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AGRIGUARD: Crop Disease Prediction and Fertilizer Recommendation System using CNN Model

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ABSTRACT:

Agriculture is one of the main economic sectors in all countries. To keep it stable, the crops' health should be recognized in time so that better crop cultivation occurs. Issues that are confronted most commonly are getting into pests, getting infected with various diseases, a lack of knowledge of minerals before planting the crops, loss due to water scarcity, etc. This indicates how important it is to resolve such an important issue to reduce environmental damage and increase the output. By using technology in the right way with the help of some sensors, AI-driven statistics, and machine learning, our project AGRIGUARD meets to solve all such problems that the farmers commonly face by indicating such problems as soon as possible and also giving direction to overcome the issues and decrease the chances of getting crop failure. Additionally, by encouraging environmentally friendly methods and lowering chemical inputs, AgriGuard makes a substantial contribution to sustainable agriculture. Its precision agriculture method reduces waste and avoids overuse of natural resources by allowing farmers to apply pesticides, fertilizer, and water just when needed. In addition to cutting expenses, this data-centric approach lessens farming's ecological impact, promoting biodiversity and soil preservation initiatives.
KEYWORDS: Machine Learning, Crop Disease Prediction, Resource Optimization sustainable farming, soil health monitoring, real-time analytics, AI analytics, environmental sustainability CNN model, precision farming, resource conservation, deep learning, smart agriculture, climate resilience.

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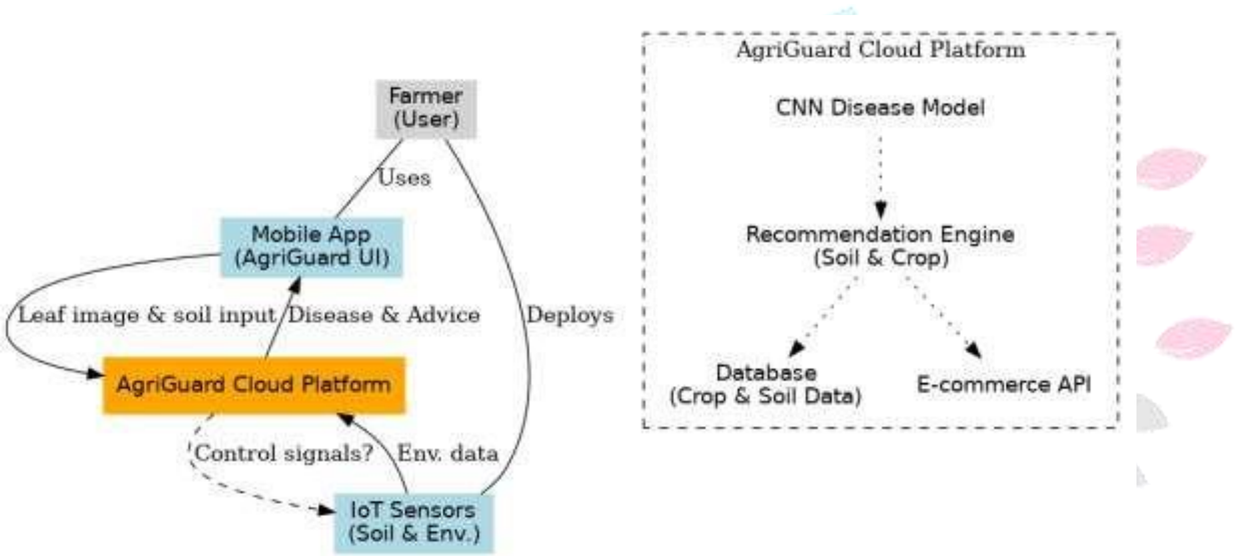
1 INTRODUCTION:

Agriculture provides a living for around 70% of the Indian population. Plant disease identification is critical to avoiding yield losses. It is a little bit difficult to keep noticing the plant and identifying the disease manually. It requires a lot of hard work and effort to do so ,and also needs expertise and a lot of time. Therefore, the help of technology can be taken by using machine learning models, which can identify the plants and crops easily in very little time with less effort. In this study, we unfold the way to identify the disease in the plants by using photographs of the leaves of specific plants we want to identify. Image processing is a subtask of signal processing in which the image content is extracted and useful information is made to use that information for our desired work. Machine Learning is a division of artificial intelligence that can automate tasks after the model is trained by giving it various types of data. So in this project, the main working of machine learning is to train with the given data and fit itself in the model to identify the disease, and may help humans in various ways. As an output, it will give the closest judgment and prediction using the model, which is trained by a large amount of data, which is for telling the plant's disease. Classification is based on leaf color, degree of damage, leaf area, and textural factors. In this study, we examined many picture metrics or various features in that detected the disease from the different plant leaves. Previously, plant diseases were detected by the chemical procedure that is done by the professionals or the detailed visuals on the leaves. So this needs a large team and a large number of specialists to inspect the leaf in detail and observe every single change, which is expensive when done on large farms. Under such situations, the proposed approach is useful for monitoring vast agricultural fields. Automatic disease identification by just looking for signs on the leaves of plants, and also this approach makes it less expensive and easier. The suggested plant disease detection method employs statistical machine learning and image processing algorithms to reduce computing costs and prediction time compared to current deep learning-based systems.

Section II discusses all related work. In this section, all the work that was done before in the field of disease identification. Section III discusses the proposed methodology. In this section, all the technology used is explained, and it is going to fulfill the objective of our project. Section IV describes all the data sets that are used to train the machine learning model. Section V discusses the classification task in machine learning and how it will classify the image of a leaf and identify the plant and disease.



2. RELATED WORK

Suresh, V. et al. discussed the disease-affected and healthy crop identification application, which has decent accuracy of the machine learning model. Kulkarni, P. et al. discussed computer vision development for plant disease detection. Also proposed is a system that is efficient due to statistical image processing and machine learning. Shoaib, M. et al. discussed the advancement of disease identification using the technology of machine learning and deep learning. Dolatabadian, A. et al. discussed the automated disease detection system with accuracy and the challenges faced, like cost and infrastructure.

AgriGuard contributes to meeting the world's food needs by increasing crop output and quality, strengthening agriculture's ability to withstand the effects of climate change. To demonstrate how technology can promote sustainable growth in the agricultural industry, this article examines AgriGuard's novel framework and evaluates its effects on resource efficiency, environmental preservation, and long-term agricultural output. By utilizing IoT sensors and CNN-based models, our model provides precise insights into soil quality, crop health, and the condition of the environment. Agriguard includes various core features, i.e.,

- Real-Time Monitoring: Continuous tracking of soil and crop conditions using IoT systems, providing live updates to farmers for immediate decision-making.
- Crop type: Category and variable representing various crops.
- Soil parameters: Data on soil pH nitrogen (N), phosphorus (P), potassium (K), and organic matter
- Soil fertility recommendations: Insights driven from analyzing nutrient levels to suggesting targeted fertilizer application.
- Crop recommendation: data-driven suggestions based on soil and environmental conditions for optimal crop selection.
- Disease indicators: Images of crops identifying healthy were his deceived samples.
- Temperature and Humidity: Checks real-time data on temperature and humidity to guide better crop cultivation practices.

This data set is solved from diverse agricultural studies and real-time monitoring systems; its structured attributes enable robust predictive modeling for crop health analysis and disease prevention.

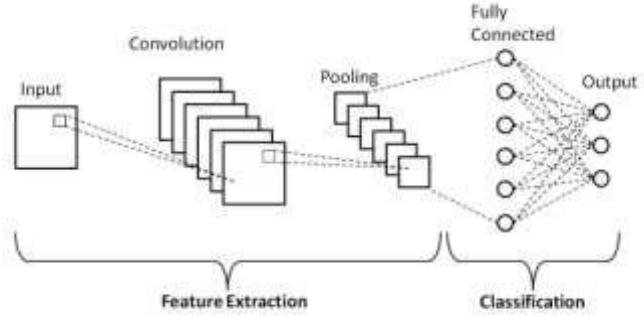
3. PROPOSED METHODOLOGY

Developed to tackle major issues in contemporary farming, AgriGuard is a cutting-edge agricultural solution that provides revolutionary instruments to improve crop yields, resource efficiency, and sustainable farming methods. Important agricultural operations, including crop monitoring, soil health evaluations, animal and pest management, and accurate fertilizer delivery, are all optimized by AgriGuard using cutting-edge technology and data-driven insights [1].

AgriGuard's primary characteristics are yield prediction, real-time crop health monitoring, and remote accessibility; these tools enable farmers to make well-informed decisions that support sustainability and resource conservation. Through the identification of early indicators of crop stress and the encouragement of targeted responses, AgriGuard helps farmers preserve crop vigor and soil quality [2].

3.1 Method for Disease Detection of Crop

The disease detection system of the plants contains the four main parts. Initially, with the help of the digital camera or the mobile phone, the image is captured of the plant leaves, or they can be obtained from the website or on the internet. The second part divides the image into multiple clusters, where various techniques may be employed. In the next part, the method of extraction feature is used; after that, the final part focuses on classifying the disease identified.

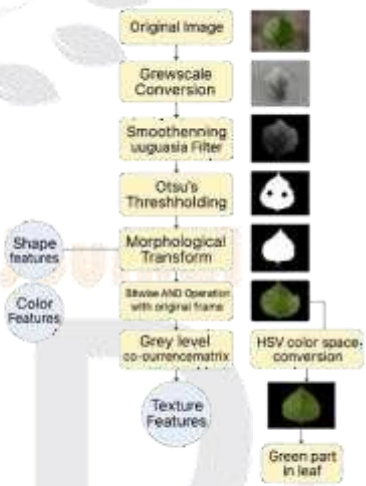


- Image Input

In this part, using the digital camera or the mobile phones that have the camera, the image of the plants is gathered, ensuring the proper and needed size and quality of the image. After downloading the images from the internet can also be used. The construction of the database of images relies entirely on the application system developer. A well-managed image database has a substantial impact on the labels and classifier's effectiveness in the detection system's last part.

- Image Partition

The goal of this stage is to simplify how an image is represented, making it easier to identify and analyze. Also, it is meaningful, which helps in understanding. This part serves like the foundation for the extraction of features and also key aspects of image processing. Numerous methods exist for segmenting images, including the algorithm of Otsu, k-means clustering, and thresholding. K-means clustering categorizes the pixels or the objects into K distinct classes based on specified features, and this classification minimizes the aggregate of squared length between the objects and their clusters to their correspondence.



- Feature Extraction

It is the part in which it is essential to extract features from the region of interest. These features are critical for interpreting the significance of a given image sample. Features can be derived from shape, color, and texture, as shown in Fig. 2. Lately, many researchers have been focusing on the features of textures to identify plant diseases. Many of the techniques for extraction of features can be implemented to develop the system, such as the gray-level co-occurrence matrix (GLCM), which is a color co-occurrence method, a spatial gray-level dependence matrix, and a feature of extraction that is histogram-based. The method GLCM is a statistical approach used for the classification of texture.

3.2 GLCM

The spatial relationship of the image's pixels is known as the gray-level co-occurrence matrix. One of the most common and traditional approaches in computer vision is to extract features of textures from gray-level co-occurrence matrices. The features listed below were taken from the gray-level co-occurrence matrix:

- Dissimilarity
- Contrast
- Energy
- Correlation

The feature selection operation is carried out following the extraction of all features from every image in the dataset.

3.3 K-means Segmentation

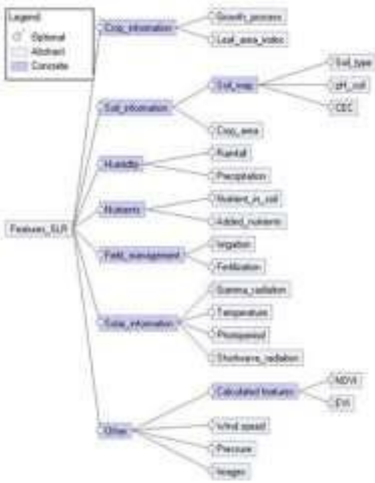
The K-means Segmentation is a technique of partitioning the leaf images into four groups or clusters based on the principle of Euclidean squared distances. The feature extraction is being done by utilizing the co-occurrence method of the leaf color to get the details about texture and color. [4]. A neural network algorithm is a methodology that is used to detect overall accuracy up to 93%. Various crop types are analyzed for fungal disease detection of plant leaves, which includes fruits, crops, vegetables, cereals, and commercial crops with suitable methods for each type [5]. For fruit, K-clustering serves as the method of segmentation, which focuses on texture features and is classified by ANN and other neural networks, which results in an accuracy of 90.73%. For the classification of vegetable crops, the Chan Vese method is used for segmentation, the local binary pattern for feature extraction, and SVM with the K-nearest neighbor algorithm for classification, which results in an accuracy of 87.825%.

3.4 Classification Tasks in Machine Learning

Classification models are used extensively in predictive tasks and can be either tree-based (e.g., decision trees), linear (e.g., logistic regression), or sophisticated ensembles (e.g., combining numerous models to increase predicted performance). Labeled data, which has both input features and their associated output labels (such as "disease present" or "no disease"), is used to train these models. Training the model to correctly identify new, as shown in Fig. 4, unseen data is the main goal. Generally speaking, classification issues fall into two categories.: Binary classification is the process of classifying information into one of two groups, such as determining if a crop is "healthy" or "diseased." Classifying data into more than two classes, such as Recognizing various crop diseases is known as multiclass classification. We use binary classification in this AgriGuard project to determine if a crop is healthy ("negative") or afflicted by disease ("positive").

Choosing an Algorithm for Features Selection:

- Crop Type: The type of crop being grown, as certain crops may be more susceptible to specific diseases.
- Region: The geographic area, which impacts climate conditions and, therefore, disease prevalence.
- Soil Moisture Level: A continuous measure that indicates water content in the soil, affecting crop health.
- Temperature: An environmental factor, as certain temperatures can increase the likelihood of disease.
- Humidity: High or low humidity levels can influence the spread and severity of crop diseases.
- Rainfall: The amount of rainfall, as excessive or insufficient rainfall can contribute to crop stress and disease development.



4. DESCRIPTION OF DATASET:

Our approach utilized PlantVillage, a public dataset for detecting plant leaf disease. The collection includes 87,000 RGB photos of leaves that are healthy and unhealthy, which are divided into 38 classifications. We only chose 25 classes to try with our algorithm. Data preparation is an essential activity for any computer having a vision-based system shows the processing procedures for every image. To obtain precise findings, eliminate background noise before extracting characteristics. The RGB image is transformed to grayscale and smoothed using the Gaussian filter. The image is thereafter binarized using Otsu's thresholding technique. After image segmentation, features such as texture, shape, and color are retrieved. The use of contours is to compute the area and perimeter of the leaf.

Plant	Disease Name	No. of Images
Apple	Healthy Diseased Scab Diseased: Black rot Diseased: Cedar apple rust	2008 2016 1987 1760
Corn	Healthy Diseased: Cercospora leaf spot Diseased: Common rust Diseased: Northern Leaf Blight	1859 1642 1907 1908
Grapes	Healthy Diseased: Black rot Diseased: Esca (Black Measles) Diseased: Leaf blight (Isariopsis)	1692 1888 1920 1722
Potato	Healthy Diseased: Early blight Diseased: Late blight	1824 1939 1939
Tomato	Healthy Diseased: Bacterial spot Diseased: Early blight Diseased: Late blight Diseased: Leaf Mold Diseased: Septoria leaf spot Diseased: Two-spotted spider mite Diseased: Target Spot Diseased: Yellow Leaf Curl Virus Diseased: Tomato mosaic virus	1926 1702 1920 1851 1882 1745 1741 1827 1961 1790

Contours are lines that connect points along the margins of objects with similar colors or intensity. The mean and standard deviation for every RGB channel are calculated. To find out the quantity of green color in an image, we convert the image into HSV color space and calculate the ratio of pixels along with a hue (H) channel intensity of 30.01 to 70.0 to the total number of pixels present in one channel. The non-green part of the image is estimated by subtracting the green color part of the images.

5. RESULT AND DISCUSSION

5.1 Experimental Results

The home page of the web application will welcome the user to a user-friendly interface and also have the option to change more than 30 languages and the lower home page shows the features that will be given and can be used by the user or farmersshows the crop recommendation page in which fields are empty.

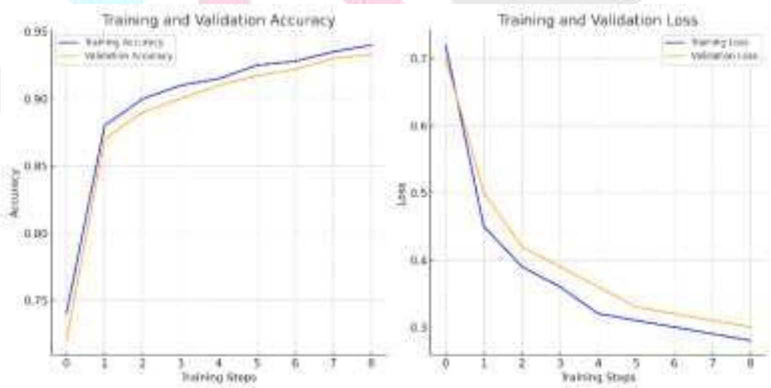
It is shown that the related data is filled, and according to those values, the best crop to plant in the area given is recommended as an output and can be seen that on this page it will get the data from the user about the nutrients present in soil as an input and then it shows that when the data is submitted, then the animation is shown as an indication that it is processing while the model is doing its work. The output is given by recommending the suitable fertilizer according to the provided data.

5.2 Accuracy Comparison

Project	Algorithm Used	Accuracy	Dataset Used	Key Features	Computational Efficiency
S. Khirade et Al. (2015)	Digital Image Processing and BPNN	-	Small Local Dataset	Uses basic feature extraction for disease classification	Moderate
Shiroop Madiwala et Al. (2017)	Digital Image Processing and SVM	83.34%	Limited Crop Image Set	Feature extraction using statistical image processing with SVM	High
Peyman Moghadam et Al. (2017)	Hyperspectral Imaging and SVM	93%	Hyperspectral Image Dataset	Uses multi-spectral imaging for early-stage disease detection	Low (Requires Specialized Sensors)
Sharath D. M. et Al. (2019)	Digital Image Processing	-	Limited Image Samples	Threshold-based segmentation and texture analysis for disease detection	High
Garima Shrestha et Al. (2020)	CNN-based Deep Learning Model	88.80%	PlantVillage Dataset	Convolutional Neural Network (CNN) for automated leaf classification	Medium
AgriGuard (Proposed Model)	**CNN-based Deep Learning** with IoT & Real-Time Crop Monitoring	**95%**	**PlantVillage + Real-Time IoT Data**	**Uses CNN models to analyze leaf textures & disease patterns.**	**Very High (Optimized for IoT & Cloud Processing, Scalable for Large-Scale Farming)**

5.3 Evaluation

The functionality of identifying diseases is more refined. The data is more filtered than other current efforts, resulting



More accurate and correct disease detection, like a real-time diagnosis of an apple leaf by using deep learning, which is based on upgraded convolutional neural networks, has lower accuracy than the suggested method since it identifies several illnesses in a single system.

Our model has more accuracy. There are two distinct training and testing conditions. One involves evaluating the model in a laboratory setting, using the same images used for training and testing. The second one involves the field condition, indicating that our model has been finally tested using real-world conditions. When we take samples from the actual field, the lighting and background characteristics of the photos are completely different; thus, there is a full possibility that our model will yield very low accuracy when it is compared to the accurate values that were obtained under our lab settings. Therefore, we thought of using a range of visuals during the event to counteract this effect.

6. CHALLENGES AND FUTURE DISCUSSION

Thus, a web application is developed that only requires a cropped image from the farmer to identify diseased and healthy plants, and our work focuses on accurate data values under real-world scenarios. It has been implemented by having some plant disease images. Additionally, the web application also has a model to recommend fertilizers after getting the data of available nutrients in the soil. Also, it can recommend the crop to plant in a particular area after getting the input from the user about the environmental status. Overall, our proposed work is done from the basics and achieves decent precision. Our future work will include increasing the number of photographs in the preconfigured database and modifying the architecture to match the dataset for improved accuracy.

Our program supports more than 32 languages that are extensively utilized around the world, particularly in India. Furthermore, it can help new farmers determine the best crop to grow in their fields based on the current situation. Other than that, it can provide a platform for fertilizer vendors and assist farmers in selecting the appropriate fertilizer to purchase based on their requirements. It will also have a business module in which we can charge the fertilizer seller to use our platform for selling their product and charge a small fee to farmers for allowing them to use the platform.

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