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PLANT DISEASE DETECTION USING ML REVIEW PAPER

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Abstract: The importance of plant disease detection in contemporary agriculture is emphasized in this paper, along with how it can reduce crop losses and increase food security. The emphasis is on Convolutional Neural Networks (CNNs) as a powerful instrument for automating the detection of plant diseases by examining the visual indicators present in leaf photos. The paper explores issues including dataset quality, model generalization, and real-world implementation while highlighting CNNs' outstanding ability to quickly and accurately distinguish between healthy and infected plants. Ethical issues such as responsible data use and model bias are addressed along with the need for large, diverse, and well-annotated datasets. In order to advance the creation and implementation of CNN-based plant disease detection systems, the abstract ends with a strong argument for cooperative research.

Keyword: CNN, automation, dataset, real-world, prediction, ML model.

I. INTRODUCTION

Agriculture, often revered as the foundation of human civilization, stands as a timeless and pivotal practice shaping societies, landscapes, and economies for millennia. Encompassing crop cultivation, animal domestication, and land stewardship, agriculture has bestowed sustenance, economic stability, and cultural identity upon diverse global communities.

In an era of burgeoning population growth, the role of agriculture in ensuring food security and sustainability has intensified. This overview spans the spectrum of agricultural practices, from traditional subsistence farming to cutting-edge, technology-driven agribusiness, addressing challenges such as climate change, resource scarcity, and the imperative for sustainable practices. It accentuates innovations holding promise in resolving these issues, framing agriculture as an intricate dance between human ingenuity, environmental stewardship, and the pursuit of nourishment—an enduring subject in the quest for a more sustainable and food-secure world.

In recent decades, agriculture has undergone a profound transformation, propelled by the pervasive integration of technology. This revolution has not only reshaped food production but positioned agriculture as a nexus for innovation and sustainability. The infusion of cutting-edge technology, including precision farming, automation, genetic engineering, and data analytics, has fundamentally altered agricultural practices. This intersection of modern agriculture and technology represents a pivotal moment in our pursuit of resilient and sustainable food systems, poised to ensure food security while safeguarding the planet for future generations.

Plant diseases present a pervasive challenge across agriculture, forestry, and ecosystems, threatening global food security. This exploration delves into the intricate world of plant diseases, examining symptoms, transmission mechanisms, and economic consequences. It explores evolving strategies and technologies to detect, prevent, and mitigate these diseases, emphasizing research and innovation's pivotal role in securing agriculture's future and the planet's well-being.

Plant disease detection systems have become indispensable tools in agriculture, horticulture, and environmental conservation. This exploration into the realm of plant disease detection underscores the significance of early detection in minimizing disease spread and promoting resource-efficient agriculture. As we navigate the intersection of technology and agriculture, these systems play a pivotal role in achieving resilient, sustainable, and food-secure ecosystems. The emphasis on research, innovation, and collaboration is crucial in addressing this pressing global challenge.

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II. SCOPE

The scope of using Convolutional Neural Networks (CNN) in plant disease detection is vast and continues to expand rapidly. CNNs have shown remarkable potential in automating the identification and diagnosis of plant diseases by analysing images of plant leaves. Here are some key aspects of the scope for plant disease detection systems using CNN:

A. *Improved Accuracy*: CNNs offer a high level of accuracy in disease identification, allowing for more reliable and consistent results. This accuracy is crucial for early disease detection and timely intervention, which can save crops and reduce losses.
B. *Early Disease Detection:* One of the primary advantages of CNN-based systems is their ability to detect diseases at an early stage. Early detection is critical for effective disease management and minimizing the spread of diseases in agricultural fields.
C. *Diverse Crop Coverage:* CNNs can be trained to identify diseases in a wide range of crops, making them applicable to different agricultural settings. This adaptability is essential for addressing plant diseases across various regions and crops.
D. *Reduction in Manual Labor*: By automating the disease detection process, CNNs reduce the need for labour-intensive and time-consuming manual inspections, thereby increasing efficiency and lowering labour costs.
E. *Data Integration*: CNNs can integrate various data sources, such as images, weather data, and historical disease patterns, to improve disease diagnosis and provide more comprehensive insights into disease management.
F. *Sustainability:* Accurate disease detection contributes to sustainable agriculture by enabling targeted treatments and reducing the excessive use of pesticides, ultimately benefiting the environment, and reducing production costs.
G. *Real-time Monitoring:* CNN-based systems can be integrated with monitoring solutions for real-time disease tracking, allowing for immediate responses to disease outbreaks.
H. *Challenges*: Despite their potential, there are challenges, including the need for large and diverse datasets, model generalization, and ethical considerations related to data privacy and bias in the models.

The scope of using CNNs in plant disease detection extends to research, agriculture, and technology development, with the potential to revolutionize disease management practices and contribute to global food security. As technology advances and more data becomes available, the capabilities and applications of CNN-based plant disease detection systems are likely to continue expanding.

III. BASIC STEPS IN IDENTIFICATION OF DISEASES

Detecting plant diseases using Convolutional Neural Networks (CNNs) involves several essential steps. Here is an overview of the basic process:

A. *Data Collection:* Gather a dataset of images that includes both healthy plants and plants affected by various diseases. The dataset should be diverse, containing images of different plant species and diseases. High-quality, well-labelled images are essential for training a CNN effectively.
B. *Data Preprocessing*: Prepare the dataset by resizing images to a uniform size, normalizing pixel values, and augmenting the data if needed (e.g., rotating, flipping, or adjusting brightness). Data augmentation helps increase the model's ability to generalize from a limited dataset.
C. *Data Split:* Divide the dataset into three subsets: training, validation, and testing. The training set is used to train the CNN, the validation set helps tune hyperparameters and assess model performance during training, and the testing set evaluates the model's final accuracy.
D. *Model Selection:* Choose a pre-trained CNN model (e.g., VGG, ResNet, Inception) or design a custom CNN architecture. Pre-trained models often offer a strong starting point, as they have already learned useful features from large datasets.
E. *Model Fine-Tuning:* Fine-tune the chosen model on the training dataset. Adjust the model's architecture to match the number of classes (disease categories) in your dataset. This involves modifying the output layer to have the same number of neurons as the disease categories.
F. *Training*: Train the CNN on the training dataset. The model learns to distinguish between healthy and diseased plants. Use an appropriate loss function (e.g., categorical cross-entropy) and optimization algorithm (e.g., Adam) during training.
G. *Hyperparameter Tuning:* Experiment with different hyperparameters, such as learning rate, batch size, and dropout rates, on the validation set to find the optimal configuration that maximizes the model's performance.
H. *Validation:* Regularly evaluate the model's performance on the validation dataset during training. This helps prevent overfitting and ensures the model is learning relevant features.

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I. *Testing:* After training, assess the model's accuracy, precision, recall, and F1-score on the testing dataset to evaluate its ability to detect plant diseases accurately.
J. *Deployment:* Once satisfied with the model's performance, you can deploy it for practical use. This could involve creating a user-friendly interface for farmers or integrating it with a mobile app for real-time disease detection in the field.
K. *Continuous Improvement:* Regularly update the model as new data becomes available or as more advanced CNN architectures are developed. The accuracy of the model can be improved by retraining it with additional data.
L. *Monitoring and Maintenance:* Monitor the model's performance in real-world applications and perform maintenance as needed to ensure its accuracy and reliability.

IV. LITERATURE SURVEY

C Jackulin, S. Murugavalli et al., (2022) [1] a comprehensive investigation has been conducted on diverse machine learning and deep learning methodologies for the identification and categorization of plant diseases. Following this, additional machine learning classification techniques may be applied to the detection of plant diseases and to help farmers automatically identify any type of crop disease that needs to be identified. This analysis talks about different DL approaches for detecting plant diseases. Additionally, a number of methods/mappings for identifying the signs of the disease were compiled. In this case, plant leaf diseases can be identified thanks to the advancement of deep learning technologies in recent years. We believe that scientists investigating plant disease detection will find this work to be a valuable resource. Additionally, a comparison of deep learning and machine learning techniques is done. Even though there has been a lot of notable progress in recent years, there are still certain research gaps that need to be filled in order to develop practical methods for plant disease detection.

Sunil S. Harakannanavar, Jayashri M. Rudagi, Veena I Puranikmath, Ayesha Siddiqua, R Pramodhini, et al., (2022) [2] an RGB to greyscale model, HE, K-means clustering, contour tracing, and other computer vision techniques are used during the preprocessing stage of the proposed model. The informative features of the leaf samples are extracted using the multiple descriptors GLCM, Principal Component Analysis, and Discrete Wavelet Transform. Leaf disease and non-disease detection is accomplished using machine learning techniques like SVM, K-NN, and CNN. In comparison with other state-of-the-art methods, the analysis of the suggested model is well suited for CNN machine learning classification technique with the desired accuracy. Future iterations of the model can look at other dataset leaf samples and be enhanced with fusion techniques for the extraction of important features.

S. Ashwinkumar, S. Rajagopal, V. Manimaran, B. Jegajothi et al., (2022) [3] has demonstrated the use of the OMNCNN model for automated plant leaf disease detection and classification. The goal of the OMNCNN model is to use leaf images to detect plant diseases as accurately as possible. The suggested model includes ELM-based classification, MNCNN-based feature extraction, EPO-based parameter optimization, BF-based image preprocessing, and Kapur's thresholding-based segmentation.

Punam Bedi, Pushkar Gole et al., (2021) [4] noted that early disease detection in plants is a difficult and demanding task. Various Machine Learning and Deep Learning techniques have been employed by numerous researchers to detect plant diseases automatically. Unfortunately, the majority of these methods have poor classification accuracy or require millions of training parameters. In this paper, a novel hybrid model based on two Deep Learning techniques, Convolutional Autoencoder (CAE) network and Convolutional Neural Network (CNN), was proposed for automatic plant disease detection. Using the encoder network of the CAE, the proposed hybrid model first obtained compressed domain representations of leaf images. CNN was then used to classify the compressed domain representations. In comparison to current state-of-the-art systems, the number of features and consequently the number of training parameters decreased dramatically as a result of dimensionality reduction using CAE. The model was tested by using it to identify the Bacterial Spot disease in peach plants. With only 9,914 training parameters, the model produced testing results of 98.38% and training accuracy of 99.35%. The time needed to train the hybrid model for automatic plant disease detection and the time needed to diagnose the disease in plants using the trained model were both greatly reduced by using fewer training parameters.

Deepalakshmi P., Prudhvi Krishna T., Siri Chandana S., Lavanya K. Parvathaneni Naga Srinivasu et al., (2018) [5] utilized convolutional neural networks to identify diseases in soy bean plants (CNN). Using photographs collected from the surrounding environment, the authors investigated the viability of CNN for the classification of plant leaf diseases. They utilized a dataset of 12,673 photos of both healthy and diseased leaves from four classes that they obtained from the Plant Village database in order to build a model using the LeNet architecture for the classification of soya bean plant diseases. The dataset consists of photos shot in various environmental conditions. The model used demonstrates that

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CNN can identify characteristics of leaves and identify diseases from photos of plants under different conditions with a 99.32% accuracy rate. Additionally, the authors noted that the data set classification is unbalanced and recommended using batch normalization to expedite the procedure and enhance accuracy.

Hassan, S.M.; Amitab, K.; Jasinski, M.; Leonowicz, Z.; Jasinska, E.; Novak, T.; Maji, A.K et al., (2022) [6] carried out a survey with the goal of identifying plant diseases using leaf images and machine learning techniques. Similar to people, plants can contract a number of diseases that prevent them from growing normally. The survey covered both deep learning (DL)-based techniques and those based on manually created features. We evaluated the efficacy of various methods taking into account preprocessing, feature selection, segmentation strategies, and the datasets used in each study. Interestingly, the results highlight how crucial preprocessing and segmentation methods are to improving accuracy. Support Vector Machines (SVM) are the most widely used technique for disease identification among the different classification methods. The survey showed that deep learning models consistently performed better than the manual, feature-based approaches. ResNet50, InceptionV3, and DenseNet201, among other notable architectures, showed exceptional suitability for plant disease identification. Furthermore, it was found that lightweight architectures like SqueezeNet and MobileNetV2 were the best options for devices with limited resources, like mobile phones.

Vijai Singh, Namita Sharma, Shikha Singh et al., (2020) [7] presented an overview of the various methods for identifying diseases is provided in this paper. Additionally, a succinct overview of several imaging techniques helpful in the early detection of plant diseases is presented. We present the Current Trends and Challenges in Plant Disease Detection with Advanced Imaging Techniques and Computer Vision. Thermal, hyperspectral, fluorescence, multispectral, and three-dimensional imaging are some of these methods. Additionally, we have discussed various methods for classifying and identifying plant diseases early on. SVM, K-means clustering, Deep learning, and K-NN are the main methods. Based on a cost-benefit analysis, this review concludes that an efficient method is required. Advances in agriculture would also be facilitated by the deployment of a dependable and effective sensor to check for the fulfilment of appropriate plant health criteria. Future research can focus on creating a reliable, strong system for early automatic tracing that can be expanded to identify every potential disease.

. S. K. et. al (2021) [8] stated organic farming, protecting crops is a difficult effort. This requires in-depth understanding of the crop being farmed as well as potential diseases, weeds, and pests. Using photos of healthy or diseased plant leaves, our system uses a unique deep learning model built on a unique architectural convolution network to identify plant illnesses. It is possible to upgrade the previously mentioned system to a real time video entry system that permits unattended plant care. An intelligent system that treats recognized illnesses is another feature that can be introduced to some systems. Research indicates that controlling plant illnesses can contribute to a roughly 50% rise in production.

Sumita Mishra, Rishabh Sachan, Diksha Rajpal et al., (2020) [9] described our nation is built on agriculture, and one of the main causes of crop production reduction is crop loss from plant diseases. It is imperative to use Artificial Neural Network (ANN) techniques with intelligent algorithms for plant disease identification to decrease crop health issues and lessen the severity of losses. This paper provides a real-time deep learning model that does not require the Internet for the identification and categorization of common corn illnesses. The average accuracy of the Deep CNN design, according to performance analysis, is 98.40%. Furthermore, an adjusted CNN model with optimally trainable parameters is implemented on NCS to conduct inference on real-time images obtained from smartphones, achieving an average accuracy of 88.66%. Even though the outcomes are encouraging,

Parul Sharma, Yash Paul Singh Berwal et al., (2020) [10] reduced performance when most deep learning models for autonomous disease identification are applied to previously unidentified real-world images. Convolutional neural network (CNN) models can be trained using segmented and annotated images instead of entire images, as they demonstrate. When the same CNN model is trained using segmented pictures (S-CNN) instead of full images (F-CNN), model performance on independent data increases from 42.3% to 98.6%. Furthermore, 82% of the test dataset showed a significant improvement in self-classification confidence, according to a quantitative study. Pre-processing images before CNN model training can be very helpful in achieving good real-world performance when richer datasets become available in the future.

André Abade, Paulo Afonso Ferreira, Flavio de Barros Vidal et al., (2021) [11] by combining the ability to extract symptomatic features with the knowledge of phytopathology experts, automated plant disease detection systems use convolutional neural networks to identify and classify plant diseases. The diversity of problems and the subtleties of real-world scenarios make it increasingly difficult to semantically catalogue the data in representative data sets with an adequate number of labelled samples.

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Narendra Pal Singh Rathore1, Dr. Lalji Prasad et al., (2020) [12] studied rice crop disease detection and recognition using deep learning with rice images is a signal. Because there are no unexplored areas that machine learning and deep learning techniques and tools cannot reveal, it has given researchers new opportunities. We could potentially achieve better disease detection outcomes by adjusting the network's configuration and parameters. An autoencoder could be used in the future to improve the suggested method rather than requiring manual image size reduction. Given that autoencoders can regenerate up to 90% of the original images, it is possible to compress data without sacrificing any essential features.

Md. Tariqul Islam et al., (2020) [13] In order to improve agricultural industry productivity, this work offers a genuine idea for identifying the attacked leaf ('Grape, Potato, and Strawberry'), and the farmer who works to produce these fruits receives a remedy. Agriculture department specialists accept the rapid disease detection process facilitated by image processing techniques as a result of the technology's quick milestone achievement. With the CNN model, the transited leaf portion can be easily segmented and analysed, and the best possible result is provided instantly. Therefore, by manually detecting plant diseases, farmers can save time and reduce the possibility of making an incorrect diagnosis. Our long-term objectives are to create an open multimedia system and software that can automatically identify plant diseases and offer remedies.

Kiran R. Gavhale1, Ujwalla Gawande et al., (2014) [14] In order to identify plant diseases, image processing methods for a number of plant species have been reviewed and summarized in the current paper. The four main methods for identifying plant diseases are SGDM, K-means clustering, SVM, and BPNN. These methods are employed to analyze the leaves of both healthy and sick plants. A few of the difficulties with these methods include the impact of background data on the final image, optimizing the method for particular plant leaf diseases, and automating the method for ongoing, automated monitoring of plant leaf diseases in actual field settings. According to the review, these methods for detecting diseases in plants have some limitations but also good potential for identifying diseases in plant leaves.

Shruthi Su, Nagaveni Veerakyatharayappa, Raghavendra B K et al., (2019) [15] This review presents a comparative analysis of five different machine learning classification approaches for the identification of plant diseases. When compared to other classifiers, the SVM classifier is employed by numerous authors for the classification of diseases. The outcome demonstrates that the CNN classifier has higher accuracy in detecting more diseases. In the future, additional machine learning classification techniques such as decision trees and the Naïve Bayes classifier may be employed to identify plant diseases and assist farmers in automatically detecting all kinds of crop diseases.

Deepkiran Munjal, Laxman Singh, Mrinal Pandey, Sachin Lakra et al., (2023) [16] summarised exploring machine/deep learning in plant leaf disease recognition, focusing on data collection, preprocessing, and classifier evaluation. Village datasets were commonly used, with SVM classification prevalent in traditional models. In deep learning, ResNet-50 outperformed with 99.7% accuracy, followed by Google Net at 99.3%. These findings offer insights for future research and applications in plant disease detection.

Nishant Shelar, Suraj Shinde, Shubham Sawant, Shreyash Dhumal and Kausar Fakirthis et al.,(2022) [17] gave conclusion for successful creation of a deep learning model for automatic detection and classification of plant leaf diseases, tested across 13 different species(Tomato, strawberry, soybean, raspberry, potato, corn, Pepper bell, peach, orange, grape, cherry, blueberry, apple) and 38 plant classes, marks a significant achievement. Utilizing Keras' image data generator API, we efficiently handled image-processing tasks and trained the advanced VGG-19 model, demonstrating accurate predictions. Deployment on an Android app was successful, with ongoing efforts to enhance both app accuracy and model performance.

Yosuke Toda and Fumio Okura et al.,(2019) [18] systematically evaluated various visualization methods for interpreting plant diseases diagnosed by CNNs. The findings underscored the inadequacy of simplistic approaches, such as naive visualization of hidden layer outputs, while highlighting the potential practical applications of sophisticated techniques like feature visualization and semantic dictionaries. The ability to extract visual features crucial for disease classification was demonstrated. This exploration of visualization methods in disease diagnosis sets the stage for a novel workflow in plant science studies, fostering collaboration between computers and plant scientists. Through machine/deep learning models, this cooperative approach offers a promising avenue for gaining deeper insights into the biology of plants.

Daneshwari Ashok Noola, Dayananda Rangapura Basavaraju Et al., (2022) [19] highlighted the importance of catching corn leaf diseases early and suggested the use of an Enhanced-KNN model for precise identification and classification. To produce fine and coarse features of high quality, the model combines improved mathematical modeling. The low-dimensional intensity relationships between neighboring pixels are optimized through the use of confined intensity-DOR, and classification accuracy is increased by segregating pixels into different sets using an optimized Directional set

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strategy. The proposed EKNN model performs better than existing and traditional mechanisms, as evidenced by its impressive accuracy, sensitivity, specificity, and AUC values. A comparative analysis reveals the model's superiority in terms of F1 score, recall, and precision.

Kushal M U, Mrs Nikitha S, Shashank L M, Partha Sarathi S, Maruthi M N et al., (2022) [20] underscores the challenges faced by farmers in overcoming crop diseases despite the presence of multiple fertilizers and chemicals. The reliance on manual inspection by plant pathologists is both costly and susceptible to ignorance and bias. Recognizing the need for automated solutions, the research introduces an Artificial Intelligence approach, specifically the capsule network model, and compares it with CNN architectural variations. Focused on ten types of tomato leaf diseases, the study highlights the potential for future work in developing a robust capsule network model capable of addressing diseases across various plant species.

Fang, Y., Ramasamy, R.P. et al., (2015) [21] An overview of the current techniques for identifying plant diseases brought on by pathogens like bacteria, viruses, and fungi is given in this article. Even though well-known methods like PCR, FISH, ELISA, IF, FCM, and GC-MS are frequently employed, they are difficult to use, need trained personnel, and require labor-intensive data analysis. Furthermore, the lack of real-time detection in these approaches renders them less appropriate for early warning systems and on-field testing. Conversely, while imaging modalities like fluorescence imaging and thermography are employed in the field for disease detection, their specificity for individual disease types is limited, and they are susceptible to variations in environmental factors. The potential of various biosensors for plant disease detection is reviewed in detail in this article. Modern nanofabrication techniques have enabled the development of highly sensitive biosensors thanks to the advent of nanotechnology. Enzymes, antibodies, DNA, and bacteriophages can all be used as specific recognition elements to greatly increase the specificity of biosensors.

Saleem, M.H.; Khanchi, S.; Potgieter, J.; Arif, K.M et al., (2020) [22] accomplished the intricate task of localizing and categorizing plant diseases within a single framework. To achieve this, cutting-edge deep learning meta-architectures such as SSD, Faster RCNN, and RFCN models were trained and evaluated on 38 distinct classes of healthy and defected plant leaves. Additionally, efforts were made to enhance their performance by optimizing weight parameters using Adam and RMSProp optimizers. Among these DL meta-architectures, the SSD model trained with the Inception-v2 feature extractor demonstrated the highest mean average precision. By employing an Adam optimizer, it achieved the most accurate identification results, with a mAP of 73.07%. The proposed approach successfully identified all classes of healthy and diseased leaves, showcasing its novelty. From a practical standpoint, the effective detection of plant diseases through DL techniques could significantly reduce the unnecessary use of fungicide spray.

Several recommendations for future research in this field are as follows:

1. The pipeline, checkpoints, and weights of the trained and evaluated DL models can be reused as a transfer learning approach for upcoming studies related to plant disease detection.
2. It is crucial to investigate various factors that influence the performance of the most suitable DL architecture, such as data augmentation techniques, batch size, aspect ratios, and more. Although the proposed methodology successfully identified all classes of the PlantVillage dataset, some achieved a lower average precision. Therefore, proposing modifications to DL networks in the future could further enhance the mean average precision.
4. This research could also prove beneficial for various robotic systems, enabling real-time identification and classification of healthy and unhealthy crops. Such advancements would greatly contribute to agricultural automation.

Serawork Wallelign, France Mihai Polceanu [23] utilized convolutional neural network (CNN) to detect and categorize diseases in soybean plants. The CNN was trained using images captured in the natural environment, resulting in an impressive classification ability of 99.32%. This demonstrates the CNN's capability to extract crucial features from the natural environment, which is essential for accurate plant disease classification. To the best of our knowledge, this is the first endeavor to employ images taken in the wild environment and achieve such remarkable performance. Furthermore, the experiments conducted revealed that applying data augmentation to the training set enhances the network's performance, particularly when dealing with a small dataset. The effectiveness of dropout and regularization techniques in mitigating overfitting was also confirmed. It is worth noting that the data sample used in this study is unbalanced, with class 1 comprising 49.19% of the data, class 2 comprising 28.13%, class 3 comprising 15.96%, and class 4 comprising 6.72%. For future research, we plan to implement deep learning methods to address the issue of sample imbalance, as suggested by Huang et al. (2016). Additionally, we will explore the potential benefits of batch normalization, as proposed by Yin et al. (2017), to expedite the training process and improve accuracy.

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Shima Ramesh, Niveditha M, Pooja R, Prasad Bhat N, Shashank N, Mr. Ramachandra Hebbar ,Mr. P V Vinod [24] the main goal of this algorithm is to identify any abnormalities that may occur on plants, whether they are in a greenhouse or in their natural environment. To ensure clear visibility, the images captured are typically taken against a plain background to minimize any obstructions. In order to assess its accuracy, the algorithm was compared to other machine learning models. By utilizing the Random Forest classifier, the model was trained using a set of 160 images featuring papaya leaves. The model demonstrated an approximate accuracy rate of 70 percent in its classification abilities. However, the accuracy can be further improved by expanding the training dataset to include a larger number of images and incorporating additional local features, such as SIFT (Scale Invariant Feature Transform), SURF (Speed Up Robust Features), DENSE, and BOVW (Bag Of Visual Word), alongside the global features.

Shree. Dolax Ray, Mst. Khadija Tul Kubra Natasha, Md. Azizul Hakim, Fatema Nur et al.,[25] presents study which proposed a system that aims to identify unhealthy carrots in order to assist farmers and agriculturists in cultivating fresh carrots. The primary objective of our research is to determine the factors that can aid growers in obtaining accurate crop details through our model and taking the necessary actions. To achieve this, pre-processing techniques were utilized to eliminate noise from the images. The well-processed images were then trained and tested using CNN models. As a result, we obtained a visually appealing training and validation accuracy graph for our design. Ultimately, we successfully implemented our anticipated outcome, which is a stylish delicacy with an accuracy of 0.99812%. Additionally, we developed a web application using this model. The application is capable of detecting carrot diseases and providing detailed information about the disease along with potential solutions or cures.

Howmick Guha Paul, Al Amin Biswas, Arpa Saha, Md. Sabab Zulfiker, Nadia Afrin Ritu, Ifrat Zahan, Mushfiqur Rahman, Mohammad Ashraful Islam et al.,(2023) [26] study focuses on the classification of tomato leaf disease. It proposes a custom CNN model and compares it with CNN models based on transfer learning (TL). The TL-based models used in this study are the pre-trained VGG-16 and VGG-19 models. The dataset used has been preprocessed and augmented. An ablation study has been conducted to determine the most suitable augmentation methods, as well as custom model layers and parameters. The performance of the proposed model has been compared to that of the transfer-learning-based VGG-16 and VGG-19 models. The evaluation of the models shows that the augmentation techniques have significantly improved the robustness of the models. Among the models used, the proposed CNN model achieves a higher accuracy of 95.00%, making it superior to other research studies addressing the same task. Furthermore, this study has implemented the most accurate classification model in a web- and Android-based application for predicting tomato leaf disease.

V. VARIOUS MODELS DEVELOPED FOR THE PLANT DISEASE DETECTION

ML algorithms such as c4.5 classifier and tree bagger are being used to predict crop yields, identify plant lesions and pests, and optimize plant growth

DL models, such as CNNs and DBNs, have been applied plant lesion identification based on image analysis and classification, providing better accuracy and robustness compared to traditional image processing methods DBN is a type of unsupervised DL model that is composed of multiple layers of Restricted Boltzmann Machines (RBMs). Using the plant lesion and pest infestation detection, DBNs have been used to test plant images affected regions to detect various diseases and types of pests, and extract features from images of plant leaves. Studies have shown that DBNs can achieve high accuracy rates in the range of 96-97.5% in classifying images of plant leaves affected by diseases and pests.

Boltzmann's Deep Machine (DBM) is generative stochastic AI model that can be utilized for unsupervised classification to detect the plant lesion. Within the context of conventional plant lesion and pest detection, DBMs have been used to predict labels for images of various plant affected regions by viruses and plant bugs, and extract features from images of plant leaves. Studies have shown that DBMs can achieve high accuracy rates in the range of 96-96.8% in classifying images of plant leaves affected by diseases and pests.

Deep Denoising Autoencoder is a variant of autoencoder, which is a neural network architecture that is composed of an encoder module along with a decoder. In the context of traditional plant disease and pest infestation detection, DDA has been used to for two different purposed i.e., noise removal from the plant leaf data and a prediction system to identify plant disease. Studies have shown that DDA can achieve high accuracy rates in the range of 98.3% in classifying images of plant leaves affected by diseases and pests.

Various Convolutional Neural Network (CNN) models which have been utilized to identify plant diseases and pest infestation are:

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AlexNet, which is the CNN model developed in 2012. The AlexNet CNN win the classification challenge by achieving the highest accuracy using the 1000 classes Imagenet dataset. AlexNet is known for its high accuracy and speed, and it has been used for a variety of tasks, including plant disease detection

Another popular CNN model is **VGG**, which was established in 2014 by the University of Oxford's at Visual Geometry Lab. VGG is known for its high accuracy and is often used for image classification tasks. It has been employed to detect plant lesions by extracting hidden patterns from plant leaf data.

ResNet, which was developed by Microsoft Research Asia in 2015, is known for its ability to handle very deep networks. It has been used for plant disease detection by using pre-trained ResNet models on the images of the plants.

GoogleNet, which was developed by Google in 2014, is known for its high accuracy and efficient use of computation resources. It has been used for plant disease detection by fine-tuning pre-trained GoogLeNet models on the images of the plants.

VI. CONCLUSION

In conclusion, the utilization of Convolutional Neural Networks (CNNs) in conjunction with large datasets for plant disease detection represents a transformative stride toward enhancing agricultural practices and food security. Through the integration of deep learning and extensive datasets, we have witnessed substantial improvements in the accuracy and efficiency of disease identification, allowing for early interventions and precise management. The wealth of data fosters robust and adaptable models, while CNNs' ability to discern intricate patterns within plant images has propelled disease detection to new heights. As we look to the future, the continued collection of diverse and expansive datasets, combined with the development of lightweight CNN architectures, holds the promise of further refining the field of plant disease detection. This approach not only empowers farmers with the tools to protect their crops but also aligns with sustainable agricultural practices by reducing resource-intensive interventions and fostering environmental stewardship. The synergy between CNNs and large datasets is poised to play a pivotal role in fortifying global food security and ensuring the resilience of our agricultural systems.

We aim to incorporate Internet of Things (IoT) technology into our ongoing project, "Plant Disease Detection using ML". As we strive for innovation and efficiency, integrating IoT into our project has the potential to significantly enhance its capabilities and bring about a transformative impact.

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