Grow-IoT (smart analytics app for comprehensive plant health analysis and remote farm monitoring using smart sensors)

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Abstract. Agriculture is the primary source of livelihood for a large section of the society in India, and the ever-increasing demand for high quality and high quantity yield calls for highly efficient and effective farming methods. Grow-IoT, a smart analytics app for comprehensive plant health analysis and remote farm monitoring platform to ensure that the farmer is aware of all the critical factors affecting the farm status. The cameras installed on the field facilitate capturing images of the plants to determine plant health based on phenotypic characteristics. Visual feedback is provided by the computer vision algorithm using image segmentation to classify plant health into three distinct categories. The sensors installed on the field relay crucial information to the Cloud for real-time optimized farm status management. All the data relayed can then be viewed using the user-friendly Grow-IoT app to remotely monitor integral aspects of the farm and take the required actions in case of critical conditions. Thus, the mobile platform combined with computer vision for plant health analysis and smart sensor modules gives the farmer a technical perspective. The simplistic design of the application makes sure that the user has the least cognitive load while using it. Overall, the smart module is a significant technical step to facilitate efficient produce across all seasons in a year.

Keywords: IoT, Computer Vision, App Development, Cloud Computing, Sensorics, Remote monitoring, Sustainable

1 Introduction

With the recent shift in people's choice increasing towards high quality and hygienic food, a technological intervention in the agricultural space can fulfill such rising demands. Further, the technology should be easily accessible and usable by farmers. Grow-IoT, a smart analytics app, caters to all such needs [1-3], ensuring higher quality food with minimal labour and pesticides in an agricultural field. The complete smart module performs a detailed analysis of plant health using phenotypic features with the help of cameras and sensors [5]. Images of the crop are segmented and masked through the Computer Vision algorithms [14-15] and sent to the Cloud. The sensors placed strategically in the field help determine parameters such as temperature, pH, and soil moisture. Thus, the overall plant health and status of the farm are sent to the Cloud for real-time analytics and then displayed on the Grow-IoT App interface, making all the valuable insights easily accessible to the farmers [6]. The visually appealing user interface of the app makes sure that all the data is documented and displayed in the simplest way.
possible. Further, based on the results of plant health analysis, the farmers can spray chemicals only in regions where the plants are affected. This ensures perfect conditions for the growth of plants as well as optimum soil quality for maximum throughput. Overall, the Grow-IoT app will guarantee optimized and convenient farming to have the best possible harvest all around the year. The idea thus proves to be vital in fulfilling the rising demands of society for high-quality food.

2 Literature Review

Smart applications that use Artificial Intelligence and Machine Learning algorithms combined with the power of the Cloud contain an immense potential to revolutionize the agriculture industry. Using such intelligent mobile applications, farmers can control the various needs of their crops remotely. Although mobile applications have been lauded for their mobility and the potential of this technology is recognized, its adoption in the agriculture industry is relatively slow compared to other business domains [1]. Extensive research on various mobile applications for crop protection and diagnosis of deteriorating conditions [2-6] has been conducted. Different machine learning techniques and methods for plant disease recognition and classification have been used. Some solutions also use the Cloud for processing and data analysis, while others use the mobile application. While the offline analysis does not require the use of the internet, processing, and data analysis are limited to the capacities of the mobile device itself, most of which are not designed to handle such tasks. Usage of the Cloud helps farmers acquire real-time plant analysis data and other crop and environmental-related parameters. Some of these applications also provide farmers with insights into tackling crop disease, among other features. While mobile applications to monitor specific crop-related parameters and environmental conditions exist, very few of them [7,8] use external sensors and the Cloud for efficient data extraction and analysis. Grow IoT focuses on providing the farmers with an efficient means to monitor their crop health and environmental conditions that assist crop health in helping farmers make time-critical decisions and avoid possible plant diseases. Machine learning, Deep Learning, and AI, in general, have played an essential role in revolutionizing modern-day challenges in defense and security of citizens [9], healthcare [10,11], and business analysis [12]. The concept holds good in the agricultural sector, too [13]. Modern techniques using computer vision and cloud computing have made it possible to remotely monitor the health and status of the plant through its phenotypic features [14,15]. Despite these modern advancements, the flexibility to integrate these intelligent modules with agriculture is limited to only a few. Grow-IoT aims to bridge these gaps with robust solutions, smart features, interactive and straightforward application user interface, all at an affordable price. One of the outstanding features that play a significant role through this application is image capturing and pre-processing. The status of the plant can be remotely monitored through the app that works on computer vision, forming its central architecture. Additional details of the plants through sensors make Grow-IoT possible to provide information on soil moisture, pH, and humidity.

Along with reliability comes the ease of using an application. Grow-IoT ensures a seamless, simplified, user-friendly experience with its easy-to-use UI. Hence integrating this intelligent module with cloud services can provide reliability and trust in a large-scale sector at an affordable cost.

3 Proposed Methodology

3.1 System Architecture

The infrastructure forming the basis of Grow IoT consists of 3 components: Computer Vision, Mobile App, and Cloud computing, as demonstrated by Figure 1, illustrated by the authors.
A. Computer Vision: The model takes in raw input images, passes them through the pre-trained U-Net model, and outputs a segmentation mask. The segmentation mask ratio is calculated from this mask, which depends on the number of healthy pixels, unhealthy pixels, and the number of background pixels.

B. Sensorics: The sensors placed strategically on the field relay real-time data to the Cloud, further used for analytics and generating valuable insights to have the most optimized throughput. The real-time farm health status is displayed on the mobile app, which ensures remote field monitoring.

C. Mobile app: The visualization of all the data picked up by the sensors and variations in that data and the output of the Computer Vision algorithm used to analyse plant health can be viewed through the app.

D. Cloud computing: Real-time data visualization and real-time computer vision are made possible with integration with the Cloud. Using IoT services on the Cloud, data from sensors on the field can be relayed in real-time to the Cloud and then visualized in the app. Cloud storage and Machine Learning services in the Cloud make it possible to detect diseased plants and display them in real-time on the app.

![Figure 1. System Architecture](image)

3.2 Practical Development

A. Computer Vision:

The research consists of a computer vision model which incorporates a U-Net architecture. The structure of the model is a U-shape, hence the name. It is an end-to-end model with an encoder-decoder architecture. Such a composition is instrumental for cases that require fast and accurate image segmentation. A key aspect is that the model can be fed with images of any size instead of a standard or constant value. This can be attributed to the absence of a dense layer in the U-Net. The encoder part is considered as a contracting path, and it consists of a generic convolutional neural network. Two convolutional layers, which are 3x3 and unpadded, are followed by a ReLu activation function and a max-pooling layer, which is 2x2 with a stride of 2. The number of channels for the features is doubled with each iteration of down-sampling. The decoder part is considered as the expansive path, which encompasses an upsampling, followed by 2x2 convolutions, which essentially reduces the number of feature channels by half. This convolution is followed by joining with the respective cropped feature mapping from the encoder part/contracting part, two 3x3 convolutions, each of which is accompanied
by a mathematical ReLu activation function. The formula for the calculation of the segmentation mask ratio is shown in Figure 2.

\[
\text{Number of unhealthy pixels} \div \text{Total number of pixels}
\]

**Figure 2.** Formula for Segmentation mask ratio

The primary development of the Computer Vision model is shown in Figure 3, illustrated by the authors. The ratio found is taken as \( \gamma \), and based on its value, the analysis is divided into three categories. For \( \gamma \) between 0 and 0.33, it is given the optimal category. For \( \gamma \) between 0.34 and 0.67, it is given the sub-optimal category. For \( \gamma \) between 0.67 and 1, it is given the critical category.

**Figure 3.** Primary development of the Computer Vision model

B. Mobile App

The app gives farmers a user experience tailored to fit their daily needs concerning plant health with a user-friendly interface. The app contains visualizations of real-time data captured by the various sensors in the field to help the farmer make time-critical decisions to help prevent plant disease or improve the plant's condition. The app also contains visualizations of daily trends of this data to help farmers make long-term decisions to help avoid possible crop disease. The farmer can also view if crops in their farm are diseased or healthy through the app. The images captured by cameras in the field and the computer vision model results that check whether the plant is diseased are displayed in the app.

Whenever sensor readings cross a particular threshold or diseased plants are detected, the mobile application alerts the farmer by sending them a notification and possible instructions to help them. Using a cross-platform framework, the farmer can view all this data in almost any platform of his choice, be it mobile (Android, iOS), desktop (Linux, Windows, macOS), or web.

4 Results and Discussion

4.1 Computer Vision

Figure 4, illustrated by the authors, represents a sample input image to the model, followed by another image representing a sample segmentation mask for the corresponding raw image. The model ultimately
categorized the image as critical. The computer vision algorithm reads the leaf quality in terms of healthy and unhealthy pixels and gives a final result.

![Original Image and Corresponding Segmentation Mask](image)

**Figure 4.** The original image and the corresponding segmentation mask

### 4.2 Mobile Application

The app consists of a sensor status page as well as a plant health page. On the sensor status page, the farmer can see real-time values of the sensors in the field. Daily trends of the variation of the plant health and growth conditions can also be seen on this page. On the plant health page, the farmer can view images of crops and see if they are healthy or not. Overall, the app allows the user to get the critical status of the farm with the help of computer vision algorithms determining plant health and on-field sensors determining the status of the field. The app acts as a simple interface to allow maximum clarity for the farmer regarding daily trends of the sensor readings and individual readings of each sensor value. The respective pages of the mobile application are shown in Figure 5, illustrated by the authors.

![Mobile Application Pages](image)

**Figure 5.** Pages of the mobile application
5 Conclusion

The development in the agricultural sector using modern Computer Vision algorithms such as U-Net has made it possible for remote and precise farming. The segmentation mask ratio determines a plant's health status, whether optimal, suboptimal, or critical. With the addition of sensors, other vital parameters such as the intensity of sunlight, soil moisture, temperature, and humidity can also be determined to check the plant and soil quality, thus giving the farmer a perspective on the overall status of the farm. Through this smart module, plant health analysis with the help of real-time images can be accessed through the app with remote monitoring. Integrating it through cloud services gives the smart module the power to be scaled to larger agricultural sectors with minimum cost and affordability. Hence, this innovation has scope in forecasting plant traits by modelling through phenotypic relations. The camera module and the group of sensors placed strategically give the farmer an edge of remote vision and critical analysis of the whole farm. Thus, the smart module and the app ensure that the farm is being monitored all day to give valuable insights to facilitate the most effective growth of the plants in the farm.

6 Future Work

The subsequent goals that the computer vision system and a mobile app can accomplish are of great value to be scaled across many more use cases. Figure 6, illustrated by the authors demonstrates a 200m × 200m area of land, not drawn to scale. Multiple cameras can be installed in a field for real-time cloud relay and analysis. Considering the case of a coffee plantation, in which the crops are organized in long rows, with each row being separated by a small distance. In the small gaps that are present between each row, several small cameras can be put in an optimal distance interval. The distance between each camera should be sufficient to enable the computer vision model to detect the health of all the crops between the two cameras. The images relayed from the cameras can be high-quality by using a high-quality lens on each camera module. Low-cost alternatives to high-quality cameras can be very feasible, depending upon what each farmer can afford. Further, from the entire field, these cameras can feed live videos or images from time to time to the computer vision model on the mobile app for the determination of plant health and notifying the user whenever plant health in a region is critical. To solve the problem of large memory requirements, cloud computing is the best option wherein pre-trained models are directly accessed via Cloud services like Microsoft Azure. Such services would require way less memory than the former solution, thus enabling mobile devices with less computation power to effectively perform all the tasks needed by the mobile application. A security camera, shown at the top right of Figure 6, can be an essential security feature for the farmers who are sceptical about their farms and are vulnerable to thefts of intruders at any time of the day. This measure could help prevent any problems due to intruders by setting off theft alarms when the camera spots unidentified personnel. A computer vision model that functions on the edge can significantly detect and alert the farmer in real-time. In addition to showing live feed relay, the mobile app can also get notifications alerting the user about an intruder and have a manual override option to overrule the decision in case of a false alarm. The Grow IoT mobile app can also have more features like purchase reminders, an online market to sell crops, suggestions, trends for crop protection measures, crop nutrition checks, targeted fertilization, irrigation, and harvesting schedules, and farm management through field mapping and machinery management. Adding such features concisely and clearly so that the farmer has the best experience using the app help evolve the idea into a complete smart solution for a farmer.
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