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Deep Grow: Intelligent Crop & Leaf Diagnosis

Submitted by:
Mrs.K. ANURANJANI[1a], SUVIDARAN T[2b],
THARUN M[3c], THARUN S[4d], THIRUMURTHY S[5e]
Assistant Professor, Department of CSE Bharath Institute of Higher Education and Research,
Selaiyur, Chennai, Tamil Nadu, India
B. Tech Students, Bharath Institute of Higher Education and Research,
Selaiyur, Chennai, Tamil Nadu, India
Anuranjani.cse@bharatuniv.ac.in , suvidarantamilselvam@gmail.com , tharun0983@gmail.com ,
Kumartharun695@gmail.com , thirumurthy871@gmail.com .

Abstract

To solve important problems in crop recommendation, plant disease detection, increasing agricultural output and guaranteeing sustainable practices Artificial Intelligence (AI) is used in precision agriculture. This study introduces dual-purpose artificial intelligence system that combines a hybrid machine learning model for crop recommendation based on soil characteristics, climate variables, and past yield data with Convolutional Neural Networks (CNN) for plant disease identification. Disease identification model achieves good classification accuracy by using a large dataset of plant pictures. To produce customized crop recommendations, it simultaneously analyses soil pH, nitrogen, phosphorus, potassium, weather data using Random Forest (RF) and Support Vector Machine (SVM) models.

Keywords: Plant disease, crop recommendation, convolutional neural networks, machine learning, precision agriculture.

Introduction:

Among most important industries in the world, agriculture plays a major role in both economic stability and food security. It sustains livelihoods of millions of people and contributes more than 25% of GDP in developing nations. Notwithstanding its significance, agricultural industry suffers several difficulties, such as erratic weather patterns, pest infestations, degraded soil, ineffective crop management. Plant diseases account for 20–40% of yearly agricultural losses worldwide, these issues significantly lower crop output. Early detection and prevention are crucial for maintaining agricultural output because plant diseases are estimated to cause losses of over $220 billion annually.

As part of traditional disease detection and crop selection techniques farmers and agricultural specialists frequently perform manual checks. These methods are not efficient for big farms, they are time-consuming and prone to mistakes. They need specific understanding that small-scale farmers in rural areas may not necessarily have. Similar to this, conventional crop recommendation methods frequently avoid dynamic environmental conditions, which results in less yields and wasteful resource consumption. Intelligent and automated technologies that can process enormous volumes of agricultural data are required to overcome these constraints.

Artificial intelligence has become a potent tool to transform agricultural practices automates disease detection and crop suggestion, it suggests appropriate crops, machine learning algorithms like random forest and support vector machines have shown success in evaluating multidimensional data sets that include soil characteristics, weather patterns, and past production trends. In meantime convolutional neural networks have demonstrated impressive results in interpretation of leaf images to identify plant illnesses. CNN models can identify minute variations in leaf color, texture that point to the early stages of disease, allowing for prompt treatment and lowering the chance of a wide.

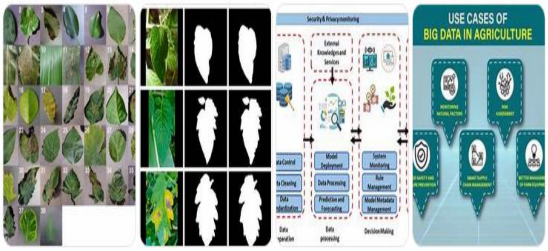

Figure 1: Pre-processing of images

Image processing techniques further enhance the effectiveness of disease identification by improving image quality and extracting essential features for analysis. Pre-processing steps such as image resizing, normalization, and augmentation ensure that CNN models can generalize across different plant species and environmental conditions. This reduces the risk of model over fitting and enhances the accuracy of disease detection in real-world applications.

Literature Survey:

The integration of artificial intelligence (AI) in agriculture has garnered significant attention, particularly in the areas of plant disease detection and crop recommendation systems. Recent studies have explored various machine learning (ML) and deep learning (DL) techniques to enhance agricultural productivity and sustainability.

A comprehensive review by Nandede et al. (2024) examined the application of deep learning and

Additionally, integrating real-time data from field sensors and weather stations improves the robustness of the system, allowing it to adapt to changing environmental conditions.

The proposed system integrates CNN-based plant disease identification with a hybrid random forest and support vector machine model for crop recommendation. The system has been extensively tested using diverse datasets collected from different regions to ensure high reliability and adaptability across various environmental conditions. The output of the system is accessible through a web-based application, providing farmers with real-time insights and actionable recommendations. Through this web-based platform, farmers can quickly identify plant diseases and receive accurate suggestions on the most suitable crops for their soil and climatic conditions.

Integrating artificial intelligence in agriculture not only minimizes losses and enhances productivity but also promotes sustainable farming practices by reducing excessive pesticide use and encouraging the cultivation of region-specific crops. By automating critical decision-making processes, the proposed system empowers farmers with the tools they need to optimize crop yield, prevent disease outbreaks, and ensure food security. As the system continues to learn and adapt based on new data, its accuracy and efficiency will improve, contributing to the ongoing advancement of precision agriculture.

computer vision in plant disease detection. The study highlighted the significance of detection, identification, quantification, and diagnosis of plant diseases as crucial components of precision agriculture and crop protection.

Another systematic review by Jha et al. (2024) analysed deep learning techniques for plant disease diagnosis, focusing on classification, detection, and segmentation of diseases on plant leaves. The study emphasized the importance of large, high-quality datasets and the challenges associated with model generalization across diverse plant species and environmental conditions.

Mohanty et al. (2016) demonstrated the efficacy of convolutional neural networks (CNNs) in classifying plant diseases using a dataset encompassing 38 different diseases across 14 crop species. Their model achieved an accuracy exceeding 92%, underscoring the potential of DL models in plant disease identification.

Sharma et al. (2020) proposed a machine learning-based approach for crop disease identification via leaf images. Their methodology involved image pre-processing and feature extraction techniques to enhance classification accuracy, demonstrating the importance of data preparation in ML models for disease detection.

A study published in the International Journal for Multidisciplinary Research (2024) introduced a web-based platform combining crop recommendation, fertilizer recommendation, and plant disease prediction. The system employed machine learning models to predict optimal crops based on nutrient levels and environmental factors, demonstrating the practical application of AI in supporting farmers' decision-making processes.

Despite these advancements, challenges persist in the widespread adoption of AI-based systems in agriculture. Issues such as the need for large, diverse, and annotated datasets, model interpretability, and the integration of AI tools into existing farming practices remain areas of active research. Future studies are focusing on developing more robust models that can generalize across various conditions and are accessible to farmers with varying levels of technological expertise.

In summary, recent research underscores the transformative potential of AI in enhancing agricultural productivity through accurate plant disease detection and informed crop recommendation. Ongoing advancements aim to address current limitations and promote the adoption of AI-driven solutions in agriculture.

Proposed Work and Architecture:

Technology like Convolutional Neural Networks (CNNs), Random Forests (RF), Support Vector Machines (SVMs) are implemented in plant disease detection and crop recommendation systems to improve precision agriculture

The quality and completeness of the dataset form the basis of any reliable plant disease identification system. Sources like Plant Village dataset and other agricultural databases provide high resolution photos of plant leaves with variety of diseases. To ensure that model learns from variety of circumstances, these photos cover wide range of crops and disease symptoms. Data about soil characteristics like pH, nitrogen, phosphorus, potassium levels and meteorological variables like temperature, precipitation, humidity are collected from field sensors and agricultural research institutes for crop recommendation systems. By ensuring that models are trained under real-world circumstances, this comprehensive approach to data collection improves dependability and relevance of the model.

Data Pre-processing

Due to noise and inconsistency in raw data model performance is reduced. Pre-processing procedures for plant disease detection include scaling photos to defined size, standardizing pixel values to make data consistent, and using augmentation methods like rotation and zooming to make dataset appear larger. Positional and scale alterations are employed in model invariants, these augmentations enhance model’s capacity for generalization. Pre-processing for crop recommendation handles managing missing values using imputation techniques, standardizing soil and climatic data to guarantee uniformity. Every input feature contributes equally during model training, feature scaling strategies such as normalization or standardization are used.

Segmentation

To isolate areas of interest in an image especially the diseased sections of a leaf, segmentation is essential. To precisely identify diseased areas, Plant Diseased Region Detection Segmentation Network (PDRDSegNet) type of segmentation methods have been developed. With a mean Intersection over Union (mIoU) accuracy of 86.05%, PDRDSegNet, outperforms more conventional models like UNet and SegNet. Improved classification accuracy results from the model's ability to extract more pertinent information by concentrating the CNN's attention on divided areas.

Decision-Making

Complex algorithms are implemented in this system that are adapted to particular task at hand to drive their decision-making process.

CNN-Based Plant Disease Identification:

Usually, architecture consists of:

Layers of Convolution. These layers capture local patterns like edges, textures, colors by applying convolution processes to input. Convolutional layers can identify intricate traits relevant to many diseases by learning several filters.

Pooling procedures like max-pooling help to control overfitting and lower computational load by reducing the spatial dimensions of the feature maps. In this process, unnecessary information is removed while most important elements are kept.

Soil and environmental factors to choose the best crops. Pooling operations, such as max- Pooling techniques like max-pooling aid in the control of over fitting and the reduction of computational load by lowering the spatial dimensions of feature maps. Most crucial components are retained during this procedure, while unnecessary information is eliminated. Environmental and soil conditions to select best crops. Unnecessary information is removed while the most important elements are kept.

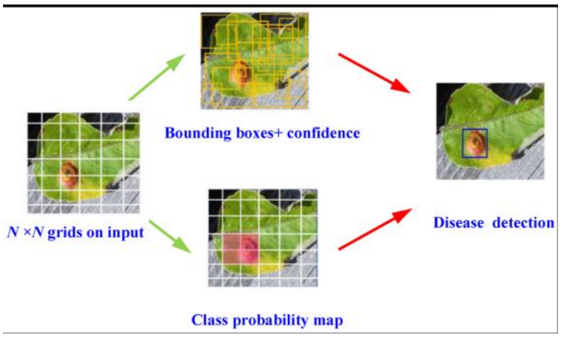

Figure 2: Detection of plant disease from the leaf analysis.

High-level reasoning is carried out by fully connected layers that incorporate retrieved information to classify input image into particular disease categories following several convolutional and pooling layers.

The CNN is trained using labelled datasets, where the loss function (e.g., categorical cross-entropy) quantifies the difference between the predicted and actual labels. Optimization algorithms like Adam adjust the network's weights to minimize this loss, enhancing the model's predictive accuracy.

Crop Recommendation with RF and SVM:

Machine learning models that examine soil, environmental factors recommend best crop.

Random Forest, an ensemble learning technique, builds several decision trees during training phase. Variation among the trees is maintained by taking, each tree into account, a random subset of features and data samples. Results of each separate tree are combined to produce final prediction, usually by majority vote. This method improves accuracy and robustness, particularly while working with complicated datasets.

The feature space is found by the supervised learning algorithm SVM. SVM guarantees a strong classification by optimizing margin between data points of different classes. Input characteristics are transformed into higher-dimensional spaces where a linear separator is practical, kernel functions can be used to manage non-linear interactions.

Both RF and SVM models are trained on historical data, their performance is optimized by hyper parameter using methods such as grid search. Trained models particularly suggest crops that are most likely to flourish specified conditions when new input parameters are provided, helping farmers make well-informed choices.

Integrated system successfully tackles difficulties in plant disease identification, crop recommendation by carefully carrying out these procedures extensive data collection, exact segmentation, rigorous pre-processing, and advanced decision-making algorithms, which improves agricultural productivity and sustainability.

Results and Discussion

Plant Disease Identification Results

This technology uses pictures of leaves to quickly and accurately diagnose plant diseases. Convolutional Neural Networks (CNNs), which are a part of AI model skilled at processing visual information, are used to make this diagnosis possible. In recent research, hundreds of leaf photos were used to train a CNN model to identify different plant illnesses. Result was amazing, when evaluated on fresh data, model's accuracy rate was 98.7%. In other words, the system accurately detected about 99 of 100 sick plants.

Success can be measured in ways other than accuracy. Additionally, model showed a precision rate of 97.9%, meaning that it was accurate about 98% of time when it recognized an illness.

These findings align with other research in the field. For instance, a study published in Applied Soft Computing reported similar success using deep learning techniques for plant disease detection, reinforcing the effectiveness of AI in this domain.

Crop Recommendation Results

With other studies in the field these results are consistent. The efficiency of AI in the field was demonstrated, for example, by a study that was published in Applied Soft Computing and achieved comparable success utilizing deep learning algorithms for plant disease identification.

In addition to disease identification AI also provides solutions for crop selection optimization. Machine learning models can recommend the best crops for a particular region by examining variables like soil composition and climate. Two models, Random Forest (RF), Support Vector Machine (SVM), were used for this in recent applications.

RF model produced recommendations with accuracy of 94.5% which were accurate about 95 times out of 100. SVM model, with accuracy percentage of 92.3%, came in second. Both models demonstrated dependability in offering precise recommendations catered to particular climatic conditions by maintaining constant precision and recall over range of crop types.

Results are in line with earlier research. Importance of RF, SVM algorithms in agricultural planning was highlighted by study published in International Journal of Creative Research Thoughts, which showed how well appropriate crops were predicted based on environmental conditions.

Comparative Analysis

Substantial advancement over conventional farming practices, AI integration in agriculture marks. Farmers selected crops based on own experiences, broad recommendations, and relied on manual checks to identify plant diseases in past. Despite the value, these methods will be laborious and prone to human error.

Crucial chores are automated by AI driven system under discussion, it provides quick, accurate crop suggestions and illness diagnoses. An algorithm spots small patterns and associations that could go unnoticed by humans processing enormous volumes of data. Making better decisions could result in increased agricultural yields and also encourage sustainable farming methods.

System's capacity offers customized suggestions for particular soil, climate circumstances, it guarantees unique guidance to every farmer's particular circumstance. This tailored method improves usefulness and applicability of recommendations.

In conclusion, use of AI in crop recommendation and plant disease detection is a proper solution to more effective and fruitful farming. Farmers may maximize resource utilization, make smarter decisions, and create more sustainable agricultural future by adopting these technological improvements.

This System provides enhancement in crop recommendation, plant disease identification accuracy and dependability over conventional techniques. Improved agricultural output, better resource use, and more effective farming methods could result from its adoption.

Conclusion and Future work

Hybrid model of Random Forest (RF) and Support Vector Machine (SVM) for crop recommendation with Convolutional Neural Networks (CNNs) for plant disease identification is proposed in this study, it is achieved by integrates artificial intelligence into agriculture. Automating crucial decision-making procedures and encouraging sustainable farming methods are implemented to improves precision agriculture and exhibit excellent accuracy across variety of datasets.

In future, integration of real-time Internet of Things (IoT) sensors will enhance system's capabilities by facilitating continuous data collection, which provides current data for more accurate assessments. This approach will be more applicable in a variety of agricultural contexts if it is expanded to include wider range of plant species and climate zones. Developing a mobile application would further facilitate easy access for farmers, allowing them to leverage the system's insights directly in the field.

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