

# An Integrated Platform for the Identification of Suitable Lands and Soil Conditions for Remunerative Crops in Sri Lanka

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**Abstract** - Agriculture in Sri Lanka faces several limitations that impact its development and productivity, including land constraints, climate change impacts, and limited technology adoption. To address these challenges, this research presents an integrated platform combining IoT, GIS mapping, remote sensing, and data analytics. The platform facilitates the identification of optimal lands and soil conditions for cultivating remunerative crops, including coconut, saffron, and vanilla. The study achieved a 98% accuracy in crop prediction using machine learning algorithms, and plant disease detection surpassed 95% accuracy. These results demonstrate the potential to revolutionize agriculture in Sri Lanka and contribute to economic growth and food security.

**Keywords:** Remunerative crops, machine learning in agriculture, smart agriculture.

## I. INTRODUCTION

Agriculture plays a significant role in Sri Lanka's economy by providing employment, food security, and export earnings contributing to economic development as well as environmental sustainability. The country's unique climatic conditions and fertile soil make it suitable for growing a wide variety of crops, which are not only important for domestic consumption but also for exportation.

Yet, 25.5% of Sri Lanka's population is engaged in agriculture, and the agriculture sector's contribution to the national GDP has substantially declined to 224946 LKR Million in the first quarter of 2023 from 241673 LKR Million in the fourth quarter of 2022.[1] The agricultural sector, which once contributed to more than half of Sri Lanka's GDP, is now facing several challenges.

There has been low adoption of mechanization in farming. The lack of private investment in agriculture due to uncertain policies limits the expansion of the sector [2].

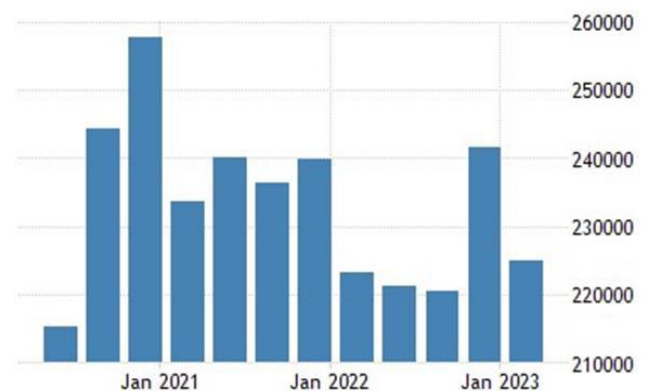


Figure 1: GDP from Sri Lanka's agriculture sector [1]

Agriculture in Sri Lanka faces several limitations that impact its development and productivity. These challenges include land constraints, scarcity, climate change impacts, pest, and disease outbreaks, limited mechanization, and technology adoption, challenges in market access and price fluctuations, and inadequate research and development. It's evident that the identified reason for the lack of progress in Sri Lanka's agriculture is the limited usage of technology.[3] Expanding on this idea, integrating technology into agriculture is of utmost importance for the advancement of agriculture in the country. Technology transformation is vital for increasing agricultural productivity; it contributes to the sustainable and resilient future of agriculture. The combination of machine learning and IoT devices is particularly powerful in agriculture. Growing commercially viable crops can contribute to economic growth by generating income, foreign exchange, and tax revenue.

The solution for Sri Lanka is to make the needed investments so that agricultural production, foreign exchange earnings, and farm incomes do not collapse as a consequence of the loss of labor in the process of economic structural transformation. Meeting the challenges will mean adopting technology to increase labor productivity, improving farm-market linkages, investing in value chains, and generating off-farm employment to absorb excess labor in rural areas. The key objective of this project is to provide the integrated platform as a service to investors and farmers.

The SmartAgro integrated platform addresses many challenges faced by Sri Lanka's agricultural sector as it provides a one-stop solution that combines cutting-edge technology, reliable data sources, and intuitive user interfaces. The proposed system consists of four vital components which are the Identification of bare lands using a GIS map and remote sensing approach, Soil testing and identification of soil conditions, Prediction, and analysis to determine whether the selected crop can be grown in each soil condition, Monitor and maintain healthy growth of crops by plant disease detection and treatment recommendations. Moreover, this research mainly focuses on growing remunerative crops such as coconut, vanilla, or saffron which can contribute to the economy. By harnessing machine learning, remote sensing, image processing, and IoT devices, agriculture can become more sustainable, productive, and resilient. It allows for proactive decision-making, early detection of issues, and precise resource utilization, ultimately leading to improved yields, reduced costs, and minimized environmental impact.

## II. OBJECTIVE

This research paper aims to develop and present an integrated platform that combines cutting-edge technologies, including IoT (Internet of Things) devices, Image processing GIS (Geographic Information System) mapping, remote sensing technology, and data analytics, to facilitate the identification of optimal lands and soil conditions for cultivating remunerative crops in the context of Sri Lanka.

The research will focus on four key components:

### A) Land Classification using GIS Map and Remote Sensing Technology

The first component entails the creation of a comprehensive GIS map integrated with remote sensing data. This will aid in the classification and characterization of bare lands, considering topography, land cover, and other relevant geospatial features to determine their potential for crop cultivation.

### B) Soil Testing using IoT Device

The second component involves the utilization of an IoT device for real-time soil testing and data collection. The objective is to enhance the accuracy and efficiency of soil quality assessment, enabling precise recommendations for suitable crop varieties based on soil characteristics.

### C) Crop Prediction and Analysis

The third component focuses on utilizing the soil test data to analyze and predict the best suitable crop to be grown in each soil condition.

### D) Plant Disease Detection and Treatment Recommendation

The final component involves the implementation of advanced image processing techniques to detect and diagnose plant diseases in real-time. The platform will provide timely recommendations for disease management and treatment, enhancing overall crop productivity.

## III. LITERATURE SURVEY

In [4]'s study, remote sensing is used to examine how changes in land use and land cover have an impact on rice farming in Sooriyawewa, Sri Lanka. Although the primary focus of this research is on changes in paddy farming, it emphasizes the use of remote sensing data and GIS technologies in tracking land use changes. The use of machine learning techniques, such as SVM and CART, may improve the precision with which bare lands are detected and classified in the research region.

Another relevant study by [5] focuses on detecting invasive *Prosopis juliflora* using GIS and remote sensing methods in Bundala National Park, Sri Lanka. Although estimating invasive species is the main goal, bare-land identification may also be accomplished via the combination of GIS and remote sensing. SVM and CART algorithms might be useful in separating bare regions from other forms of land cover. Additionally, the Google Earth Engine and machine learning [4] propose a mapping strategy for detecting changes in land use, land cover, and other variables in the Rahuri watershed in India. Although the research region is distinct, Sri Lankan bare land mapping may apply machine learning techniques for land cover categorization.

The use of IoT devices in soil testing offers several advantages over traditional methods.[6] Jayasiri and Karunarathne (2021) proposed an IoT-based smart farming system that incorporates soil sensors to monitor soil health parameters such as moisture, pH levels, and temperature. Their study demonstrated how real-time data from IoT devices can optimize irrigation and fertilization practices, leading to

improved crop yield. Similarly, [7] Premaratne et al. (2018) developed a wireless sensor network specifically designed for soil monitoring in Sri Lankan agriculture, utilizing IoT devices like soil moisture sensors to collect real-time data. They highlighted the potential of IoT technologies in optimizing crop productivity through effective soil monitoring.

The research paper titled "IoT-based Smart Soil Testing System for Precision Agriculture" by Bhattacharya and Sarkar (2020) presented at the International Conference on Recent Advances in Electronics and Communication Technology (ICRAECT) focuses on the development of a smart soil testing system using IoT for precision agriculture. The authors recognized the importance of precision agriculture in optimizing resource usage and maximizing crop productivity. They proposed an IoT-based solution that integrates wireless soil sensors to monitor crucial soil parameters, including moisture content, pH levels, and nutrient concentrations. By continuously collecting data from the soil sensors, the system provides real-time information about the soil conditions.

Crop analysis and prediction is a critical facet of modern agriculture, with far-reaching implications for food security and sustainable farming practices. Extensive research in this field has led to the development of sophisticated models and technologies aimed at enhancing crop yield forecasts and optimizing agricultural decision-making. Researchers like Vaddadi et al. (2021) have leveraged machine learning algorithms to predict crop output, achieving remarkable accuracy rates of up to 89% by incorporating soil, climatic, and topographic data [9]. Such advancements empower farmers with actionable insights into crop management, ultimately contributing to improved agricultural productivity.

Moreover, multi-criteria decision-making methods, as demonstrated in studies like Zeng et al. (2020), have proven invaluable in selecting the most suitable crops for specific regions based on an array of factors, including soil quality, climate conditions, and market demand [10]. The integration of remote sensing techniques and IoT technologies holds promise for identifying barren lands and assessing crop suitability, further streamlining agricultural processes. As the global population continues to rise, the continued advancement of crop analysis and prediction methodologies is essential to meet the growing demand for food while ensuring the sustainability of agriculture. These innovations underscore the pivotal role of research in shaping the future of agriculture and its profound impact on global food systems.

According to Xuewei Sun et al., traditional digital image processing methods extract disease features manually, which has low efficiency and low recognition accuracy [11]. To overcome this problem, a convolutional neural network

architecture FL-EfficientNet (Focal loss EfficientNet), which is used for multi-category identification of plant disease images was proposed. Firstly, through the Neural Architecture Search technology, the network width, network depth, and image resolution are adaptively adjusted according to a group of composite coefficients, to improve the balance of network dimension and model stability. Secondly, the valuable features in the disease image are extracted by introducing the moving flip bottleneck convolution and attention mechanism. Finally, the Focal loss function is used to replace the traditional Cross-Entropy loss function, to improve the ability of the network model to focus on the samples that are not easy to identify. The experimental results show that the accuracy of FL-EfficientNet in identifying 10 diseases of 5 kinds of crops is 99.72%. At the same time, FL-EfficientNet has the fastest convergence speed, and the training time of 15 epochs is 4.7 h.

As stated by Emma Harte et al. Networks (CNNs) are considered state-of-the-art in image recognition and offer the ability to provide prompt and definite diagnosis [12]. The research investigated the performance of a pre-trained ResNet34 model in detecting crop disease. The developed model is deployed as a web application and can recognize 7 plant diseases out of healthy leaf tissue. A dataset containing 8,685 leaf images captured in a controlled environment, is established for training, and validating the model. Validation results show the proposed method could achieve an accuracy of 97.2% and an F1 score of greater than 96.5%. This demonstrates the technical feasibility of CNNs in classifying plant diseases and presents a path toward AI solutions.

Nagoor Mydeen, et.al proposed an approach [13] of plant disease prediction framework based on CNNs that can effectively identify and classify diseases in plant leaves. The proposed model leverages a large dataset of labeled plant images and employs transfer learning techniques to enhance its predictive capabilities. Experimental results demonstrate the effectiveness of the CNN-based approach, achieving high accuracy rates in disease identification across multiple plant species.

Sri Lanka's agriculture faces challenges like land scarcity, climate change, and low-tech adoption. An integrated platform using IoT, GIS, remote sensing, and data analytics addresses these issues. Existing methods have inefficiencies and data gaps, underlining the need for a new solution.

The research achieves 98% crop prediction accuracy and 95% plant disease detection accuracy. This platform could revolutionize Sri Lanka's agriculture, making it more sustainable and productive.

#### IV. METHODOLOGY

This integrated system stands as a testament to the potential of technology to revolutionize modern farming practices. The proposed system comprises four main components integrated into a single platform to provide services to investors and farmers. The outcome of the proposed system includes a web application provided as a subscription-based service. Initially, the users need to identify the land in which they want to cultivate the crops, the platform facilitates accurate classification of bare lands by harnessing the capabilities of Geographic Information System (GIS) mapping and remote sensing technology. By combining high-resolution satellite imagery and topographical data, it offers a bird's-eye view of the landscape's intricacies. The users can then conduct the soil testing process using the IOT device which has smart sensors for providing real-time data on crucial parameters such as pH levels, moisture content, NPK rate, and electric conductivity. The data from the soil test is sent for lab testing to acquire high-accuracy data for analyzing and predicting the best suitable crop to be grown in the given soil condition. The integration of advanced image processing techniques empowers the platform to swiftly identify signs of plant diseases. To monitor the health of the plants the users need to capture the image of the plant leaves as an input to the system, users can then see the symptoms and disease for early detection and precise intervention. The system not only detects diseases but also provides treatment recommendations and prescribes where the users can purchase those products. By merging IoT soil testing, GIS land classification, crop prediction, and disease detection and treatment recommendation, this platform offers a comprehensive toolset to optimize farming practices.

##### A) Identification of Bare Land using GIS Map and Remote Sensing Technique

Satellite image acquisition involved obtaining high-resolution satellite imagery of the study area in Sri Lanka. This was done using satellite sensors such as Landsat or Sentinel, which captured images in various spectral regions (e.g., visible, near-infrared, and thermal). Data preprocessing was the critical phase that ensured the quality and consistency of the satellite imagery. Atmospheric correction removed atmospheric effects, such as haze or scattering, from the images. Training data collection involved obtaining ground truth data that represented various land cover divisions in the study location. This could be done through field surveys, where researchers visited specific locations and visually classified land cover categories. Existing land cover maps or other reliable reference datasets were also used as training data sources. Classification algorithms were applied to the extracted features to designate land cover classes for each

pixel of the image segment. Supervised classification algorithms, such as Support Vector Machines (SVM), or Decision Trees (e.g., CART), were trained using ground truth data to understand the patterns and characteristics of various land cover classes. Accuracy Assessment evaluated the performance of the classification algorithms and the resulting land cover maps. Metrics such as error matrices, kappa coefficients, or user/producer accuracy were used to quantify the agreement between the classified and reference data.

##### B) Soil Testing using IOT Device

The initial step in developing the IoT device involved conducting comprehensive research and carefully selecting appropriate sensors to measure soil parameters, including temperature ( $^{\circ}\text{C}$ ), soil moisture, TDS (Total Dissolved Solids), and turbidity. This research made significant scientific contributions in the IoT device implementation and the acquisition of sensor data, resulting in substantial pattern recognition and valuable insights. Factors such as sensor accuracy, compatibility with IoT platforms, power consumption, and cost were taken into consideration during the sensor selection process. The chosen sensors for the device were the DS18B20 for temperature measurement, MD0751 V2.0 for soil moisture measurement, a TDS sensor for measuring Total Dissolved Solids, and MD0591 for turbidity measurement.

Subsequently, the selected sensors were integrated into the device along with the necessary hardware components and software modules. The sensors were carefully calibrated, and their measurement accuracy was validated against reference standards and laboratory tests to ensure their reliability and precision.

To enable seamless data transmission from the device to a cloud platform, various wireless connectivity options, such as Wi-Fi, Bluetooth, or cellular networks, were implemented. This allowed for real-time data collection and analysis.

Furthermore, a user-friendly interface was designed to facilitate user interaction with the device. Users could configure settings and visualize the data collected by the IoT device, making it accessible and convenient for field use.

The developed IoT device was then deployed in real-world agricultural settings, and field tests were conducted to assess its performance, reliability, and user satisfaction. These tests provided valuable insights into the device's practical functionality and its ability to meet the needs of agricultural users.

### C) Crop Analysis and Prediction to Determine the Suitable Crop to be Grown in Given Soil Condition

In the context of crop analysis and prediction, data related to factors such as temperature, soil characteristics, pH levels, and NPK (Nitrogen, Phosphorus, Potassium) levels were gathered. A total of 5,000 datasets of soil parameters were collected. After preprocessing and selecting pertinent features, a predictive model, encompassing regression models and machine learning algorithms (such as random forest, support vector machines, KNN Classifier, and XGBoost Classifier), was trained and validated using historical data.

This advanced model was harnessed to forecast crop yields based on key input variables like temperature and soil conditions. Continuous monitoring was carried out to ensure accuracy and adaptability, ultimately assisting farmers in making informed decisions to optimize crop management and enhance yields. The success of this methodology hinged on precise data, efficient prediction algorithms, and a representative dataset for training.

### D) Plant Disease Detection and Disease Recommendation

The proposed component was developed to provide an efficient and accurate method for identifying and diagnosing diseases in plants. By utilizing image processing techniques, such as computer vision and machine learning algorithms, researchers and farmers could analyze images of plant leaves or other parts to detect visual symptoms associated with diseases. This technology aimed to automate the process, allowing for early detection and timely intervention, which could significantly reduce crop losses and increase agricultural productivity. Additionally, by incorporating treatment recommendation systems based on the identified diseases, guidance was received on appropriate measures to control and manage plant diseases effectively.

The first step involved gathering a diverse dataset of images containing healthy plants and plants affected by various diseases. For the initial development, coconut was selected, and nearly 4,046 images of coconut leaves affected by diseases were collected from the Coconut Research Institute (CRI). Once the datasets were collected, the next important step was cleaning and preprocessing the collected images to enhance the quality of the dataset. The preprocessed images were segmented to separate the plant regions from the background. Relevant features were extracted from the segmented plant regions, including color histograms, texture descriptors, shape properties, or other discriminative characteristics that differentiate healthy and diseased plants.

The next step was training a machine learning model. This step was done using Mobilenet, a convolutional neural

network (CNN) algorithm, utilizing the extracted features and the corresponding labels from the dataset. Based on the extracted features, this model learned to classify the plant images into healthy or diseased categories. Next, the trained model was applied to new and unseen plant images to detect diseases and test the accuracy of detection.

Upon completing the disease detection phase, a system was implemented to offer tailored treatment recommendations based on the identified diseases. This entailed suggesting precise pesticides, fungicides, cultural practices, or other relevant interventions to address the specific disease detected. Essentially, this component was developed as an integral part of the integrated platform, capable of receiving plant images as input, conducting disease detection, and delivering treatment recommendations to end-users.

## V. RESULTS & DISCUSSION

The implementation of the "Support Vector Machine" (SVM) algorithm in ArcGIS involved a series of stages to achieve precise land cover classification. In a similar vein, the "CART" algorithm was applied within the Google Earth Engine Code Editor, encompassing dataset preparation, decision tree construction, and model training for land cover classification. To assess the accuracy and reliability of the land cover classification results, the confusion matrix algorithm was utilized in the Google Earth Engine Code Editor. This algorithm provided a comprehensive breakdown of the classification performance by quantifying the number of correctly classified and misclassified samples for each land cover class.

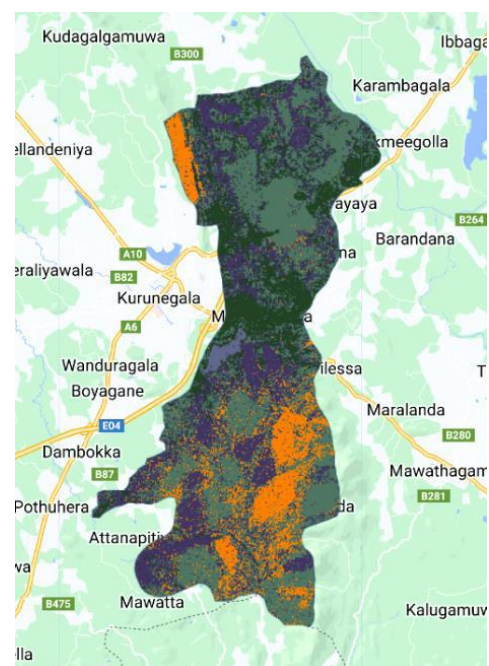


Figure 2: Land cover classification in Mallawapitiya



Figure 3: Mallawapitiya SMAP

Following the outlined methodology, we successfully developed and deployed a device that continuously monitored key parameters, including temperature, soil moisture content, DS (Total Dissolved Solids), and turbidity. Through the integration of sensors, wireless communication, and data analytics, the IoT device provided valuable insights into soil and water quality patterns. The collected data was processed, stored, and visualized on user-friendly dashboards, enabling users to make informed decisions regarding irrigation, fertilization, and other agricultural practices.



Figure 4: Moisture sensor

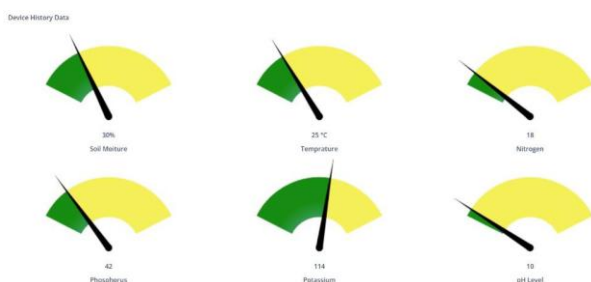


Figure 5: Web application dashboard

Figure 5 illustrates the readings of the testing device. The dashboard provides an intuitive and comprehensive display of soil test readings, presenting essential information at a glance. Users can easily monitor key parameters such as temperature, soil moisture content, Total Dissolved Solids (TDS), and turbidity. These readings are graphically represented, enabling users to track historical trends and patterns. Additionally, the dashboard offers real-time updates, ensuring that users have the most current information at their fingertips. Its user-friendly interface allows for easy navigation, data visualization, and the ability to configure settings for specific agricultural needs. This invaluable tool empowers farmers and agricultural stakeholders with actionable insights for informed decision-making and improved soil management.

The results of crop prediction and analysis using the Random Forest algorithm were highly promising. The model demonstrated exceptional performance in predicting crop yields based on key input variables such as temperature and soil conditions. The overall accuracy of the model on the testing data was calculated at 98%, indicating that the model correctly classified 98% of the samples. This high level of accuracy showcased the model's ability to make precise predictions regarding crop yields.

Furthermore, the Random Forest Classifier emerged as the top-performing algorithm among the models tested. Its superior accuracy and robustness made it a valuable tool for crop prediction and analysis. By leveraging Random Forest, farmers and stakeholders could make informed decisions about crop management, leading to improved agricultural productivity and more efficient resource allocation. The success of this predictive model underscored the potential for data-driven approaches to revolutionize crop management practices in agriculture.

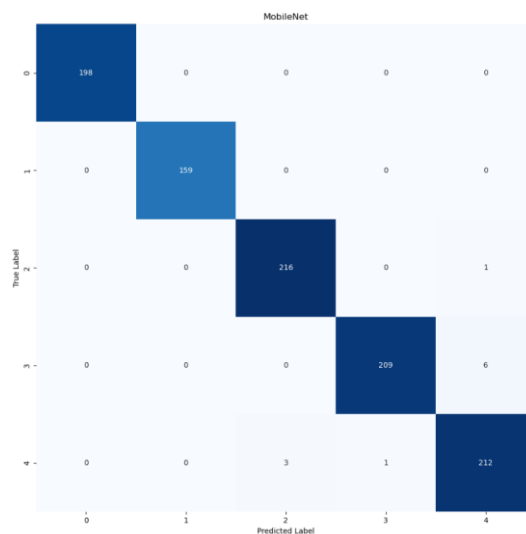


Figure 6: Mobilenet Confusion matrix for disease detection

The presented Figure 6 provides a visual representation of the confusion matrix generated for the MobileNet model. The high true positive values found within the confusion matrix indicate that the MobileNet model excelled in correctly identifying instances of plant diseases. This practical observation signifies the model's effectiveness in identifying diseased plants when they were indeed present.

Additionally, the compact size of the model proved to be advantageous, as it implied efficient resource usage and faster processing. This aspect held particular significance for real-time applications and resource-constrained environments, where swift and efficient processing of data is crucial. The Plant disease detection and treatment recommendation system exhibited outstanding performance in disease detection and treatment recommendation tasks. The deep learning models achieved an accuracy rate exceeding 95% in accurately identifying various diseases in coconut leaves, surpassing traditional methods, and demonstrating superior generalization to new and unseen disease instances. The Mobilenet model, a deep learning architecture, consistently demonstrated excellent performance in a range of image classification tasks, including plant disease detection. Additionally, the treatment recommendation system offered customized and effective strategies for disease control, leading to enhanced crop health and increased yields. The integrated platform leverages advanced image processing and machine learning to precisely identify diseases based on visual symptoms and provide targeted treatment recommendations. The significance of disease identification using the proposed technology lies in its ability to provide a faster, more accurate, and scalable solution compared to traditional methods. This can lead to improved crop management, reduced losses, and ultimately increased agricultural productivity.

## VI. CONCLUSION & FUTURE WORK

The integrated platform presented in this research comprises four main components: land cover classification using GIS mapping, soil testing via an IoT device, crop prediction and analysis, and plant disease detection with treatment recommendations. The ultimate output is delivered through a web application, serving as a valuable service for investors.

The GIS-based land cover classification offers a comprehensive view of Sri Lanka's diverse landscapes, empowering stakeholders to make well-informed decisions based on precise geospatial data. This, in turn, promotes efficient land use and sustainable agricultural practices.

The integration of plant disease detection and treatment recommendations equips farmers with essential tools for disease identification and diagnosis, leading to healthier

yields. Real-time soil data from soil testing enables data-driven decisions on crop selection and soil management strategies.

By seamlessly integrating these four distinct yet interconnected components, this platform marks the advent of data-driven, precision agriculture. It provides investors with the knowledge, insights, and tools needed for sound investment decisions, fostering a more resilient, sustainable, and prosperous agricultural sector in Sri Lanka.

Among the notable future developments for this proposed system are the expansion of crop disease databases, crop databases, and land cover images using UAV drones. Additionally, there are plans to integrate the system with precision agriculture technologies such as variable rate application equipment, automated irrigation systems, and AI-driven autonomous machinery. While the web application is currently in place, there are also intentions to develop a mobile application in regional languages in the future.

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