DEVELOPMENT OF AI BASED MODEL FOR PLANT DISEASE DETECTION

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ABSTRACT

This project provides an innovative method for detecting plant diseases that leverages the power of ReactJS for the front-end interface and Flask for the back-end, backed up by a powerful deep learning model based on ResNet architecture. Our dataset collection contains over 20,600 high-resolution photos of diverse plant types and illnesses. Pretrained on this massive dataset, the deep learning model employs the cutting-edge ResNet architecture to achieve precise and reliable plant disease categorization across a wide range of plant kinds. This method is a vital tool for farmers, agricultural specialists, and researchers, allowing for speedy and precise plant disease identification, resulting in increased crop output and global food security. We also made a web application for the above AI model which will expect an image and detect it against diseases and provides result with coordinates, confidence, etc. The web application is mainly made with React js and Flask, which will be a very good addition to the user experience. In summary, we are creating a plant disease detection application using ReactJS, Flask, and deep learning model (ResNet50) to achieve precise and reliable plant disease categorization.

Keywords: ResNet50, Image classification, Web Application, Image processing techniques.

1. Introduction

In the improvement of modern agriculture, ensuring optimal crop health is of paramount importance. Plant diseases have long been a persistent challenge for farmers worldwide, leading to significant crop losses and economic setbacks. To tackle this issue effectively, there has been a growing interest in leveraging cutting-edge technologies like Artificial Intelligence for plant disease detection and management. The advent of AI has revolutionized various industries, and agriculture is no exception. AI-powered systems have shown tremendous potential in automating processes, analyzing vast amounts of data, and making informed decisions. Among the various AI models, the Residual Network (ResNet) architecture has emerged as a prominent contender for image recognition tasks, including plant disease detection. Traditional methods of plant disease detection often rely on human visual inspection and laboratory analysis. These methods can be time-consuming, labor-intensive, and sometimes prone to errors, leading to delayed or inaccurate diagnosis. Moreover, as global populations grow, the demand for sustainable agricultural practices intensifies. Minimizing the use of pesticides and optimizing resource allocation are crucial aspects of sustainable farming. AI-based plant disease detection systems offer a potential solution to these challenges. By utilizing computer vision algorithms, AI models can rapidly analyze images of plants and accurately identify diseases. This enables early detection and proactive management, thereby reducing crop losses, ensuring food security, and promoting environmentally friendly agricultural practices. In the context of plant disease detection, ResNet has demonstrated exceptional performance. Its multi-layered structure enables it to capture intricate patterns and features associated with diseased plants, resulting in higher accuracy and robustness. Moreover, the ResNet model can be fine-tuned and trained on large-scale datasets containing images of healthy and infected plants, empowering it to make accurate diagnoses.

1.1 Advantages of ResNet

I. ResNet's deep architecture enhances the accuracy of disease identification, minimizing false positives and false negatives.

II. AI-based systems can process large volumes of image data rapidly, enabling real-time or near-real-time disease detection.

III. Once trained, the AI model can operate autonomously, reducing the need for extensive manual labor and human intervention.

IV. AI systems can be scaled up to analyze vast agricultural areas, providing a comprehensive and holistic view of crop health.

1.2 Applications of ResNet

I. AI-powered systems can detect diseases at their incipient stages, allowing farmers to take prompt measures to prevent their spread.

II. By identifying specific areas affected by diseases, farmers can apply treatments with precision, optimizing resource usage.

III. AI models can be integrated into drones and other surveillance devices to monitor vast agricultural lands efficiently.

IV. AI-based systems can identify a wide range of plant diseases, including fungal infections, viral diseases, and nutrient deficiencies.

2. Related Works and Literature Survey

Alatawi et al. (2022) study focuses on using artificial intelligence—more especially, a VGG-16 convolutional neural network — to detect plant diseases in contemporary agriculture. The research uses cutting-edge image analysis algorithms to identify 19 distinct kinds of plant illnesses in an effort to preserve good agricultural production. On a dataset comprising 15,915 plant leaf pictures (both damaged and healthy leaves) from the Plant Village dataset, the model demonstrated an amazing accuracy of almost 95.2%. This study contributes to the growth of IoT and automation in the farming sector by highlighting the potential of deep learning-based illness diagnosis for prompt intervention and treatment in agriculture[1]. Kaushik et al. (2020) uses convolutional Neural Networks, a kind of deep neural network, to provide a tomato leaf disease detection system. First, the dataset for tomato leaves is separated. In order to apply transfer learning, ResNet-50, a pre-trained model, is adjusted to the particular classification problem. Data augmentation is utilized to enhance the model's functionality and bring it closer to actual disease scenarios. In PyTorch, the implementation is completed. The parameters that are learned using ResNet-50 are used to validate the testing dataset. Finding six common illnesses in tomato crops is part of the classification process. With the help of data augmentation, the dataset is quadrupled, and the disease identification model achieves an astounding 97% accuracy[2]. Latif et al. (2020) present a smart drone precision farming system with the goal of autonomously diagnosing and treating plant problems. To precisely monitor large farming areas, the suggested system makes use of very precise cameras, robust computation, and image processing methods, such as a modified ResNet architecture. The SMART system links to a cloud server to generate reports, including agricultural yield projections, and detects sick plants and decides the needed chemical treatments. By analyzing 70,295 leaf photos that represented 26 distinct illnesses in 14 different plants, the ResNet architecture achieved an amazing average accuracy of 99.78%. For the identification and treatment of plant diseases, the suggested ResNet design performs better than other comparable approaches, according to comparisons with other methodologies in the literature[3].

Sujatha et al. (2021) examine the efficacy of deep learning and machine learning techniques in identifying citrus plant illnesses from leaf photos. DL approaches Inception-v3, VGG-16, and VGG-19 were examined in addition to ML methods such Support Vector Machine , Random Forest and Stochastic Gradient Descent. In terms of disease detection accuracy, experimental data indicated that DL methods performed better than ML methods. RF-76.8% < SGD-86.5% < SVM-87% < VGG-19–87.4% < Inception-v3–89% < VGG-16–89.5% was the classification accuracy attained for the various approaches. With regard to classification accuracy, VGG-16 outperformed all other approaches, whereas Random Forest came in last[4]. Lohith et al. (2022) use computer-aided systems and deep learning techniques based on convolutional neural network models that have already been trained within the PyTorch framework to automate the diagnosis of tomato leaf disease. Using photos of tomato plants with natural backdrops, the researchers evaluate the efficacy of the ResNext-50_32x4d, EfficientNet-B0, and MobileNet-V2 models for classified diseases. According to the results, MobileNet-V2 has the lowest validation loss of 0.356 (with a learning rate of 0.001 and a batch size of 16), whereas ResNext-50_32x4d has the maximum accuracy of 90.14%. Regarding inference, ResNext-50_32x4d outperforms the other models as well. In order to choose appropriate models for smart farming and precision agriculture applications, researchers and developers will benefit from this study[5].

2.1 Limitations of Previous Work

While the research projects cited above indicate amazing results in employing deep learning as well as artificial intelligence towards plant disease diagnosis for precision agriculture, they all share some limitations. To begin, all of these research rely largely on picture-based datasets, which may be influenced by factors such as lighting, image quality, or background clutter, thereby reducing a model's real-world applicability. Second, when applied to different crop kinds or disease types, the performance of such models may vary, limiting their generalizability. Furthermore, while pre-trained models are useful for transfer learning, they may not represent the complexities of every specific plant diseases. The robustness for such models in the context of new and developing diseases continues to be a source of worry. Furthermore, real-world deployment factors, such as the cost and feasibility of deploying drones with cameras in huge agricultural areas, are frequently overlooked. Finally, while precise rates are emphasised, the practicality and cost of these remedies for small-scale , resource-limited farmers is not often investigated, restricting the availability to a wider agricultural community.

2.2 Novelty and Contributions

The innovative approach we offer to this project is the incorporation for the ResNet-50 architecture within a web application built with React on the front end and Flask on the back end. While the use of deep learning models to plant disease diagnosis is not novel, the method we are utilising ResNet-50 and putting it into a web-based application that is easy to use represents a significant advancement in agricultural technology. Our contribution is divided into two parts: First, we improve the accuracy & robustness for plant disease diagnosis by using a cutting-edge convolutional neural network such ResNet-50. This not only assists farmers and agricultural professionals, but it also ensures the continued production of healthy crop harvests by detecting diseases early and accurately. With its depth and complexity, ResNet-50 enables the model to differentiate among a wide range of crop diseases, promoting an integrated approach towards agricultural health management. Second, incorporating this sophisticated paradigm into a web-based application makes a significant contribution to accessibility and usability. The front-end portion of our programme is built with React, which is known because its user-friendly design and interaction, which makes it intuitive & visually appealing. Meanwhile, Flask handles communication between the user's interface and the potential ResNet-50 model, allowing for rapid and smooth disease diagnosis. This advancement broadens the reach of modern technology, making it available to farmers & agricultural specialists who may not be well-versed on machine learning for computer programming. In essence, the uniqueness and contribution of our project focus on the smart fusion between cutting-edge technology with user-friendly design. We use ResNet-50's power to enable accurate and thorough plant disease detection and make this advanced technology available to a wider audience. This not only enhances precision agriculture, but it also corresponds to the goals set by the modern agricultural business by increasing efficiency, decreasing crop losses, or ultimately assisting in global food security. Our method represents a huge step forward towards delivering the benefits for artificial intelligence to people in the agriculture industry who need it the most.

3. Proposed Work

During the first phase, a vast dataset of plant photos will be gathered from multiple sources, including open-source repositories and web scraping. To provide thorough coverage, this dataset will include a wide range of plant species and illnesses. Data augmentation techniques such as scaling, normalization, and data augmentation will be used to improve dataset variety and model resilience. ResNet Model Development: The system's core is based on the use of a ResNet-based Convolutional Neural Network (CNN) model. The ResNet architecture will be selected after thorough assessment of factors such as model complexity, available computational resources, and prior performance. Preprocessing will be performed on the dataset to standardize image sizes and quality. ReactJS Frontend Development: The ReactJS framework will be used to create and construct the system's user-friendly frontend. The major goal is to provide an easy and responsive user interface that allows users, mostly farmers and agronomists, to simply contribute plant photos for disease assessment..

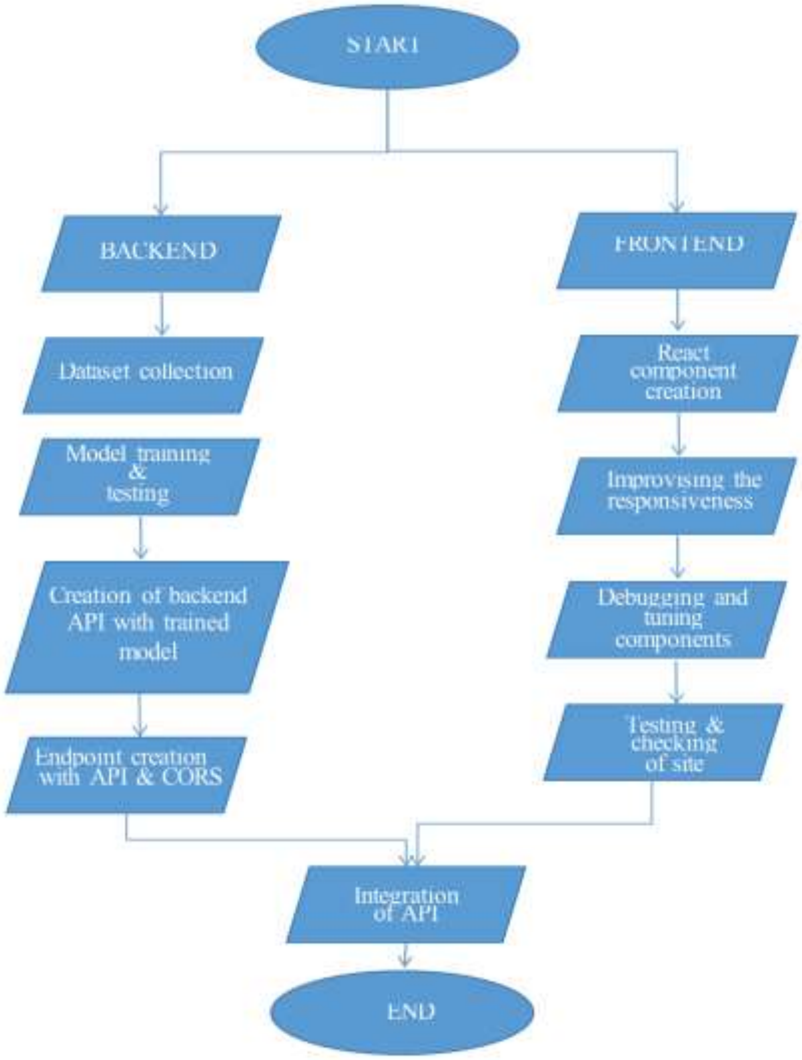

Fig 1 – Work flow chart.

3.1 Web application

Flask Backend Development: The Flask framework will serve as the system's backend's base. It will be in charge of orchestrating a variety of processes, such as image uploads, activating the CNN model for inference, and sending findings to the frontend. Deployment and Monitoring: The system will be put on a suitable hosting platform or cloud infrastructure after it has been designed and extensively tested. Monitoring and logging systems will be implemented to track system performance in real time, discover anomalies, and assist quick troubleshooting. We hope to establish a highly efficient plant disease detection system that contributes to sustainable agriculture, improves food security, and empowers farmers and stakeholders in their efforts to combat plant diseases by diligently following this methodology.

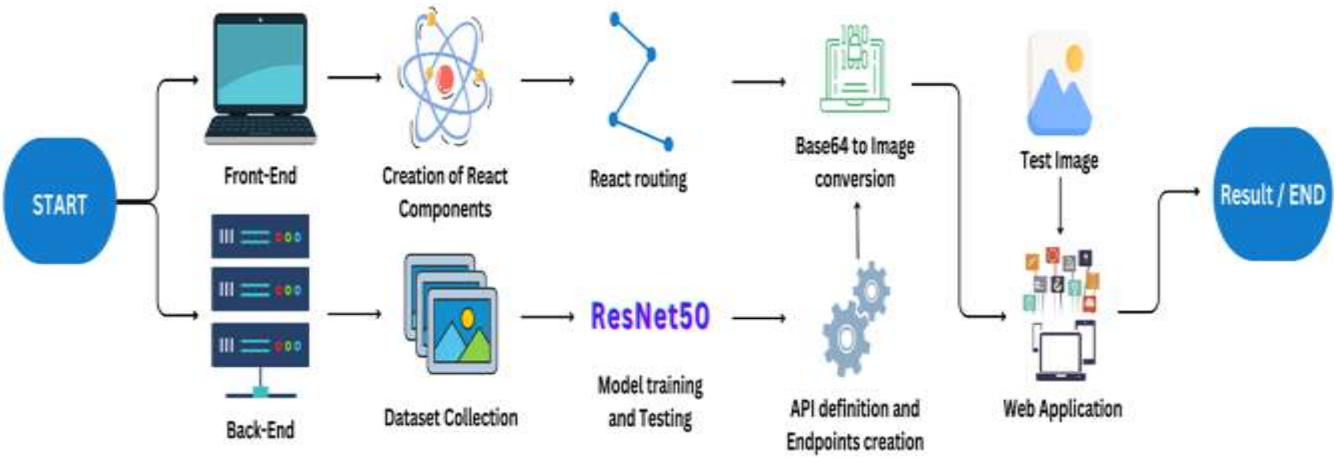

Fig 2 – Entire process of creating the project.

3.2.1 Encrypting image into Base64

Encrypting an image to Base64 is a process that enhances the security and portability of image data. Base64 encoding is not encryption in the traditional sense but rather a method of encoding binary data into a textual format, making it suitable for data transmission, such as within URLs or JSON payloads. When an image is converted to Base64, it becomes a long string of alphanumeric characters, making it less prone to corruption during transmission and easier to embed within different data formats. This method also provides a level of obfuscation, as the encoded image is not immediately recognizable as the original picture. However, it's important to note that Base64 encoding does not provide true encryption, as the data can be easily decoded by anyone with access to the encoded string. To achieve actual encryption of image data, additional cryptographic techniques like AES or RSA should be employed to protect the image's content from unauthorized access or tampering.

3.2.2 Decrypting Base64 into image

Decoding from Base64 is a process that reverses the encoding of binary data into a textual format, restoring the original data, which is particularly useful when working with encoded images. Base64 decoding retrieves the original image data from the Base64-encoded string. This method allows data to be easily converted back to its binary form, making it suitable for various applications, including displaying images on websites or processing image data in different programming languages. It's essential to understand that Base64 decoding does not provide any form of encryption; it merely reverses the encoding process. Therefore, sensitive image data should be encrypted before encoding to Base64 if security and confidentiality are paramount concerns. Additionally, Base64 decoding is a reversible operation and can be executed by anyone with access to the encoded Base64 string, as it is not a security mechanism but rather a data format conversion technique.

3.2.3 Accuracy Comparison

A detailed study was carried out in order to improve the accuracy of both plant & disease classification, with an emphasis on the assessment and choice of the most appropriate models. The study included a diverse set of machine learning as well as deep learning algorithms, all customized to the job of plant or disease classification. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), support vector machines (SVMs), decision trees, and ensemble techniques were among the models used. The experimentation was carried out using Google Colab's strong GPU runtime, which enabled rapid model training as well as assessment. The main goal was to determine the performance of every model through thorough testing and validation. The study meticulously captured the precision of validation and training measures for each model, providing a thorough foundation for comparisons and selection.

Model	**Accuracy**	**Precision**	**F1_score**	**Recall**
ResNet	0.893	0.790	0.730	0.909

CNN-inception	0.805	0.699	0.689	0.860
VGG	0.794	0.700	0.699	0.850

Tab 1 – Accuracy.

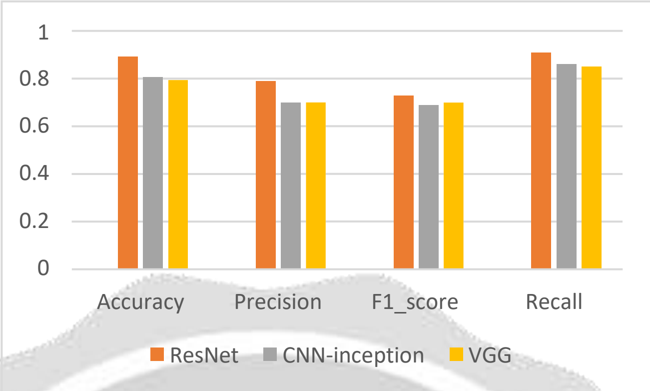

Fig 3 – Accuracy chart.

4. Result

Accuracy and Performance: ResNet routinely outperforms several other models in a variety of computer vision tasks. Its deep design with residual connections enables it to effectively capture intricate information, making it an excellent candidate for tasks such as image classification, object identification, and segmentation. Computational Efficiency: ResNet is computationally effective when compared to other deep networks. It achieves higher precision with fewer parameters, which reduces computational complexity.

5. Conclusion

Our effort to create a plant disease detection system using ResNet, React for the UI, and Flask for the backend is an important step toward addressing major agricultural challenges. We created a system that has the potential to revolutionize plant disease detection and improve global food security by combining cutting-edge deep learning techniques, user-friendly interfaces, and robust backend architecture. Our ResNet-based model, which was trained on a varied dataset of over 20,600 photos from 27 plant classes, excels at disease recognition. The React frontend guarantees a user- friendly and responsive interface, allowing stakeholders with diverse technical expertise to access the system. Meanwhile, Flask provides a scalable and secure backend infrastructure, which is required for dealing with user requests, data processing, and model inference.

6. References

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