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IoT Based Smart Agriculture and Plant Disease Prediction

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IoT Based Smart Agriculture and Plant Disease Prediction

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Abstract. Agriculture is a very prominent sector in our country and has been one of the highest contributors to the GDP. During the 1960s, an all-time high was reached with approximately 50% contribution to the GDP of the country, as more than half of the population was rural and focused primarily on agriculture as means of their livelihood. But from the latest records of 2019, the contribution by this sector has decreased to 15.96 percent. IoT plays a significant tole in remote sensing with machine learning in monitoring crops and surveying, which in turn aids agriculturists in ways for efficient field management. The proposed work integrates the role of Internet of Things and Deep learning deployment in farm management and disease identification of leaves. With the use of Internet of Things through remote sensing this work monitors the agriculture field parameters in remote cloud environment. With modified Resnet model deployed on the cloud for the purpose building a smart disease prediction. This system achieves 99.35% accuracy for the dataset. Overall this approach will provide an opportunity for agriculturists to test the plant disease with a smart phone connected to Internet and take appropriate actions.

1. Introduction

Agricultural Industry in India contributes so much to the GDP of the country, as shown in figure 1. But, though the contribution of agriculture to the GDP has significantly come down two 18 percent from 40 percent in 1960's. Part of the reason for this is the fact that the sector has not adapted to advances in technology as other sectors have. Most techniques being used are decades, and at times, centuries old. While some modernization has occurred, the rate of this is much lesser than that of other industries. This work proposes a twofold system in technological advancements in agriculture industry. The first part consists of an IoT deployment which aims to use an array of sensor networks in conjunction with Cloud enablement for real-time monitoring of environmental factors such as light intensity, temperature, soil moisture, etc. and thereafter communication of related data over a small-scale wireless network. This focused data collection may be used to develop a user-friendly application to control irrigation activities like watering of plants and monitoring plant health. It should also be noted that it is difficult to combat persistent disease traits which plague crops and trouble farmers. Therefore, the second part allows farmers to detect diseases in their plants by capturing an image and loading them into the module, which uses a CNN model to predict what diseases the plant has, if any.

To quote (Rawal 2017, p.1) , "Automation of farm activities can transform agricultural domain from being manual and static to intelligent and dynamic leading to higher production with lesser human

supervision." This novel work integrates the Internet of Things and Deep learning to provide a better atmosphere for agriculturist to better understand their field and take appropriate control measures.
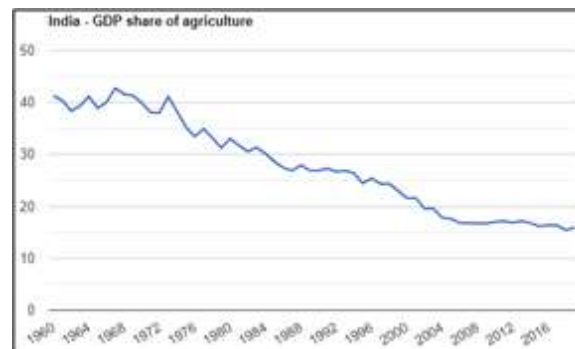

Figure 1. India - Percentage GDP share of agriculture 1960-2019 (Source: The World Bank)

2. Related Work

IoT platform that enable the farmers to remotely check the status of sprinklers installed on the farm by the recorded sensor values [1]. Support Vector Machine (SVM), and KNN based system for plant leaf disease detection and classification .The dataset consists of plants with one of the three diseases - early blight, late blight, and black rot. k-means clustering is used for the segmentation of image [2]. An IoT based smart irrigation system was proposed for monitoring soil moisture, humidity, temperature sensor values present in the soil and also using an anemometer to check the weather condition. The system is also used to control the water level automatically by stating if the pump is on or off. This complete system relies on ATmega microcontroller which enables the control and information capturing [3-5]. A GPS based remote controlled system for smart agriculture to complete farm duties like detecting weed, moisture, scaring of birds, etc. [6]. Using Multi-SVM, CNN model and a Learning Vector Quantization (LVQ) algorithm based technique to identify diseases and classify tomato leaves classifier an automated system based on an Android application is used for detecting disease based on pictures for effected jute plants and send them to the dedicated platform [7], [8]. DNN based system is implemented for system which allows detecting weeds within crops [9], [10].

3. Methodology

3.1. IoT Model type

The IoT Smart Monitoring System is designed to smartly monitor factors such as light intensity, soil moisture etc., which are key environmental features in the growth of plants. A basic model overview of the Smart Monitoring System in the form of a block diagram can be observed in Figure 2.
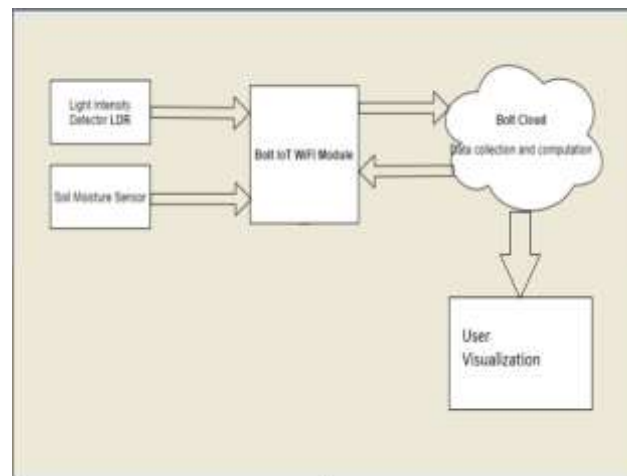
Figure 2. IoT Smart Monitoring System Block Diagram

The system consists of the following major components: Bolt IoT Wi-Fi module, Sensors, and the Cloud.

1. *The Light Intensity Sensor and Soil Moisture Sensor* constantly measure the environmental values which are sent to the cloud by the Bolt Wi-Fi module. These values are presented for the user to view in form of line graphs and visualization.
2. *Bolt IoT Wi-Fi module*: Bolt IoT Wi-Fi module is a fully integrated IoT platform which acts as a WiFi module while also providing cloud services.
3. *LDR/Photoresistor*: The PG-5 is a photoresistor that measures the intensity of the ambient light. This is used to measure the amount of sunlight received by the plants.
4. *Soil Moisture Sensor*: The Soil Moisture Sensor is used to measure the content of water in the soil. This is used to decide when to water the plants/water requirement. This work used the MH-sensor series soil moisture sensor for gauging activities.

Bolt Cloud: This is Bolt IoT's owned Cloud platform for management and enablement of its cloud services. It has smooth interfacing and pipelining methods to seamlessly establish connection over a Wi-Fi network and host data gathered from local or wireless sensors for visual presentation and computational analysis by the user.

3.2. Plant Disease Prediction System

The Plant Disease Detection System is modelled to allow farmers to quickly and easily identify the diseases the plants might be suffering from. The fundamental structure of this module is illustrated in the figure 3. This work employs the Mohanty [11] dataset of Epidemiology lab, EPFL, Geneva for training and validating the plant disease identification.
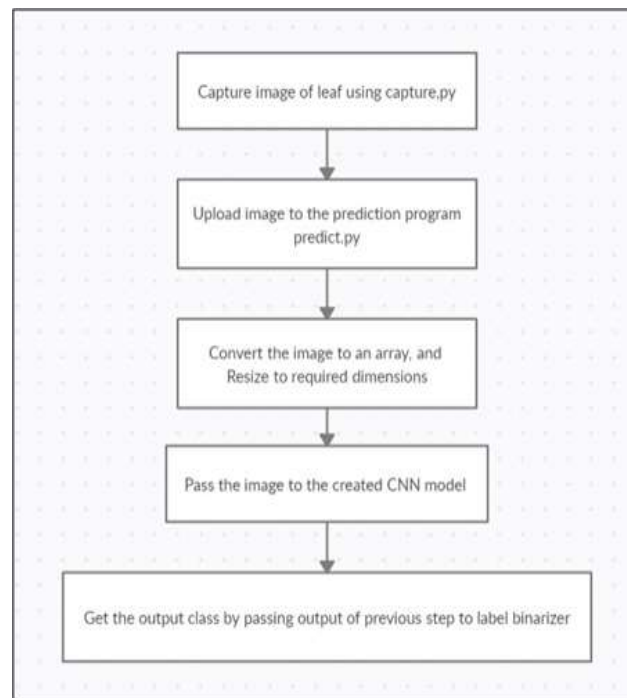
Figure 3. Plant Disease Detection System Block Diagram

This system comprises of two major components:

1. *Creating the CNN model*: The first step is to create a Machine Learning model. This work is carried out using a Convolutional Neural Network (or CNN) model. The main contributions of this research are:
   a. A comprehensive study of Deep neural networks models for plan disease identification
   b. Improvising the Resnet model for the dataset by deploying a "One cycle Learning Rate Policy" instead of traditional fixed learning rate
   c. The hyper parameters are further optimized for weight decaying and gradient clipping to suit to the training the plant disease identification.

2. *Using the model to predict*: The next step is to use the created model to predict the condition of the leaf. This would include capturing the image of the leaf, and then the module should output the condition of the leaf. This step would be carried out in real-time.

The model is trained on a Nvidia GPU for faster processing purposes. This model is trained using Resnet architecture for feature extraction. The model is trained for 65,89,734 params. These features are used to train class specific intermediate convolutional neural layer.

4. System Architecture

Our proposed architecture consisting of two derivative sub-models will work along these separate flow tracks. The will eventually function along these lines:
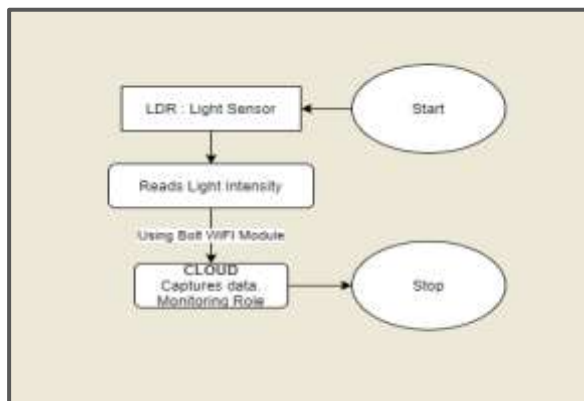
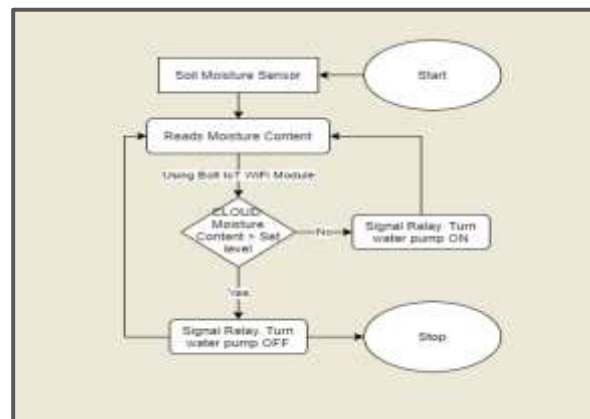**Figure 4.** Light Intensity Sensor pathway

Figure 5. Soil Moisture Pathway

4.1. IoT Smart Monitoring System
1. Sensors will be used to detect local analog readings.
2. Data gathered will be relayed to the cloud platform using Wi-Fi module.
3. Visualizations and presentation in form of graphs and plots present on Cloud server.

Figure 4 and 5 depicts the sensor based pathways for the Light Intensity Sensor and the Soil Moisture Sensor respectively. As it is observed in the figures, the LDR/photoresistor is a sensory device that measures the Light Intensity. This value is sent to the Bolt Cloud using the Bolt Wi-Fi module. These values can then be utilised by the user for visualizations as line plots, charts, graphs, etc. As for the soil moisture sensor, the initial flow is similar to that of the LDR. The moisture content in soil is detected by the sensor and sent to the Cloud using the Bolt IoT Wi-Fi module which not only ensures effortless interfacing options between itself and the sensor, but also offers easy Cloud pipelining and services enablement options for decent line plot, graphical visualisations and analysis. The user can utilise this data to derive water requirements of their plants and understand watering needs based on a pattern analysis study.

4.2. Plant Disease Prediction System

1. Run Python program and capture real-time image using computer webcam.
2. The program on running resizes and re-adjusts images captured according to set dimensions of our prediction model and generates a new folder. This forms our test class or the new disease class.
3. Load the new data into the CNN prediction model to get classifications regarding the plant disease as per trained model.

The images are both of healthy plants and of plants with certain diseases. Some of the diseases covered in the dataset are Bacterial spot for Bell Peppers, Early blight and late blight for Potatoes, and Early blight, Late blight, Leaf Mold, Septoria Leaf spot, Spider mites, Mosaic Virus, and Curl Virus for Tomatoes. The CNN created contains 5 convolutional 2D layers, with dropout layers in between them. It also contains a MaxPooling 2D layer, and 2 dense layers. All layers except the last dense layer which has softmax activation, have ReLU as the activation parameter. The network is trained for 4 epochs.

5. Results

In this proposed system by accurately connecting our sensory components with the Bolt Wi-Fi module and powering the setup using a Type-A USB port, siphoning energy from a personal computer or

laptop. The CNN model is trained to utilize around 20k images of plant disease classes from the Plant Village Dataset and cross-validate its accuracy using a test set. This is used to remodel and generate new disease class for a real time analysis, classification and plant disease prediction. Our model is characterized by the ability to identify the cash crops - potato, tomato and bell pepper.

Figure 6. IoT Smart Monitoring System

5.1. IoT Smart Monitoring System

From the figure 7, the hardware implementation of this study in conjugation with a potted ornamental plant for real time sensor data collection of light intensity and soil moisture.

5.2. Plant Disease Detection System

Using the Resnet as the feature extracting process, the model achieved 99.35% accuracy for the test data deployed. All the trainable parameters in this Deep Neural Network model used one rate learning policy. The training loss also linearly narrows down as the learning increases. From the respective plots it can be safely conclude that there is positive growth of model accuracy, whereas there is a steady decline for the model loss.

Finally this model will generate the following overall test accuracy percentage as depicted by Figure 7 and 8, for the CNN model built.
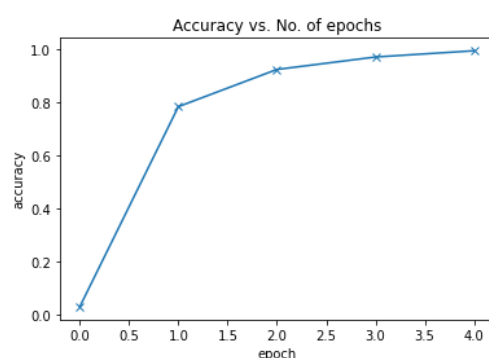

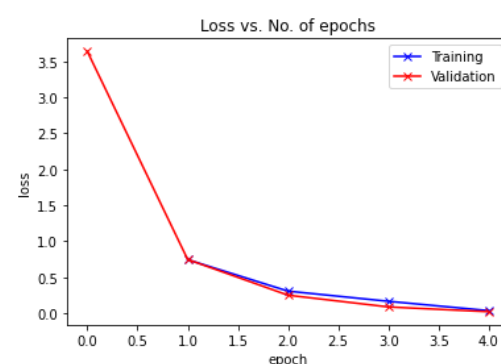**Figure 7.** Accuracy vs epoch of Resnet Model for test dataset

Figure 8. Loss vs epoch of Resnet Model for test dataset

6. Conclusion

The main aim of this work is to build an Integrated IoT system and Plan disease identification using Deep Neural Network model. From a public dataset this model achieved 99.35% accuracy for the test dataset in identifying the diseases with one rate learning approach policy. The deep learning approach uses weight decaying and gradient clipping to prevent weights from decaying and also to prevent undesirable changes in the training parameters gradients not to be adjusted. Further, this model can be deployed for predicting the levels of soil moisture and light at any time. This can have any range of applications from nominal water requirement pattern analysis to complex ensemble weather prediction models. This can be combined with the plant disease identification model and an application can be developed to integrate these features and create a complete smart agriculture and irrigation system.

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