Agri Watch: Precision Plant Health Monitoring using Deep Learning

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Abstract. The growth of deep learning technologies allows us to achieve higher accuracy in the classification of plant diseases, as well as in other domains. This research reveals the performance of several DL approaches, including custom convolutional neural networks (CNNs) and models which are pre-trained namely VGG16 and ResNet34, which were used for the recognition of diseases in plants that are depicted through the images. These models may obtain the necessary growing environment for training and assessing the models by using a publicly accessible dataset that includes pictures of both healthy and diseased plants, in total there are 14 unique plants used. The results of the experiment suggest that all the models combinedly gave 98.46% accuracy in the classification of diverse plant diseases. In addition to this, the paper discusses the hyperparameters like learning rate and optimizer choice that affect the model furthermore, the project discusses the methods involved in training deep learning models on GPU devices computationally speaking. Thereby, this project can be added to the field of agriculture vision by showing that deep learning methods are good for plant disease classification.

Keywords – Accuracy, Hyperparameters, Optimizer, Crop Management, GPU Computing, Agriculture Vision.

1. Introduction

Agriculture provides a base for human civilizations, Agriculture makes feeding possible for billions of people and It makes livelihoods on the planet possible. Notwithstanding, agriculture is exposed to the multiple problems like climate change and resource use restrictions and continues to deal with the diseases of plants that invade them. Among these challenges, the plant diseases that are newly emerging and spreading all over the world are the biggest obstacle to global food security, livelihoods, and economic stability. Diseases of plants can reduce a large extent to crops which in turn leads to a decline in agricultural yields and the earnings of farmers. It is therefore imperative that one identifies and questions these pests/diseases early enough so that they can warrant needed control measures to reduce their impact on food production. Traditionally, plant disease diagnosis has only been done through identification of symptoms, and with the knowledge of an expert, which invents errors, is time consuming and subjective. Moreover, the possibilities of the disease spreading worldwide have become more reachable and real; therefore, it is high time to come up with new, efficient, and cheap approaches to diagnose and cure diseases. AI and DL has appeared recently, and it has been recently used to help solving a great number of problems in the field of agriculture. CNNs for instance have proved to bring out tremendous results on the classification and recognition of images as well as categorization of images into various classes or categories. Using these data sets that have been labelled, deep learning enables the discovery of several patterns and features, in which each of them is unique, hence making the classification of these diseases is an easier task and more precise. The performance evaluation of three different DL models for the categorization of plant diseases is examined in this study: The team used three models namely CNN architectures, VGG16, and ResNet34. CNNs are the family of advanced deep neural networks designed particularly for image processing with the application in image mode tasks like disease classification. VGG16 and ResNet34, at one hand, are CNN models that have already been trained on training picture datasets with the ability of intelligently discovering and extract features out of images.The central issue of the study is the evaluation of the accuracy, reliability, and scalability of these models in the identification and classification of a wide range of diseases in plants. Let's start by comparing an architecture of custom CNNs with models namely VGG16 and ResNet34 which have been trained on huge datasets before. Apart from that, the paper also go into the bearing of hyperparameters involved such as learning rate, and optimizer among others on the performance of these models. For our arguments to be strong, done extensive research and development, using both code implementation and theoretical insights to support our conclusions. The combination of both applied interaction and theoretical discussion is going to be one of the essential components of our work, that will let participants learn more about the practical efficiency of DL algorithms for the purposes of classification of plants based on their disease. At the same time, the models that can diagnose the diseases and facilitate the management are to be created and shared among all the members of the agricultural value chain, so that the stakeholders are armed with the necessary tools and knowledge which promote the reinforcement of the global food systems and the encouragement of sustainable agricultural practices.

2. Literature review

[1] With reference to this Too et al. (2019) conducted the study to investigate the function of different DL architecture for the classification of diseases of plants based on images of leaves. They analyse the architectures like VGG 16, Inception V4, ResNet and DenseNets and then claim that DenseNets are the best considering testing accuracy score i.e. 99. 75%. They provide the worth of the fast and specific models in the beginning of plant disease identification to enhance the food security aspects.

[2] Ferentinos and his team (2018) used a sizable library of leaf photos to create CNN models for the identification and treatment of plant diseases. Their most successful model identified several plant-disease pairings with a success percentage of 99.53%. They push for broader integration of their models into actual farming situations, highlighting their potential as useful advice tools for farmers.

[3] Li et al (2021) provide a review of DL technology's progress in crop leaf disease identification. The benefits of deep learning in objective feature extraction, enhancing research, and accelerating technological transition have all been covered. Researchers interested in plant disease detection and insect pest control will find their review to be a valuable resource as it tackles current concerns in the area.

[4] Saleem et al. (2019) Examine the use of deep learning models in the identification and

categorization of plant diseases. They draw attention to the shift from conventional machine learning techniques to deep learning approaches, highlighting improved accuracy as a primary benefit. Their evaluation identifies research gaps for further study and provides insights into various DL structures and visualization approaches utilized in plant disease diagnosis.

[5] Devaraj et al. (2019) suggested a method for the automated identification and categorization of plant diseases that is based on image processing. They stress the role of agriculture in providing food for the populace as well as the necessity of addressing crop losses brought on by illness. Their study focuses on creating software that uses leaf pictures to identify and categorize crop illnesses, demonstrating the value of image processing methods in agricultural settings.

[6] Guo et al. proposed a mathematical model to achieve better accuracy, applicability, and training speed in smart farming for the plant disease detection and recognition tasks using deep learning techniques. To locate leaves in complex environments they employ the use of region proposal network (RPN) in their model. Images are then segmented by utilizing the CV method so that symptom information can be extracted. Then a transfer learning model is trained using the segmented leaves and its own dataset containing images of plant diseases. The results obtained in the experiments indicate significant performance enhancement as compared to the existing methods in terms of accuracy which is 83. 57% on a variety of diseases such as rust, bacterial plaques and black rot. This strategy can be helpful to the cause of environmental conservation as well as encouraging sustainable agriculture.

[7] Chen et al. (2020) analyze the application of deep transfer learning to image-based plant disease diagnosis. They use their own data set containing plant diseases; they further filter or fine tune pre-trained convolution neural networks models like VGGNet and the inception module which they all learnt from data sets like ImageNet. Their technique gave a substantial performance enhancement when compared with earlier techniques by reusing pre-trained networks for the initialization of weights. They achieve mean average accuracy of 92% for rice plant picture classification and valid accuracy of 91.8% on a public dataset. The avenues for further research on plant disease detection and the application of deep transfer learning in agriculture are shown in the future research.

[8] Khirade and Patil (2015) tackle the problem of plant disease detection to stop losses in agriculture quantity and productivity. They suggest employing image processing methods, which include picture capture, pre-processing, segmentation, feature extraction, and classification, to identify diseases. In this study, segmentation and feature extraction techniques are emphasized while discussing several approaches and algorithms utilized for plant disease detection from leaf photos. They want to enhance sustainable agricultural practices by advancing accurate and efficient disease identification through the use of image processing.

[9] Saleem et al. (2020) focus on the use of deep learning meta architectures for the identification of image-based plant diseases. Using the TensorFlow object detection framework, they use three deep learning meta-architectures: SSD, Faster RCNN, and RFCN. Their models reach a mean average precision (mAP) of 73.07% after it was controlled and trained on a dataset using an SSD model with an Adam optimizer. It shows the originality of their study that they can accurately identify 26 varieties of sick leaves and 12 species of healthy leaves under one framework. They only recommend that in the future real -time disease diagnosis could be conducted in other agricultural applications by using their approach.

[10] Fang and Ramasamy (2015) Examine existing and potential plant disease detection techniques, highlighting the necessity of enhanced disease detection and prevention in agriculture to reduce crop losses and maintain sustainability. In addition to laboratory-based

procedures like PCR, IF, FISH, ELISA, FCM, and GC-MS, they offer a thorough review of indirect approaches including fluorescence imaging, thermography, and hyperspectral techniques for disease detection. They also go over the possibility of using biosensors with specific bio-recognition components to identify crop diseases early on. This thorough analysis advances the control of agricultural diseases.

[11] The importance of contemporary deep learning-based automatic image recognition systems for early plant disease diagnosis is emphasized by Singh et al. (2020). They highlight the need for precision algorithm development in leaf-based photo categorization and show how well Random Forest distinguishes between healthy and sick leaves. They have developed a scalable approach that uses machine learning and image processing to identify plant diseases on a big scale.

[12] Lee et al. (2020) present fresh viewpoints on the characterisation of plant diseases using deep learning methods. They look at how well-trained models may be adjusted for plant identification tasks and suggest a new approach that takes crop diseases into account separately. Their results cast doubt on the conventional wisdom around crop disease classification and call for a review of the methods currently employed in the characterisation of plant diseases.

[13] Ramesh and his team (2018) concentrate on applying machine learning, especially Random Forest, to identify plant diseases.. They talk about how crop diseases pose a major threat to food security and propose a method that combines dataset creation, feature extraction, and classification. Using a HOG for feature extraction demonstrates machine learning-based large-scale plant disease diagnosis.

[14] Shruthi and the team (2019) give an overview of machine learning classification methods for identifying plant diseases, emphasizing the use of Convolutional Neural Networks (CNNs) to achieve high accuracy in a variety of crop types. They stress the use of machine learning techniques in evaluating results based on data, comparing different categorization approaches, and offering insights into the many phases of a general plant disease detection system.

[15] Kaur et al. (2019) has out a survey on the diagnosis and categorization of plant diseases using photographs of the leaves, highlighting the efficiency of computer vision technology in automating this procedure. They evaluate the effectiveness of cutting-edge methods, compile a summary of the advantages and disadvantages of previous studies in this field, and suggest areas for further investigation.. Their survey provides valuable insights into computer vision applications in plant disease detection, aiding researchers in understanding the research landscape and advancing the field.The literature on plant disease detection and classification demonstrates significant advancements in leveraging technology to address critical agricultural challenges, such as ensuring food security and sustainable practices. Papers 1 to 15 collectively highlight the emergence of sophisticated imaging techniques, ML algorithms, and DL methodologies for early identification and characterization of plant diseases. From the exploration of CNNs to the application of Random Forest and other ML classifiers, researchers have showcased the effectiveness of these approaches in accurately identifying various plant diseases across different crops. Additionally, surveys and reviews have provided valuable insights into the strengths, weaknesses, and future directions for this field, emphasizing the importance of ongoing innovation and collaboration to tackle evolving plant disease threats and promote global agricultural resilience. Papers 16 to 20 further illustrate the potential of advanced computational techniques in plant disease detection. Custom CNNs, pre-trained models like VGG16 and ResNet34, and lesion-focused approaches have demonstrated robust accuracy in classifying plant diseases. Large datasets and specific spectral disease indices (SDIs) for crops like sugar beet show promising results in early disease detection. Transfer learning with models like ResNet50 and DenseNet121 enhances strawberry disease identification

accuracy while reducing training time. These studies collectively affirm that advanced ML and DL techniques, coupled with innovative data processing and large datasets, can significantly improve plant disease detection, suggesting a strong potential for integration into automated systems for precision agriculture.In conclusion, the combined findings from papers[1] to [20] underscore the transformative impact of ML and DL in identification of plant diseases. The integration of these advanced techniques into agricultural practices holds considerable promise for enhancing early disease detection, improving crop management, and fostering sustainable agricultural practices globally. Continued research and collaboration are essential to fully harness these technologies' potential and address the evolving challenges in plant disease management.

Proposed architecture

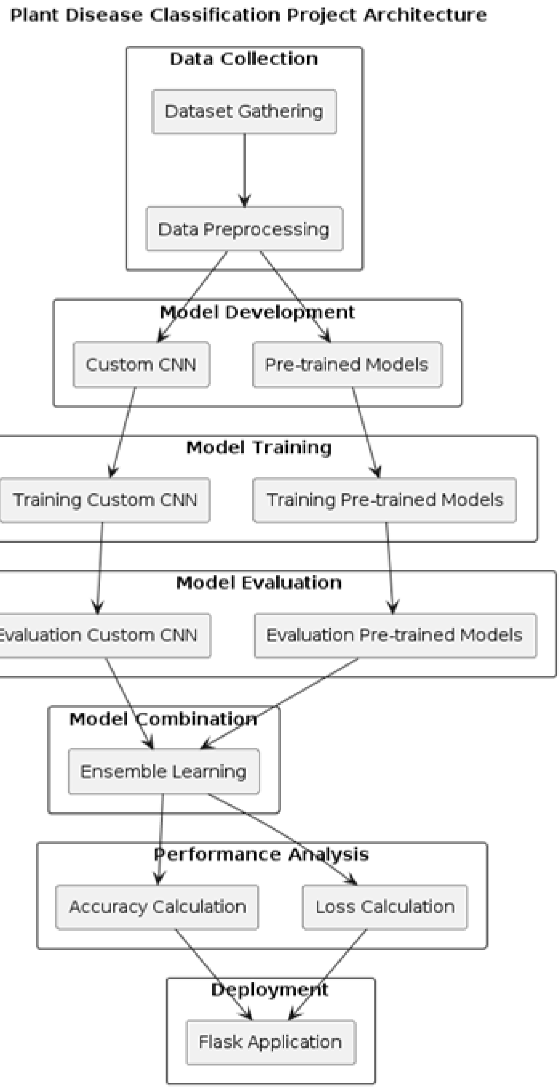

Fig1. Proposed Architecture of the Model.

A plant disease sample classification system is designed through an architecture that is system-based and employs deep learning methods as flowchart shown below shows the systematic procedure of the system. The first step in the procedure is to create a data collection including pictures of both healthy and damaged plant leaves. Resizing and normalizing procedures are part of pre-processing; these procedures bring these templates to the same scale and standardize them for the following stages.The model development phase encompasses two main strategies: custom CNN architecture design and the utilization of the models which are already trained such as VGG16 and ResNet34. These models are then trained using the pre-processed data, optimizing their parameters to minimize a defined loss function. After training, a different validation dataset is used to assess the models' performance by measuring things like accuracy and loss. The predictions of the bespoke and pre-trained models are combined using ensemble learning techniques, which take advantage of each model's unique characteristics to increase overall accuracy and robustness. To make sure the ensemble model achieves the intended goals, its performance is examined. Finally, the trained model is deployed using a Flask application, allowing users to interact with the system by uploading images of plant leaves and receiving real-time predictions about their health status. This comprehensive architecture ensures a structured and systematic approach to building an effective plant disease classification system, delivering accurate and reliable results to end-users.

3. Results and analysis:

Our studies have demonstrated the high degree of accuracy with which the ensemble model may be utilized to classify plant diseases. The ensemble model turned up an excellent accuracy of 98.46%. The model's accuracy of 98.42% on the test set shows that it can distinguish between a variety of plant diseases.. The high accuracy of this combined model confirms the importance of using different models to take advantage of their individual strengths and enhance overall performance. The in-depth investigation also brought to the fore more details about the behaviour of the ensemble model; areas that needed improvement and also opportunities for further study. Also the accuracy of the models in the test and the train set is so close which indicates the chances of overfitting of the model is very low.There are so many irregularities due to the complexity of the model. Which is not a good sign but as the data is complex fluctuations are bounded to be happening.Line graphs of the model's training and validation sets are shown in Fig. 3 The model is being trained flawlessly, as evidenced by the fact that the loss during training is continuously decreasing and the loss during validation is occasionally rather large. However, there are occasions when the volatility in the validation suggests that the model is overfitting, but the combine model used for the project is not overfitting because the graph does not have a lot of ups and downs.

4. Conclusion

It was demonstrated in this study that many DL models, including the use of personal CNN and Pretrained models such as VGG16 and ResNet34, are effective for the classification of plant disease through picture information. The analysis presented in this work indicates that DL methods allow for the accurate classification of several plant diseases from digital images. The tailored-made CNNs successfully monitored whether a plant was healthy or sick by understanding complex patterns. The results obtained from the ensemble model showed overall accuracy of 98. 46% and a test accuracy of 98. 42% Accuracy which shows that they had not much of overfitting but the individual models did not mention their specific accuracy. Due to their high ability of categorizing different types of illnesses from given symptoms, pre-trained models formed a strong foundation for the ensemble model, thus enhancing its performance. Through the implementation of ensemble learning which places diverse models into one and enables the achievement of greater accuracy than any single model could have managed on its own. This work conveys the significance of applying DL methods in the field of plant pathology and agriculture in accurately identifying diseases at an early stage, thus reducing crop losses and improving agricultural production and profitability. Also the development of computer based applications for the management and or identification of diseases remotely can help boost food security in a country ad also help in conservation and sustainability of agricultural practices.

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