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Agro Care AI: Plant Disease Detection and Fertilizer Recommendation System

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Abstract

The agricultural output is largely affected by the economy. Plant diseases are increasingly widespread in agricultural settings, and because of the reasons given above, it is now possible to identify plant diseases with greater ease. Nowadays, there is a lot of focus on plant disease identification while monitoring crops in different types of fields. When switching from one disease management approach to another, farmers face a lot of difficulties.The conventional method for detecting leaf diseases involves identifying them or noticing them with the help of surveillance and monitoring specialists. If adequate control measures are not implemented, the factories will suffer significant consequences, which in turn will impact the quality of the trousers produced. Because it reduces an excessive amount of labor required for surveillance in large-scale farming, disease detection by some mechanical approach and methodology is efficient and constructive. When plant illnesses are in their early stages, we may see them on the leaves of infected plants. This study may be used to find the method that plants utilize for automated categorization in order to detect leaf diseases. Additionally, it delves into several disease categorization systems that are used for plant disease identification.We may offer fertilizer for agricultural leaves depending on illness after disease detection is complete.

Introduction

In the earth has very larger into distributing the variety into species be plays into vital roles from our life and the more important in the medicine is prepares among the plant therefore we knows to each plants form the plants name recognizes it is taken into leafs, flowers and fruit with the plant and main thing is the problems are they didn't took the flower & fruit so as to the limited periods in the plants therefore it is identified among the purposed in the flower & fruit is not appropriate. Suppose they will not taking the leaves with the plants so it will have all through the years. In the projects to find into the plants name also, it is done to be uses from the leaf on the plants, a number of the feature extractions in the leafs are such as quality of the leafs and shapes and areas of the plants. In this projects are develops into the Google collaboratory & the we are using into machine learning into deeply learned algorithm person is multilayer perceptron (MLP) & (SVM) so as to mean to supporting the vector machines & the machine learning is a technique of data analytics system else it will told about to system how it will works like a human being & in the machine learning it will be working on a training data or testing data & these are having supervising into learning, unverified learning in this project and it is used to the verified machine learning. Google collaboratory is done by open CV, Open CV is one of the library packages for image processing within python languages & it is converted into color image into gray image. They will be finding about the perimeters, areas, physiology width, aspects ratio, rectangularity, circularity, mean, standard, correlations, physiology length, contrast, inverse difference moments, entropy are all find into leafs.

Automatic species is identified between the presents 12 year since that can be challenges other than very shows potential solutions into the development of the novel researches activity into classification, Biological otherwise ecologically. Within the developmental of the increases number for web & mobile application base on the visual data's analyses, in the civil societies were able into new to assess in the progress at domain, because it is to provide new data's form the developmental of

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the large scale system. In evaluates in the performances of the automate plants identifications technology into sustainable & repeated ways, an dedicate to the systems oriented the benchmarks are setup into contexts in the evaluation. The challenges are called as Plant is organizes in that contexts uses dataset into produced within acting in the civil societies like as educate, nature lover, hiker. Yearly following year, in the complex & sizes of the test bench is increases about allows the drone of the research team to evaluates in the progress & limited in the machine learning system. The Plants is to challenges are organizes into a datasets to covering 15,000 plant species. It is 1st evaluations at scales into the worlds, & the result is promises into imposing within accurate reaches of the correct identifications form the best systems. It is amazing to high performances raise into the questions so as to far automatic system is to form in the human expertise's & the whether it is a upper bounded into that exceeded.

Problem Statement

Agricultural output and farmer revenue are being hit hard by the rising incidence of plant diseases. Due to visual similarities between symptoms and limited expert availability, early and effective identification of leaf diseases may be hard. The goal of this research is to create a system that uses artificial intelligence and deep learning to identify plant leaf diseases automatically. In order to assist farmers improve crop productivity and sustainability, the system would suggest appropriate fertilizers or treatments based on the discovered illness.

Objectives

A viable strategy to transform agriculture by guaranteeing better crops and decreasing losses is the detection of plant leaf diseases using CNNs. The model's robustness will be shown by its performance in generalizing from real-world circumstances. Consistently excellent results in this setting demonstrate how cutting-edge deep learning methods may revolutionize established norms. By doing so, you're laying the groundwork for sustainable farming by improving disease detection and generating wiser fertilizer recommendations.

Literature Review

Title: *Leaf Disease Detection and Fertilizer Recommendation using Deep Learning*
Year: 2025
Authors: (multiple — online project/paper)
Abstract: This research presents a comprehensive deep learning pipeline that uses convolutional neural networks to identify leaf illnesses in photos; next, it uses this information to provide specific fertilizer recommendations for different crop types. So that farmers may take pictures of leaves while working in the field and get immediate feedback on their crops' nutritional needs, the system is designed to be easily installed on smartphones. To take into account variations in lighting and poses, data is preprocessed using augmentation. To make models more generalizable, they are trained on datasets that include many crops. The suggestion module determines the best fertilizer kinds and doses by integrating disease diagnosis with crop and soil information. Using held-out test sets, the authors assess the system's performance and find encouraging results for illness categorization and fertilizer recommendation. Low latency inference, practical usage, and mobile-friendly model sizes are the main focuses of the effort. Concerns about data privacy and offline functioning are among the deployment hurdles covered.

Title: *Fertilizer Recommendation System using Machine Learning Algorithms*
Year: 2023
Authors: (researchers compiling ML-based fertilizer recommender)
Abstract: Based on soil test results, meteorological conditions, and crop type, this research examines and applies machine learning techniques for fertilizer recommendation. For the purpose of predicting the best nutritional combinations and rates of application, the writers evaluate regression and classification models. Key preprocessing techniques include feature engineering and normalization; data sources include previous soil evaluations and yield results. The accuracy and interpretability of predictions are tested using a number of models, including decision trees, random forests, support vector machines, and ensemble approaches. By preventing over-application, the system is able to increase productivity without negatively impacting soil health. Possible automated recommendation pipelines and Internet of Things (IoT) soil sensor integration are covered in the article. Smallholder farmers are the target audience. We emphasize local calibration, scalability, and explainability as significant practical issues.

Title: *Data-Driven Analysis and Machine Learning-Based Crop and Fertilizer Recommendation*
Year: 2023
Authors: C. Musanase et al.
Abstract: This study builds a data-driven ML-based integrated recommendation engine for crop

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and fertilizer regimen suggestions. For the purpose of making suggestions that are both productive and environmentally friendly, the algorithm takes into account past yields, weather predictions, and local soil characteristics. We use regional datasets for model training and cross-validation and field experiments for validation. Soil and weather factors that are most important may be identified with the use of the architecture's support for feature selection. Predicting yield responses to fertilizer inputs is one way ML may help with precision nutrient management, as shown in the research. Furthermore, the authors discuss methods for deploying extension services and how to integrate them with mobile platforms so that farmers may use them.

Title: *Site-Specific Fertilizer Recommendation Using Data Driven Approaches*
Year: 2024
Authors: F. Liben et al.
Abstract: This study examines the impact of site-specific fertilizer recommendations provided by machine learning on resource usage efficiency and yield in wheat cultivation. This research trains models to anticipate nutrient requirements at the sub-field level using field management data and soil that is geographically referenced. By comparing the ML recommendations to blanket guidelines and farmer practice, we find that data-driven prescriptions increase production while decreasing fertilizer consumption. In order to keep the results relevant to agronomy, the article delves into uncertainty quantification and the significance of local calibration. This study shows how commercial cropping systems may operationalize precise suggestions.

Title: *KrishiCare: AI-based Plant Disease Detection and Fertilizer Recommendation System*
Year: 2024
Authors: (research group; ResearchGate listing)
Abstract: KrishiCare provides context-aware recommendations by combining a fertilizer recommendation engine with image-based illness detection using convolutional neural networks (CNNs). By comparing the leaf picture with soil data and the crop's development stage, the system is able to diagnose diseases and provide nutritional treatments. To ensure that suggestions are both unique and applicable, the model incorporates weather integration and agronomy laws that are relevant to regions. For implementation at the farm level, the authors include mobile and online interfaces, and they address data governance and privacy. According to the findings of the field test, the integrated system helps farmers make better decisions and uses less unneeded chemicals.

Existing Model

While new technology have benefited agriculture, they have benefited every other industry. Past research has shown that plant leaf diseases are the only source of the 42% loss in agricultural productivity. This method for detecting diseases in plant leaves from input photos may help with this big problem. Preprocessing, segmenting, and feature extraction were some of the procedures included in this process. The results of these three steps are then subjected to K-Nearest Neighbor (KNN) classification. Training and classification, however, get far less data for larger datasets. We used recommended technique analysis to make improvements

Disadvantages

The KNN technique relies on the complete dataset for classification, which means it uses a lot of computer resources.Inadequate Discriminatory Power: KNN has difficulties in accurately differentiating between classes when distributions of characteristics overlap.Reduced Precision: When dealing with complicated datasets, the precision is significantly diminished due to inadequate training and oversimplified categorization methods.

Proposed Method

To correctly identify plant leaf diseases and suggest suitable nutrients, the suggested technique uses a CNN dense model independent algorithms. In order to classify identify certain illnesses, the CNN model first extracts significant characteristics from the input pictures of leaves.The combination of these two methods guarantees accurate illness detection and connects the findings to specific recommendations for fertilizer to boost crop health. The system is connected via a Flask-based web app that offers a platform for real-time detection and suggestions in an easy-to-use manner. The suggested approach successfully detects plant leaf diseases and recommends fertilizer by combining state-of-the-art deep learning with web-based technologies. At the outset, the system amasses a complete dataset by gathering high-quality photos of leaves from several plant species. To make sure the model is getting consistent input, these photos go through preprocessing operations including scaling, normalizing, and noise removal. To avoid model overfitting and boost dataset variety, data augmentation methods including flipping, zooming, and rotating are used. A dense model of a Convolutional Neural Network (CNN)

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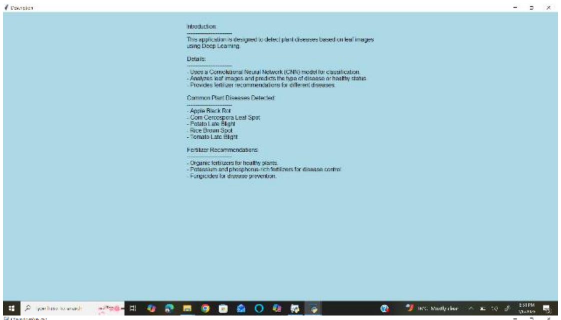
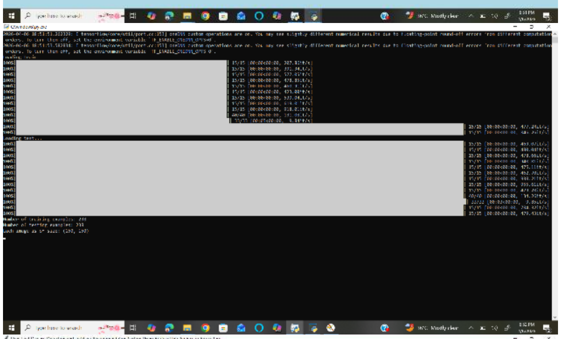
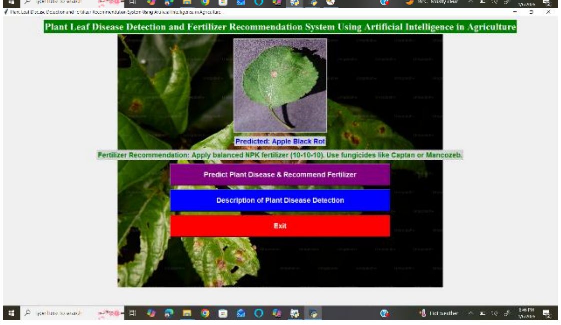
lies at the heart of the detection system; it automatically pulls useful hierarchical features from the input photos. As more and more plant illnesses are detected, the CNN layers gradually pick up on the textures, edges, and intricate patterns linked with them. The dense classifier uses the characteristics that were extracted from the features to determine which disease is present in the leaf. In addition to the CNN, other algorithms are used to deal with ambiguous circumstances and improve classification accuracy. Connected to a fertilizer suggestion module, the system then recommends the best nutrients to boost plant health and harvest when a disease has been detected. The nutritional needs of different diseases and agronomic standards informed these suggestions. An intuitive interface for farmers and agricultural specialists is provided by integrating the whole process into a web application that is built using Flask. The user may just submit a picture of a leaf, and the system will instantly analyze it and provide the findings. Additionally, the app keeps records of past assessments to monitor plant health and provide insights from the past. The approach prioritizes modularity, which allows for modifications to the CNN model or fertilizer database to be applied independently of other parts. Validation of the model's efficacy is achieved by tracking performance indicators including F1-score, recall, accuracy, and precision. Furthermore, the system is equipped with error-handling methods to handle input images that are either ambiguous or incorrect. Because of its computational efficiency-optimized design, the CNN architecture may be deployed on conventional hardware without the need for high-end GPUs. Learning rate scheduling and early stopping are two advanced training approaches that help reduce overfitting and promote generalization. By using cross-validation, we can be confident that the model will work reliably for all plant species. In order to help users better grasp the process, it uses explainability elements, such as highlighting unhealthy locations in leaf photos. To make the fertilizer suggestions as realistic as possible, we have included dose instructions and application frequency. Disease severity and growth prediction visuals are provided via the online interface. User data is safeguarded from unwanted access by using security measures. Integrating with bigger agricultural datasets is also possible because to the system's scalability. All parties involved in agriculture may now work together remotely thanks to cloud storage alternatives. To keep up with new illnesses and environmental changes, the system is constantly retrained with fresh photos. This approach is well-suited for practical agricultural uses because of its emphasis on precision, dependability, and user-friendliness. The approach encourages healthier crops and increased output by integrating CNN-based disease diagnosis with fertilizer recommendations. Its resilience has been shown via extensive testing and validation across various crops and environmental situations. In order to improve forecasts and suggestions, we have integrated user feedback channels. In subsequent revisions, the approach may be extended to accommodate many crops and several diseases. Trends in diseases and information on fertilizer consumption are shown on visualization dashboards. To make it easier for farmers in rural regions to obtain their products, we are planning to integrate with mobile platforms. The method strikes a compromise between advanced technology and the real-world demands of farming. Using web technology and deep learning, the system automates and streamlines the process of plant health monitoring. Improved crop health and efficient resource usage are guaranteed by the suggested technique, which offers a comprehensive solution for disease identification and fertilizer management.

RESULTS AND DISCUSSION







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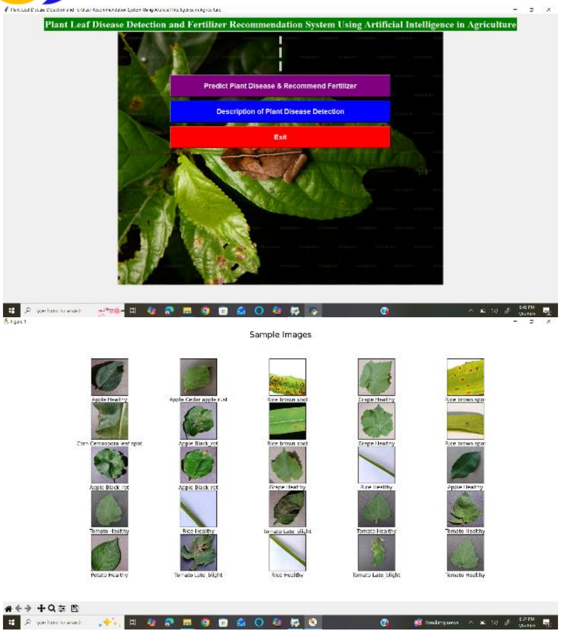

We utilized a number of criteria to assess how well the machine learning models detected diseases in plant leaves. Both the training and testing datasets included several classes that stood for various plant diseases. A mix of deep learning architecture and feature extraction approaches were used to train the models. Figure 1 shows examples of failing models, and the wrong picture sample classifications are seen there. When 24 out of 1,106 labels were determined to be inaccurate, the classification error rate was determined. Image samples being incorrectly identified may be caused by a number of things, such as classifier generalization restrictions, overlapping entity categories, and hazy picture features. Better training data sources, more efficient extraction techniques, and enhanced computing performance technologies are all needed to further create models with high accuracy, as shown in the figure. By analysing incorrect labels, researchers are able to find model shortcomings and create effective strategies to avoid future errors.

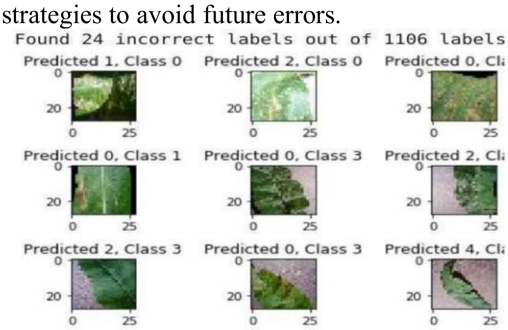

Fig.1. Incorrect Classification of Image Samples

Figure 2 shows the results of the model's accurate picture identification and labeling. The model accomplished the remarkable feat of accurately classifying 1,082 items after processing 1,106 picture labels.
With only 24 reclassified samples out of 1,106 total labels, the margin of error is quite small. Since it shows the classification model's dependable performance in picture recognition, the figure reveals that it is successful in category distinction. The model is well-suited for picture classification tasks, and it shows good performance in image categorization as a result of correctly identifying many image examples.

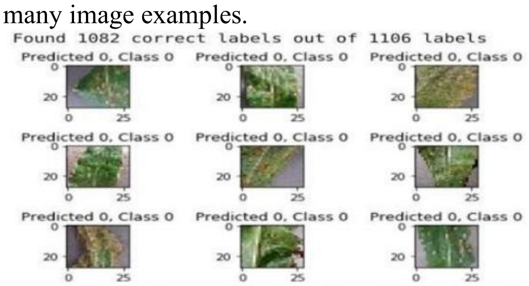

Fig.2. Correct Classification of Image Samples

Figure 3 displays the model accuracy metrics, which demonstrate the training accuracy result and validation accuracy throughout many training epochs. There is a graph with the number of epochs on the x-axis and accuracy on the y-axis. Accuracy in training rises from a poor base and approaches perfection as the model trains. Validation accuracy, like training accuracy (orange), begins with rapid rise before leveling off due to minor outliers. Beginning epochs have greater validation accuracy rates, which eventually intersect with training accuracy at a peak level. Without experiencing significant structural difficulties during training, the model is able to effectively extract patterns from the data, resulting in strong generalization.

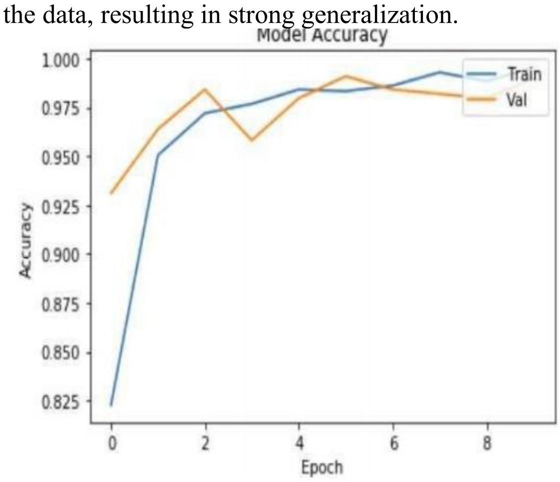

Fig. 3.Model Accuracy Metrics

Training and validation loss both reduce as the learning system matures, as seen in figure 4, which displays the model loss metrics throughout numerous training epochs. The loss values are located on the y-axis, while the number of epochs is shown on the x-axis. Before the model starts to learn patterns in the data, the training loss is significant, but it soon drops. Validation loss values have a similar decreasing trend as the orange curve, but with less variation as it falls. Despite both loss curves reaching very low values, the model exhibits small variations when validation loss computation is performed. Model performance and robustness are both improved by minimizing overfitting during training.

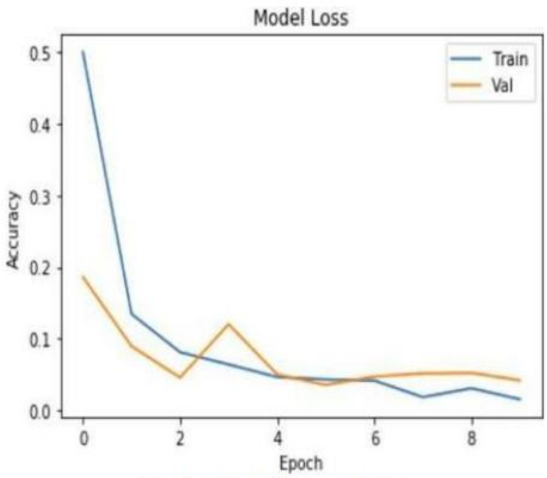

Fig. 4. Model Loss Metrics

CONCLUSION AND FUTURE SCOPE

Conclusion

The suggested approach proves that Convolutional Neural Networks (CNNs) can identify plant leaf diseases accurately and automatically. The algorithm successfully detects disease categories from leaf photos using deep learning-based image analysis, eliminating the need for human feature extraction. When contrasted with more conventional machine learning techniques, the CNN method exhibits considerable improvements in accuracy, speed, and scalability. In addition, farmers may get useful insights via the integration of a fertilizer suggestion module that is based on the discovered illness. This allows for better nutrient management and early treatment. Improved crop health, less crop loss, and more support for sustainable agricultural practices are all outcomes of this AI-driven approach.

Future Scope

For ongoing illness tracking, this system may be enhanced with sensors that are Internet of Things (IoT) enabled and with real-time field monitoring. To make the CNN model even more resilient to different kinds of crops and weather, we may use transfer learning with bigger, more varied datasets. Farmers in outlying areas may have easier access to the solution via integration with cloud or mobile systems. More informed, data-driven fertilizer recommendations may be achieved by integrating the disease detection module with precision agriculture technologies and soil nutrient monitoring. Building an all-encompassing agricultural advice system powered by AI to facilitate sustainable, intelligent, and self-operating farming is part of the long-term plan.

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