for the crops.

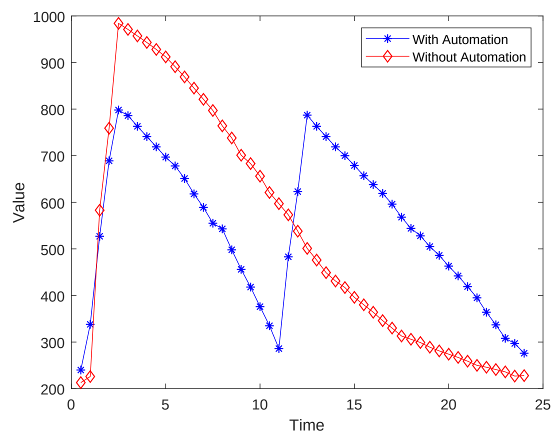


Fig. 17: A complete day soil moisture value change comparison between automated irrigation scenario and with automated irrigation scenario.

C. Comparative Perspective with Related Works

The proposed IoAT solution is developed to overcome the drawbacks of existing solutions in terms of energy efficiency, cost-effectiveness and robustness of sensors. The proposed IoAT solution is solar powered which makes it energy efficient and overcomes the drawbacks of [15]–[19], [21]. The developed soil moisture sensor overcomes the drawbacks of [16], [19]. Unlike [15]–[17], [19], [21], the proposed solution does not require any additional hardware to connect to the cloud database. The trained CNN plant disease classifier overcomes the low accuracy drawback in [19], [24], [25], [28] and usage of high computational resources in [25], [27].

X. Conclusion and Future Works

In this paper, a solar enabled smart agriculture system coupled with crop disease prediction is proposed to aid the farmer in making agriculture more profitable and less arduous. The deployment of the proposed method is demonstrated in real-time. A developed soil moisture sensor, DHT11 sensor, and a camera module integrated with the NodeMCU comprise the solar sensor node. The solar sensor node is powered by a solar panel, and this sets the proposed solution on an energy-efficient side when compared with the existing solutions. The soil moisture values help in the automation of the water pump for irrigation, and the camera snapshots of the crops are sent to the ThingSpeak cloud for storage and further processing. Besides, the IoAT app is provided for tracking the irrigation process and helps in analyzing the crop images from IoT cloud to predict the disease, if any.

In the future aspects of the proposed solution, the developed IoAT app can be made available for usage in various regional languages for the ease of use by the farmer and a multi-platform app can also be developed enabling app usage in Android and iOS. A database for various other crop diseases can be built and used to train the model, increasing the efficiency of the solution and enabling coverage of more number of crops and their diseases. Security and privacy issues in the smart agriculture also needs research within the energy consumption constraints [35]–[37].

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References

[1] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour, and E. M. Aggoune, "Internet-of-Things (IoT)-Based Smart Agriculture: Toward Making the Fields Talk," *IEEE Access*, vol. 7, pp. 129 551–129 583, 2019.

[2] agrocares, "What is the difference between precision, digital and smart farming?" 2019, last Accessed on 08 May 2020. [Online]. Available: https://www.agrocares.com/en/news/precision-digital-smart-farming/

[3] J. Lowenberg-DeBoer, *The economics of precision agriculture*, Nov 2018, pp. 461–494.

[4] A. Gupta, H. P. Gupta, P. Kumari, R. Mishra, S. Saraswat, and T. Dutta, "A real-time precision agriculture monitoring system using mobile sink in wsns," in *2018 IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS)*. IEEE, 2018, pp. 1–5.

[5] S. K. Ram, S. R. Sahoo, B. B. Das, K. K. Mahapatra, and S. P. Mohanty, "Eternal-Thing: A Secure Aging-Aware Solar-Energy Harvester Thing for Sustainable IoT," *IEEE Transactions on Sustainable Computing (TSUSC)*, vol. XX, no. YY, p. Accepted on 08 Apr 2020, 2020. [Online]. Available: http://dx.doi.org/10.1109/TSUSC.2020.2987616

[6] N. Ahmed, D. De, and I. Hussain, "Internet of Things (IoT) for Smart Precision Agriculture and Farming in Rural Areas," *IEEE Internet of Things Journal*, vol. 5, no. 6, pp. 4890–4899, December 2018.

[7] S. Shekhar, J. Colletti, F. Muñoz-Arriola, L. Ramaswamy, C. Krintz, L. R. Varshney, and D. Richardson, "Intelligent Infrastructure for Smart Agriculture: An Integrated Food, Energy and Water System," *arXiv CoRR*, vol. abs/1705.01993, 2017.

[8] S. Saraswat, H. P. Gupta, T. Dutta, and S. K. Das, "Energy efficient data forwarding scheme in fog-based ubiquitous system with deadline constraints," *IEEE Transactions on Network and Service Management*, vol. 17, no. 1, pp. 213–226, 2019.

[9] S. P. Mohanty, "AI for Consumer Electronics—Has Come a Long Way But Has a Long Way to Go," *IEEE Consumer Electronics Magazine*, vol. 9, no. 4, pp. 4–5, July 2020.

[10] S. P. Mohanty, U. Choppali, and E. Kougianos, "Everything You Wanted To Know About Smart Cities: The Internet of Things is the Backbone," *IEEE Consumer Electronics Magazine*, vol. 5, no. 3, pp. 60–70, July 2016.

[11] M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, "A Survey on the Role of IoT in Agriculture for the Implementation of Smart Farming," *IEEE Access*, vol. 7, pp. 156 237–156 271, 2019.

[12] S. S. Roy, D. Puthal, S. Sharma, S. P. Mohanty, and A. Y. Zomaya, "Building a Sustainable Internet of Things: Energy-Efficient Routing Using Low-Power Sensors Will Meet the Need," *IEEE Consumer Electronics Magazine*, vol. 7, no. 2, pp. 42–49, March 2018.

[13] T. W. Bank, "Agriculture, forestry, and fishing, value added (% of GDP)," 2019. [Online]. Available: https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS

[14] O. Elijah, T. A. Rahman, I. Orikumhi, C. Y. Leow, and M. N. Hindia, "An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenges," *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 3758–3773, October 2018.

[15] R. N. Rao and B. Sridhar, "IoT based smart crop-field monitoring and automation irrigation system," in *Proc. of the 2nd International Conference on Inventive Systems and Control (ICISC)*, Jan 2018, pp. 478–483.

[16] H. Benyezza, M. Bouhedda, K. Djellout, and A. Saidi, "Smart Irrigation System Based Thingspeak and Arduino," in *Proc. of International Conference on Applied Smart Systems (ICASS)*, Nov 2018, pp. 1–4.

[17] F. Karim, F. Karim *et al.*, "Monitoring system using web of things in precision agriculture," *Procedia Computer Science*, vol. 110, pp. 402–409, Dec 2017.

[18] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour, and E.-H. M. Aggoune, "Internet-of-Things (IoT)-Based Smart Agriculture: Toward Making the Fields Talk," *IEEE Access*, vol. 7, pp. 129 551–129 583, 2019.

[19] W.-L. Chen, Y.-B. Lin, F.-L. Ng, C.-Y. Liu, and Y.-W. Lin, "RiceTalk: Rice Blast Detection using Internet of Things and Artificial Intelligence Technologies," *IEEE Internet of Things Journal*, vol. 7, no. 2, pp. 1001–1010, Feb 2020.

[20] S. Kumar, G. Chowdhary, V. Udutalapally, D. Das, and S. P. Mohanty, "gCrop: Internet-of-Leaf-Things (IoLT) for Monitoring of the Growth of Crops in Smart Agriculture," in *Proc. of the 5th IEEE International Symposium on Smart Electronic Systems (iSES)*, 2019, pp. 53–56.

[21] F. Bing, "Research on the Agriculture Intelligent System based on IoT," in *Proc. of International Conference on Image Analysis and Signal Processing*, 2019, pp. 1–4.

[22] T. He, K.-W. Chin, S. Soh, and C. Yang, "On Optimizing Max Min Rate in Rechargeable Wireless Sensor Networks with Energy Sharing," *IEEE Transactions on Sustainable Computing*, vol. 5, no. 1, pp. 107–120, Jan 2020.

[23] N. Ahmed, D. De, and I. Hussain, "Internet of things (IoT) for smart precision agriculture and farming in rural areas," *IEEE Internet of Things Journal*, vol. 5, no. 6, pp. 4890–4899, 2018.

[24] D. Ashourloo, H. Aghighi, A. A. Matkan, M. R. Mobasheri, and A. M. Rad, "An investigation into machine learning regression techniques for the leaf rust disease detection using hyperspectral measurement," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 9, no. 9, pp. 4344–4351, 2016.

[25] M. Al-Amin, T. A. Bushra, and M. N. Hoq, "Prediction of Potato Disease from Leaves using Deep Convolution Neural Network towards a Digital Agricultural System," in *Proc. of 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*, 2019, pp. 1–5.

[26] V. Pallagani, V. Khandelwal, B. Chandra, V. Udutalapally, D. Das, and S. P. Mohanty, "dCrop: A Deep-Learning based Framework for Accurate Prediction of Diseases of Crops in Smart Agriculture," in *Proc. of the 5th IEEE International Symposium on Smart Electronic Systems (iSES)*, 2019, pp. 29–33.

[27] S. Kaur, S. Pandey, and S. Goel, "Semi-automatic leaf disease detection and classification system for soybean culture," *IET Image Processing*, vol. 12, no. 6, pp. 1038–1048, Feb 2018.

[28] N. Materne and M. Inoue, "Iot monitoring system for early detection of agricultural pests and diseases," in *Proc. of 12th South East Asian Technical University Consortium (SEATUC)*, vol. 1, 2018, pp. 1–5.

[29] Y.-W. Lin, Y.-B. Lin, and C.-Y. Liu, "AItalk: a tutorial to implement AI as IoT devices," *IET Networks*, vol. 8, no. 3, pp. 195–202, 2019.

[30] S. Liao, Y. Xie, X. Lin, Y. Wang, M. Zhang, and B. Yuan, "Reduced-Complexity Deep Neural Networks Design using Multi-Level Compression," *IEEE Transactions on Sustainable Computing*, vol. 4, no. 2, pp. 245–251, Apr 2017.

[31] S. Mohanty, *Plant Village Dataset*, last Accessed on 08 May 2020. [Online]. Available: https://github.com/spMohanty/PlantVillage-Dataset

[32] S. K. Mandal, R. N. Mahapatra, P. S. Bhojwani, and S. P. Mohanty, "IntellBatt: Toward a Smarter Battery," *IEEE Computer*, vol. 43, no. 3, pp. 67–71, March 2010.

[33] OmniVision-Technologies, "ESP8266 NodeMCU," 2020. [Online]. Available: https://cityos-air.readme.io/docs/esp8266-nodemcu

[34] OmniVision Technologies, “CAMERACHIP Image Sensor,” 2006. [Online]. Available: http://web.mit.edu/6.111/www/f2016/tools/OV7670_2006.pdf

[35] M. Gupta, M. Abdelsalam, S. Khorsandroo, and S. Mittal, “Security and Privacy in Smart Farming: Challenges and Opportunities,” *IEEE Access*, vol. 8, pp. 34 564–34 584, 2020.

[36] A. Shahid, A. Almogren, N. Javaid, F. A. Al-Zahrani, M. Zuair, and M. Alam, “Blockchain-Based Agri-Food Supply Chain: A Complete Solution,” *IEEE Access*, vol. 8, pp. 69 230–69 243, 2020.

[37] A. J. Alkhodair, S. P. Mohanty, E. Kougianos, and D. Puthal, “McPoRA: A Multi-Chain Proof of Rapid Authentication for Post-Blockchain based Security in Large Scale Complex Cyber-Physical Systems,” in *Proc. International Conference on Intelligent Sustainable Systems (ICISS)*, 2020, pp. 446–451.

[38] V. Udutalapally, S. P. Mohanty, V. Pallagani, and V. Khandelwal, “sCrop: A Internet-of-Agro-Things (IoAT) Enabled Solar Powered Smart Device for Automatic Plant Disease Prediction,” *arXiv Electrical Engineering and Systems Science*, no. arXiv:2005.06342, May 2020.

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