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Leafguard: Smart Plant Health Detection

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Abstract

Machine learning techniques, including traditional (shallow) ML, deep learning (DL), and augmented learning (AL), are being increasingly utilized for leaf disease classification. These methods involve feature extraction, data augmentation, and transfer learning to enhance model effectiveness and reduce the need for labeled data. The success of machine learning approaches in this domain hinges on the quality and quantity of data available. LeafGuard is a cutting-edge device with intelligent sensing systems for plant health monitoring and maintenance. LeafGuard provides a comprehensive solution for detecting and resolving plant health issues through the use of sophisticated sensors, machine learning algorithms, and real-time data processing. This study explores the features, advantages, and possible uses of LeafGuard in horticulture and agriculture, as well as its operating principles.

Keywords: Machine learning techniques, deep learning, augmented learning, including traditional (shallow) ML

INTRODUCTION

Machine learning has emerged as a powerful tool for automating the detection of leaf diseases in plants. By leveraging various algorithms and techniques on digital images of leaves, machine learning models can effectively identify the presence and specific types of diseases, facilitating timely interventions to mitigate crop losses. This innovative approach involves acquiring leaf images, preprocessing them to enhance features and reduce noise, extracting key characteristics such as color, texture, and lesion patterns, training models to differentiate between healthy and diseased leaves, and evaluating their performance using metrics like accuracy and precision. While traditional machine learning methods like SVM and KNN have been used, deep learning models, particularly convolutional neural networks (CNNs), have demonstrated superior results by automatically learning discriminative features from raw image data. Despite challenges such as obtaining labeled training data, distinguishing between visually similar diseases, and ensuring robustness to environmental variations, the application of machine learning in leaf disease detection holds immense potential to revolutionize crop management practices, enabling proactive monitoring and control of plant health for improved agricultural outcomes. The application of machine learning has revolutionized the field of leaf disease detection, enabling rapid and accurate identification of diseases in plants. Researchers have explored various approaches to tackle this challenge, including traditional machine learning techniques, deep learning models, and augmented learning methods. While traditional algorithms like SVM and K-NN have been utilized for distinguishing between diseased and healthy leaves, deep learning models, particularly convolutional neural networks (CNNs), have demonstrated superior performance by automatically learning discriminative features from raw image data. These deep learning models reduce the need for manual feature engineering and can

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effectively learn from large datasets, although they may require more labeled data compared to traditional methods. E-learning is used in the majority of augmented learning installations. In desktop computing environments, an on-screen, pop-up window, toolbar, or sidebar provides the student with additional contextual information. The learner connects the extra material with the key text that is chosen via a mouse, touch screen, or other input devices when navigating a website, email, or document. Augmented learning has also been implemented on tablets and smartphones in mobile situations. Corporate learning and development providers frequently use augmented learning, with a focus on "learning-by-doing", to impart leadership and creative thinking abilities. It is necessary for participants to apply the knowledge they have learned on e-learning platforms to actual situations. With the utilization of data, each participant receives a customized learning program that includes remediation and additional information.

LITERATURE SURVEY

Qin *et al*. [1]: A framework for deep learning for rice identification of diseases is proposed in this study. The framework utilizes convolutional neural networks to identify diseases in paddy fields based on unmanned aerial vehicle (UAV) images.

Ganatra and Patel [2]: This study investigates the use of deep convolutional neural networks (CNNs) in image-based plant disease classification. The authors achieved high accuracy in detecting several plant diseases on tomato leaves.

Kaur *et al*. [3]: has presented a study on "Neural network application on foliage plant identification". This study investigates the use of deep convolutional neural networks (CNNs) in image-based plant disease classification. The study highlights the potential of this approach for early and accurate disease identification.

Guo *et al*. [4]: This research presents a novel approach to plant disease detection that blends machine learning methods for disease classification with picture segmentation to extract regions of interest. The authors demonstrate the effectiveness of transferring knowledge gained from a large, pre-trained image dataset to a new dataset specifically focused on plant diseases.

Abid *et al* [5]: This paper investigates the use of machine learning algorithms like Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) for classifying plant diseases based on features extracted from leaf images. The significance of picture preprocessing for increased accuracy is emphasized in the study.

Kadir *et al.* introduced the Polar Fourier Transform, and three types of geometric features were used to represent shape features; color features were represented by color moments made up of mean, standard deviation, and skewness; texture features were taken from GLCMs; and vein features were added to enhance the identification system's performance [6].

Rajani and Veena used leaf photos to categorize therapeutic plants that are readily available locally. The experiment used 1500 photos in total and had taken into account 100 species out of every 15 distinct species. The suggested algorithm's accuracy in the current work gives 98.7% [7].

A computer vision method was presented by Sabu *et al.* to identify species of ayurvedic medicinal plants that are found in India's Western Ghats. The suggested system classified using a k-NN classifier and combined SURF and HOG features that were taken from leaf pictures [8].

In order to acquire unsupervised representations of characteristics for 44 distinct plant species that were gathered at the Royal Botanic Gardens in Kew, England, Lee *et al.* researched convolutional neural networks (CNN) [9].

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An automated approach was created by Kumar and Talasila to identify the many medicinal plants that are important to Ayurveda. They concentrated on using pattern recognition algorithms and image processing to identify plants [10].

Based on patterns that were taken from the leaves, Sainin *et al*. suggested a framework for identifying and categorizing tropical medicinal plants in Malaysia. Several angle features are used to extract the patterns from the leaves of medicinal plants [11]. Gao and Lin conducted research and developed an automated approach for identifying medicinal herbs. The system uses the most recent image processing and neural network technology, with the main focus being the leaf image recognition of medicinal plants [12]. An automated approach for identifying medicinal plant leaves gathered from the western Ghats region's suburbs was given by Arun *et al*. [13].

Azlah *et al*. set out to examine and assess how different plant classification techniques were applied and performed. Each method for recognizing leaf patterns has benefits and drawbacks. The quality of leaf photos is crucial, thus before leaf detection and validation, the machine learning algorithm must be established using a trustworthy source of leaf databases [14].

Szegedy *et al*. used aggressive regularization and appropriately factorized convolutions to maximize the efficiency of the additional work. The researchers compared their techniques against the validation set of the ILSVRC 2012 classification challenge and observed significant improvements over the state of the art. For single-frame evaluation, they utilized a network with fewer than 25 million parameters and a computational cost of 5 billion multiply-adds per inference, achieving error rates of 21.2% for top-1 and 5.6% for top-5 [15].

SYSTEM DESIGN

The system design for leaf disease detection using machine learning involves data acquisition, preprocessing, feature extraction, model training, evaluation, deployment, and continuous improvement. It aims to automate disease identification in plants for proactive crop management. This systematic approach leverages machine learning algorithms to analyze leaf images, enabling accurate disease detection. By integrating data acquisition, model training, and deployment, it enhances agricultural practices for improved crop health. Design is the process of using marketing data to create the design of a product that will be made, if the more general topic of product development "blends the perspectives of promotional activities, design, and manufacturing into a single approach to product development." Therefore, the process of defining and creating systems to meet specific user needs is known as systems design.

System Architecture

The current technique forecasts the optimal crop for a specific plot of farmland using a fuzzy model and expert experience. Fuzzy sets represent expert knowledge about the land, weather, air, and agronomists. The final rules are aided in their formation by professional competence. In contrast, the fuzzy technique makes use of several state variables in order to get the intended outcome. The system architecture is shown in Figure 1. The created subsystems and system components that will cooperate to implement the entire system can make up a system architecture. Architecture description languages (ADLs) are a group of formalized languages that have been developed to describe system architecture.

Proposed Design

The hybrid ensemble technique was used in this suggested approach to forecast higher agricultural yields. There is just a single process node in it, and it generalizes all the system's operations about outside entities. The context diagram treats the system, identifying and displaying all its sources, sinks, and inputs in Figure 2.

The system uses the only NPK (Primary Nutrients) which is used only for the intimation of the soil fertility. In this proposed method we are going to use Hybrid ensemble technique to predict the better

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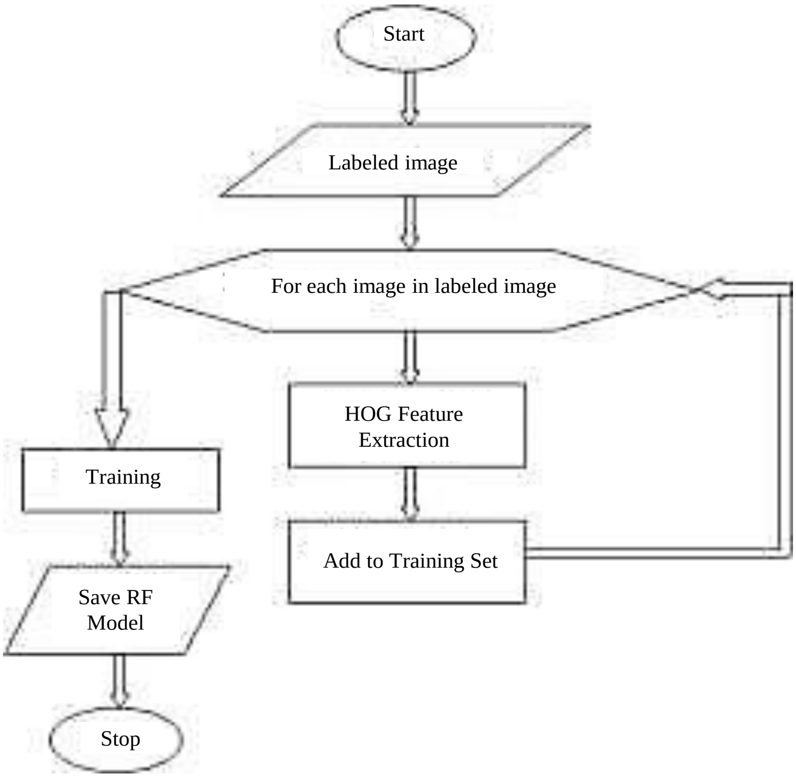

Figure 1. System architecture.

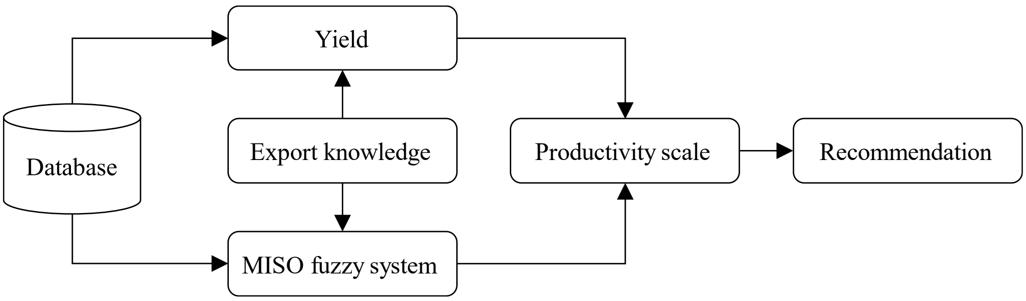

Figure 2. Proposed system.

crop yields and the major factors as pH, Temperature, Average rainfall, Humidity involves affecting the better growth of crop. This will suggest which type of crop will be suitable for that soil. In this project, have done comparative analysis between most famous Classification algorithms to predict the best crop for the soil. The algorithm used for comparative analysis are: Logistic Regression, Decision Tree, Random Forest Classification, SVM, and Naive Bayes Classification. Voltage regulators 7805 and 7833 step down the 9 V battery to 5 and 3 V, ensuring stable operation of the microcontroller and motors.

Context Flow

Context flow diagram is a top level (also known as level 0) data flow diagram. It contains only one process node that generalizes the functions of the entire system in relationship to external entities. In context diagram the entire system is treated as single process and all its inputs, sinks and sources are identified and shown in Figure 3. Once connected, the user selects the specific area of the head that is experiencing pain from the available options (front, right, left, top, or back). Following this, the application initiates the therapy session, starting the vibration motors in the helmet at the designated pain area based on the user's input. The duration of the therapy is determined by the intensity of the headache as reported by the user, with options for low (30 sec), medium (45 sec), or high intensity (60 sec).

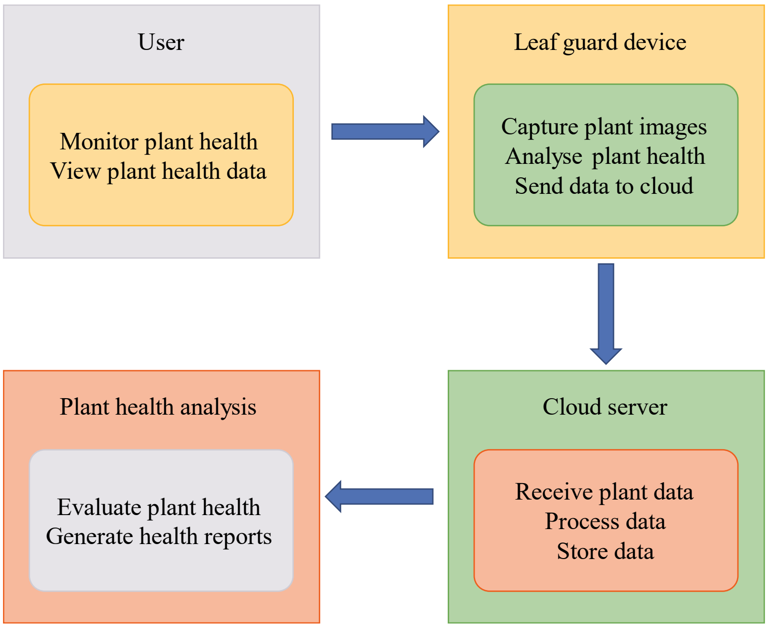

Figure 3. Use case diagram.

Use Case Diagram

In its most basic form, a use case diagram is a depiction of a user's interaction with the system that illustrates the connection between the user and the many use cases that the user is involved in. A use case diagram, which is frequently supplemented by different kinds of diagrams as well, can identify the many use cases and user types of a system.

Training Workflow

A flowchart is a type of diagram that represents an algorithm, workflow or process. The flowchart shows the steps as boxes of various kinds, and their order by connecting the boxes with arrows. This diagrammatic representation illustrates a solution model to a given problem. Flowcharts are used in analyzing, designing, documenting or managing a process or program in various fields. Training workflow is presented in Figure 4.

Testing Workflow

Structured charts help specify the high-level design of a computer program. They assist programmers in breaking down a large software problem into manageable parts through a process called top-down design or functional decomposition. Functions are represented as rectangles, with hierarchy displayed through linking rectangles with lines. Inputs and outputs are indicated with annotated arrows: an arrow entering a box implies input, while an arrow leaving a box implies output.

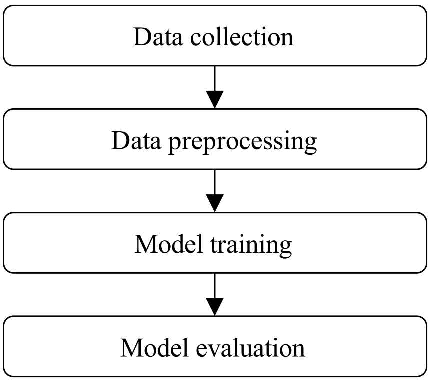

Figure 4. Training workflow.

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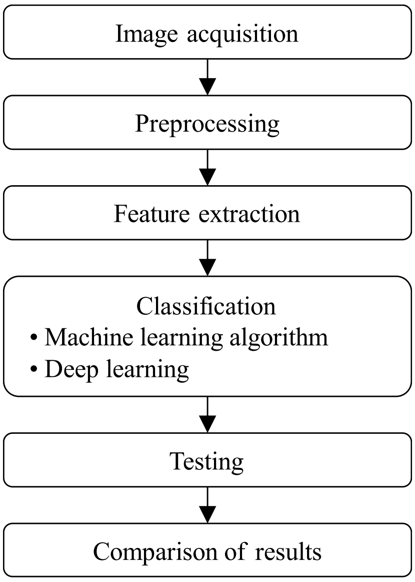

Figure 5. Testing workflow.

Figure 5 shows the structured chart diagram of the workflow of our project. The entire project implementation has been decomposed into four main stages:

1. Image acquisition.
2. Preprocessing.
3. Feature extraction.
4. Classification and disease detection.

RESULT

The research emphasizes the importance of accurate experience pain. Controlled by a sophisticated microcontroller, these motors operate based on detailed user inputs received from the mobile application. This application plays a pivotal role, not only in collecting user data but also in managing therapy sessions and providing additional health recommendations tailored to the individual's needs. By leveraging real-time data and advanced algorithms, the application ensures that the therapy delivered is both precise and effective. The communication interface facilitates seamless interaction between the helmet and the mobile application, ensuring that user preferences and therapeutic adjustments are accurately conveyed and implemented. Additionally, the robust power supply ensures that the microcontroller and motors operate consistently and reliably, delivering uninterrupted therapeutic benefits. Mango leaf which is in normal state could be presented in Figure 6.

This comprehensive and innovative approach addresses many limitations of disease identification for effective crop management. The application of machine learning and deep learning techniques has shown promising results in the field of leaf disease detection as shown in Figure 7. Studies have demonstrated high accuracy in differentiating between healthy and diseased leaves, as well as identifying specific types of diseases.

For classifying leaf diseases, Convolutional Neural Networks (CNNs) have proven to be the most successful deep learning models. They eliminate the need for manual feature engineering by automatically learning discriminative features from raw picture data. CNN models like VGG and ResNet have achieved state-of-the-art performance, with accuracy rates exceeding 95% in some cases. Overall, the results of machine learning-based leaf disease detection are highly promising. By enabling rapid, accurate, and automated diagnosis, these techniques can help farmers and agronomists proactively manage crop health and reduce yield losses. As the field continues to evolve, we can expect to see even more advanced and robust models for leaf disease detection soon.

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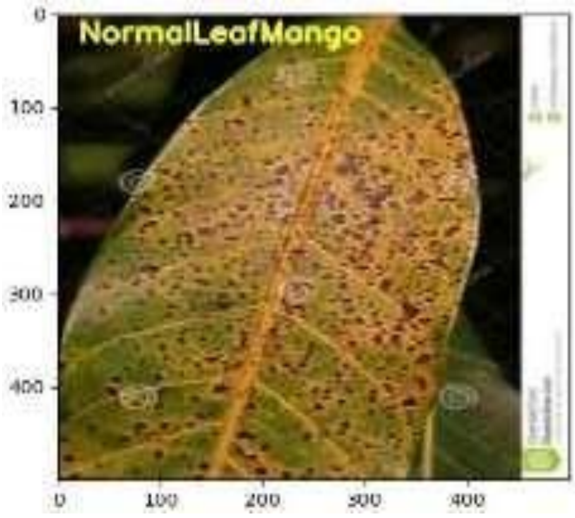

Figure 6. Normal Leaf Mango.

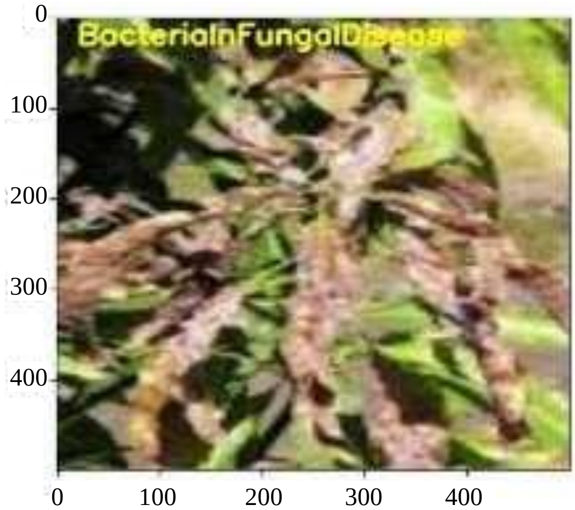

Figure 7. Bacterial fungal disease.

CONCLUSION

To develop a leaf recognition system, we begin by creating a dataset of leaf images for training. Instead of face detection, we utilize leaf detection methods powered by machine learning to identify and capture leaf images in real-time using a camera. During the initial phase, the system prompts information about the leaf, such as its species or type. Subsequently, the camera captures multiple images of the leaf from various angles and orientations, totaling around 300 images. Next, the system proceeds to extract texture features from each input leaf image. We utilized methods like Convolutional Neural Networks (CNNs) to extract features from leaf photos.

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