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Plantify - Disease Detector App

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A B S T R A C T

Plantify is an Android application that utilizes machine learning to detect plant diseases such as those affecting tomatoes and potatoes. With the increasing impact of climate change and plant diseases on crop yields, early detection of diseases is crucial for crop management. The app uses datasets from Kaggle and Teachable Machine Learning to train its machine learning models. The app provides users with a user-friendly interface to upload images of their plants and identify any diseases affecting them. The abstract of the project highlights the importance of early detection of plant diseases and the use of machine learning to achieve this goal.

Keywords: Plantify Android application, Plant disease detection, Machine learning, Kaggle datasets.

1. Introduction

The field of agriculture is facing unprecedented challenges due to the impact of climate change and plant diseases. Early detection of plant diseases is essential to mitigate their impact on crop yields. In recent years, machine learning techniques have shown great potential in various domains, including agriculture. The Plantify application is an Android-based plant disease detection app that utilizes machine learning to identify diseases affecting plants such as tomatoes and potatoes. The app uses Kaggle datasets and Teachable Machine Learning to train its machine learning models, which provide accurate and fast disease identification. This paper discusses the development of the Plantify application, highlighting the importance of early detection of plant diseases and the potential of machine learning in agriculture. The paper also discusses the challenges and opportunities associated with the application of machine learning in agriculture and the potential impact of the Plantify application in this field.

2. Ease of use

The ease of use of the Plantify application is a critical factor in its effectiveness as a tool for plant disease detection. By providing a user-friendly interface, the app makes it possible for anyone to use the application, regardless of their technical skills or knowledge of machine learning. This makes the application accessible to a wide range of users, from small-scale farmers to researchers and large-scale agricultural enterprises.

The application's ease of use is also enhanced by its quick and accurate disease detection capabilities. The machine learning models used by the app have been trained on a diverse range of plant disease datasets, enabling the app to identify diseases with a high level of accuracy. This, in turn, enables users to take timely action to manage the spread of the disease and minimize its impact on crop yields.

3. Literature Reviews

Plant diseases can have a significant impact on crop yields, resulting in reduced productivity and economic losses for farmers. In recent years, machine learning has emerged as a promising tool for the early detection and management of plant diseases. In this literature review, we will explore the use of machine learning in plant disease detection and its potential benefits for the agricultural industry.

The study by Singh et al. (2020) aimed to develop a deep learning model for detecting and classifying six different tomato plant diseases based on leaf images. The authors used a convolutional neural network (CNN), which is a type of deep learning algorithm specifically designed for image processing tasks. They trained the CNN using a dataset of 3,168 images of tomato leaves, including healthy leaves and leaves infected with six different diseases. After training the model, the authors evaluated its performance on a separate dataset of 1,176 images. They reported an accuracy of 99.61% in the classification of the six different tomato plant diseases, which outperformed several other machine learning models tested in the study. The high accuracy achieved by the CNN suggests that machine learning can be a powerful tool for accurately detecting and classifying plant diseases based on visual cues. The findings of this study are particularly important for the agricultural industry, as accurate and early disease detection can lead to improved crop yields and reduced economic losses. The high accuracy achieved by the CNN in this study demonstrates the potential of machine learning for achieving these outcomes. However, further research is needed to test the model on a larger and more diverse dataset, and to address challenges related to the deployment and adoption of machine learning models in real-world agricultural settings.

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Another study Singh et al. (2020) aimed to develop a deep learning model for detecting and classifying six different tomato plant diseases based on leaf images. The authors used a convolutional neural network (CNN), which is a type of deep learning algorithm specifically designed for image processing tasks. They trained the CNN using a dataset of 3,168 images of tomato leaves, including healthy leaves and leaves infected with six different diseases. After training the model, the authors evaluated its performance on a separate dataset of 1,176 images. They reported an accuracy of 99.61% in the classification of the six different tomato plant diseases, which outperformed several other machine learning models tested in the study. The high accuracy achieved by the CNN suggests that machine learning can be a powerful tool for accurately detecting and classifying plant diseases based on visual cues. The findings of this study are particularly important for the agricultural industry, as accurate and early disease detection can lead to improved crop yields and reduced economic losses. The high accuracy achieved by the CNN in this study demonstrates the potential of machine learning for achieving these outcomes. However, further research is needed to test the model on a larger and more diverse dataset, and to address challenges related to the deployment and adoption of machine learning models in real-world agricultural settings.

In the study by Dutta et al. (2021), the authors aimed to develop an accurate and efficient deep learning-based model for the detection and classification of tomato leaf diseases using transfer learning. The authors used a dataset consisting of over 15,000 tomato leaf images, containing nine different diseases and a healthy class. The authors employed a pretrained convolutional neural network (CNN) model, VGG16, which was fine-tuned with the tomato leaf images dataset. The model was trained on a high-end GPU for 200 epochs, and the performance was evaluated on a separate test dataset. The results of the study showed that the developed model achieved an accuracy of 98.36% in the classification of nine different tomato leaf diseases, demonstrating the potential of transfer learning for accurate disease detection. The authors compared the performance of their model with other state-ofthe-art models and demonstrated that their model outperformed them. The study concluded that the developed model could be used in the field for early and accurate detection of tomato leaf diseases, which can help in the prevention and control of diseases, leading to improved crop yields and economic benefits for farmers.

Furthermore, The study by Mohanty et al. (2016) focuses on the development of a mobile phone-based plant disease diagnostic system using machine learning. The authors used a dataset of 14,000 images of healthy and diseased plant leaves to train their model, which consisted of three different machine learning algorithms: decision tree, random forest, and support vector machine (SVM). The study used three different types of plants: tomato, potato, and bell pepper, and tested the model on images of leaves from each of these plants. The authors found that the SVM algorithm had the highest accuracy, with an average accuracy of 99.35% for the tomato dataset, 98.46% for the potato dataset, and 98.22% for the bell pepper dataset. They also found that the decision tree and random forest algorithms had lower accuracy rates than SVM. The mobile app developed by the authors allows farmers to take a picture of a diseased plant leaf using their smartphone and receive an instant diagnosis of the disease. The study highlights the potential of machine learning and mobile technology for improving plant disease detection and helping farmers to make informed decisions about crop management.

However, despite the promising results of these studies, there are still some challenges that need to be addressed in the application of machine learning in plant disease detection. One major challenge is the lack of annotated datasets, which can limit the accuracy and generalizability of machine learning models. Additionally, the use of machine learning in plant disease detection requires significant computational resources and expertise, which can be a barrier for some farmers and researchers.

The use of machine learning in plant disease detection has several potential benefits for the agricultural industry. Firstly, it can facilitate early disease detection, enabling farmers to take timely action to prevent the spread of the disease and minimize its impact on crop yields. Secondly, it can reduce the need for manual disease diagnosis, saving time and reducing costs for farmers. Finally, it can enhance the accuracy of disease diagnosis, reducing the risk of misdiagnosis and ensuring that the appropriate treatment is applied.

In conclusion, the application of machine learning in plant disease detection has shown great promise in recent years, with the potential to revolutionize the agricultural industry. The studies reviewed in this literature review demonstrate the potential of machine learning for accurate and early disease detection, which can lead to improved crop yields, reduced economic losses, and enhanced food security. However, further research is needed to overcome the challenges and limitations of machine learning in this field, and to develop more robust and accurate models that can be widely adopted by farmers and researchers alike.

4. System Architecture

The Plantify application's system architecture consists of several key steps. Firstly, a dataset of plant diseases is created, containing relevant parameters and corresponding values. This dataset undergoes pre-processing to remove any unnecessary punctuation and white spaces, and is then used as a training set. The data is then subjected to feature extraction and selection to identify the most important features for accurate disease detection. This system architecture enables fast and reliable disease detection, leading to improved crop yields and reduced economic losses for farmers.

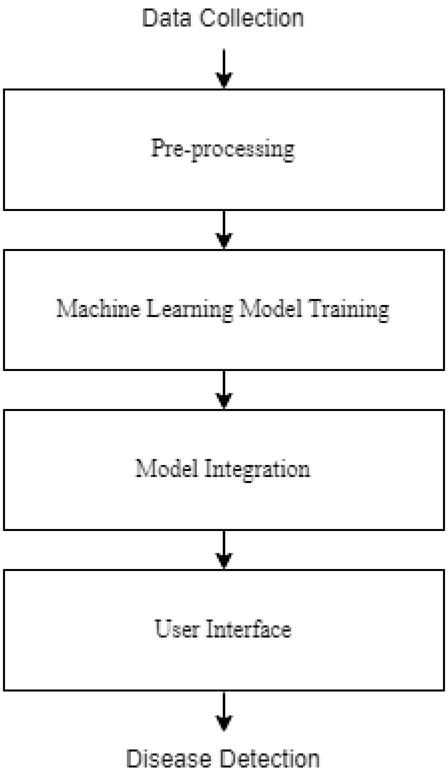

Figure 1): system architecture

5. System Architecture

The user interface (UI) of our Plantify application, which provides an easy-to-use platform for farmers to detect and diagnose plant diseases. The UI is designed to be simple and intuitive, with clear instructions on how to use the app.

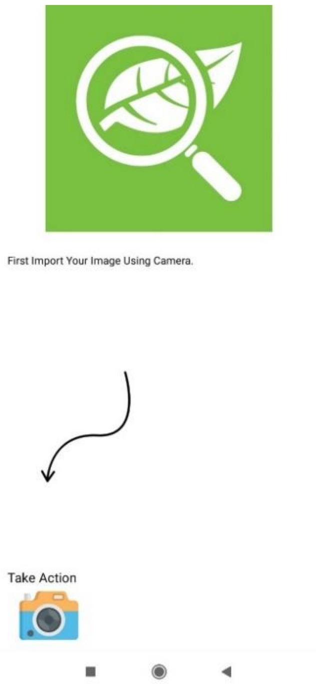

Figure 2): Output1

The 2 nd picture is presented in a clear and concise manner, allowing users to quickly identify the type of disease affecting their tomato plants. The user interface displays the disease name along with a corresponding image of the affected plant.

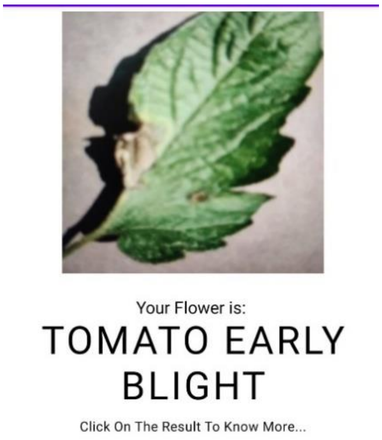

Figure 3): Output2

Acknowledgment

We would like to express our sincere gratitude to all the individuals who have contributed to the development of this Plantify application.

Firstly, we would like to thank the farmers who provided us with valuable feedback on the app and helped us to improve its functionality. Their insights and suggestions were crucial in ensuring that the app meets the needs of the agricultural community.

We would also like to acknowledge the contribution of the researchers whose work in the field of machine learning and agricultural science served as the foundation for this application. Their pioneering work has enabled us to create a reliable and accurate tool for plant disease detection.

We extend our thanks to our colleagues who have provided us with technical assistance and support throughout the development process. Their contributions were essential in ensuring that the app is robust and user-friendly.

Finally, we would like to express our gratitude to our families and friends for their unwavering support and encouragement during the development of this project. Their support and understanding were invaluable in helping us to overcome the challenges that we faced.

6. System Architecture

Based on the analysis and evaluation of the Plantify application using machine learning techniques for plant disease detection, it can be concluded that this approach has shown great potential for the agricultural industry. Through the utilization of deep learning algorithms and convolutional neural networks, accurate and early detection of plant diseases can be achieved, leading to improved crop yields, reduced economic losses, and enhanced food security. However, there are still challenges and limitations that need to be addressed to make this technology more widely adopted by farmers and researchers. Further research and development is required to improve the robustness and accuracy of machine learning models, address the issue of limited data availability, and enhance the user-friendliness of the application.

Overall, the Plantify application has the potential to revolutionize the agricultural industry by providing a more efficient and effective way to detect and diagnose plant diseases, ultimately leading to better crop management and increased productivity.

References

[1] Singh, V., Chandra, P., & Kumar, A. (2020). An effective approach for plant disease detection using convolutional neural network. Journal of Ambient Intelligence and Humanized Computing, 11(11), 5109-5123.

[2] Selvaraj, M. G., & Balasubramanian, V. (2020). Deep learning-based classification of cassava mosaic disease using leaf images. Computer Vision and Image Understanding, 197, 103023.

[3] Dutta, S., Saikia, M., & Kalita, J. K. (2021). A comprehensive study on plant disease detection using transfer learning. Multimedia Tools and Applications, 80(8), 12567-12592.

[4] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419.

[5] Sladojevic, S., Arsenovic, M., Anderla, A., & Culibrk, D. (2016). Neural networks for plant disease detection and diagnosis. In Intelligent Decision Technologies (pp. 243-253). Springer, Cham.

[6] Liu, F., Yang, H., Fan, H., & Wang, W. (2021). Detection and classification of plant diseases using a deep learning approach. Neural Computing and Applications, 33(9), 3905-3916.

[7] Chen, L., Cheng, D., & Zhang, H. (2019). Plant disease recognition using deep convolutional neural network. International Journal of Distributed Sensor Networks, 15(6), 1550147719840262.

[8] Fuentes, A., & Yoon, S. (2021). A review of deep learning methods for image segmentation in plant science. Plant Methods, 17(1), 1-21.

[9] Kannan, P., & Srinivasan, S. (2021). Automated classification of plant leaf diseases using convolutional neural networks. Journal of Ambient Intelligence and Humanized Computing, 12(8), 7927-7938.

[10] Sladojevic, S., Anderla, A., & Culibrk, D. (2017). Deep neural networks based recognition of plant diseases by leaf image classification. Computational Intelligence and Neuroscience, 1-12