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Automated Tree Leaf Disease Detection System Using Deep Learning and Image Classification

Srijan Thanga Ramanesh[1], Upadhye Varun Santosh[1], Vaibhav S[1], Vinod M[1], Yashas H[1*], Gajanan M Naik[1]

[1]Department of Computer Science and Engineering, RV Institute of Technology and Management, JP Nagar-560076 Bengaluru, Karnataka, India
*Email: yashas210@gmail.com & Mob: 8310718483

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ABSTRACT

Plant leaf diseases remain one of the persistent challenges in agricultural production. Diseases have rapid spread, are often hard to detect at an early stage, and when the symptoms manifest, it may be too late to take necessary corrective measures. At the moment, detection relies on a field survey performed by experienced personnel who visually inspect the state of each plant. This process is both lengthy and highly inaccurate. Our solution is a system capable of automatically identifying various plant diseases using Convolutional Neural Networks to analyze leaf images. We designed an app which was able to successfully operate with leaf pictures taken in natural conditions. Upload the image — get your diagnosis. This was our goal. The neural network we used was initially trained using 54,303 images (healthy as well as those exhibiting symptoms). Combining basic image preprocessing methods along with more sophisticated deep features extraction allowed us to build a model capable of detecting the first stages of diseases, which could otherwise go unnoticed. Classification accuracy amounted to 93.2%, and precision was 94.5%.

Keywords - *Convolutional Neural Networks, Deep Learning, Automated Disease Detection, Precision Agriculture, Image Classification.*

1. INTRODUCTION

We eat food produced by farms. Stable climates depend on forests to some extent. This may seem like a straightforward statement, but it highlights the importance of agriculture and forestry. They support a substantial part of the global economy and natural systems [1]. For developed countries, the poor yield is a mere economic issue. For developing countries, it is a potential disaster [1]. The danger that keeps agronomists awake at night is biological. Fungi, bacteria, viruses, or other types of pathogens appearing on crops first and foremost, almost invariably on leaves [2]. And they act swiftly. An initially modest infection of some crops in one area of land can soon spread across the whole farm, leading to a drop in the yields, deteriorated quality of crops, and loss of income for farmers who have no other means to cover losses [2]. The annual billion-dollar losses to plant diseases reported by the FAO [3] is quite impressive – and probably understates the actual cost, because some are unreported. Here's the catch: much of it is avoidable. Diagnose an infection soon enough and a specific, localized treatment should work well; no requirement for flooding a whole field with chemicals that damage the soil ecosystem, affect wildlife, and encourage antibiotic resistance in the very organisms you're trying to destroy [4]. Biology favors the farmer, provided he diagnoses the problem in time.

1.1. Literature Review

For centuries, detection of plant diseases involved inspecting the affected plant for physical signs such as lesions or discolored areas. In cases where the problem could not be detected visually, laboratory testing of samples followed. Reliable enough? Yes, but the procedure was time-consuming and expensive, while it remained entirely impossible to perform during an emerging epidemic. The problems of manual diagnosis and its slowness led to attempts to apply computer vision technology, resulting in amazing success. Indeed, a number of papers demonstrated the development of special CNN architectures which could be deployed successfully in case the computational resources were low. Thakur et al. created an innovative architecture VGGICNN which provided a high level of classification and at the same time had relatively low computational complexity [5]. Additionally, deep CNN models could be used for diagnosing tomato disease with up to 98.5% precision [6]. However, the thing is that while being accurate enough in terms of a research, they still are far from being used in practice. Indeed, the most important part of the development is missing as all mentioned above studies represent only a concept. It is not quite clear whether the developed method will be able to cope with practical conditions, including non-uniform data, or whether it will be generalized and applied to another data sample. This point does not refer to precision rate, but to other important aspects of the model usability..

1.2 Gap in the Existing System

Manual inspection faces a practical upper limit because it relies on knowledgeable people, and even experienced agronomists may misunderstand the symptoms, particularly during field work or if the crops are suffering from multiple infections. The laboratory tests eliminate this limitation but have another one; they take too long and cost too much to be used in any rapid application [7]. The computer vision community has made genuine technical strides, but almost all research ends with the development of an algorithm. They train the model, evaluate it, publish it in some scientific database where it does no good to anyone [8], and leave. Without any form of interface that would allow farmers to access the trained models in their phone, even the most reliable and precise machine learning model will do no good.

1.3 Gap in the Existing System

Traditional visual assessments rely on the person who performs them, rendering them highly subjective and prone to human errors. Although lab tests can be considered accurate, they require additional resources and time and would thus not be suitable for rapid application in any case. In this respect, by the time results are obtained, there would be no point in carrying out timely preventive measures since it would be too late.

While machine learning technologies can boast of high efficacy, they are generally never used outside laboratory environments. All that can usually be found about them is an abstract describing some kind of model which is never implemented into any user-friendly interface or application, and therefore such algorithms remain completely impractical for end-users who need an instant solution using their smartphones.

2. METHODOLOGY

2.1 System Architecture and Components

The platform uses the combination of Python and TensorFlow [9], comprising a four-level processing chain: Image Acquisition, Pre-processing, Feature Extraction, and Classification. Each level is immediately connected to the next one, ensuring the workflow's efficiency. On a practical note, the user is required to upload only a single image of a leaf via an app. Then, the TensorFlow engine takes the image and performs all computations on its own, as part of the chosen architecture (please refer to Figure 1 below). By moving the entire deep learning inference from the client-side to the server-side, we ensure that the user only needs a simple internet-enabled device that can take photographs (a usual smartphone will do just fine [10]). The complex computations will be done by other devices, those designed specifically for this type of task.

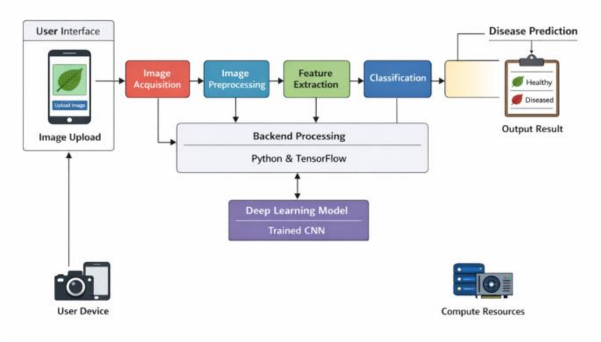

Fig. 1 Disease Detection System Architecture

2.2 Step-by-Step Working Process and Algorithm

CNNs are central to this method, and there's no way around that for a very simple reason. Their ability to detect spatial features automatically makes them the default choice for solving computer vision tasks [11]. The first thing to be done before any classification takes place is to resize each leaf image to a certain fixed size and normalize it. It may seem not particularly exciting, but it is a must-do process because it prepares the input data for processing by the network. Convolutional layers analyze the image looking for visual features, while pooling layers compress them from time to time [13]. There's a double benefit in doing that: it helps keep the number of operations required to a minimum, and the compression prevents the network from overfitting by picking up too many features. When the convolutional parts are done, all the multidimensional feature maps are flattened and analyzed via fully connected dense layers. This is where the real magic happens. The output layer uses a softmax function to assign probabilities to each disease type, and whichever one of them wins, it is declared the result of the analysis and reported to the user.

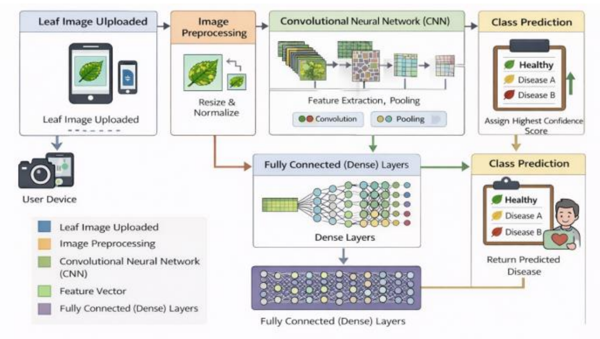

Fig. 2 Step by Step Working Process and Algorithm

3. RESULTS AND DISCUSSION

3.1 System Deployment and User Interface Execution

Closing the gap between model creation and field application was the key objective of this project, and the online tool fulfills that aim. While the application tested out its inferencing capabilities in the field, it managed the complexity of the CNN process without the user's interference, giving him a clean and easy-to-use interface. A user simply uploads an image of a leaf, after which the tool returns three responses – the plant species, the disease category, and a level of confidence in the prediction. This enables farmers to not only get their answer, but also decide on its importance.

3.2 Real-Time Inference and Classification Performance

The ability of the model to operate effectively under realistic circumstances can be verified by testing various types of samples, both healthy plants and those that have been infected with diseases, across several species. It turns out that the developed neural network is effective in solving the task under different scenarios. Identification of healthy plants. First, it is important that the model is able to identify healthy samples of plants without producing false-positive results. Thus, a healthy Pepper Bell leaf was correctly identified by the network with 92.5% probability. Fungal infection identification. As for fungal infections, their symptoms create unique visual patterns, which makes it easier for the model to detect an infected sample. So, when it comes to identifying a Tomato leaf infected with Septoria Leaf Spot, the model operates with 96.8% accuracy. Bacterial infection identification. However, when it comes to bacterial infections, they produce less visible patterns, thus making it more difficult for the system to work with them. Nevertheless, the system managed to identify a Pepper Bell leaf infected with Bacterial Spot, though with 81.4% confidence level.

3.3 Discussion of Diagnostic Confidence

Variation in the confidence scores between the sample types is not a flaw in the system, but a direct result of how the architecture reacts to the varying levels of visual difficulty inherent to each disease. In the case of Septoria Leaf Spot, the visual characteristics are sufficiently distinct to result in a very confident prediction (96.8%). In the case of Bacterial Spot, this is no longer the case. The 81.4% confidence is low compared to others, but this is the expected behavior and not a problem with the system design itself.

3.4 Quantitative Model Evaluation

In addition to the field testing of the system, there was also an assessment done using a portion of the initial dataset as a test set. In both cases, regardless of the testing method used, the neural network demonstrated an average performance of 93.2% for all disease classes. Overall, the combination of high quantitative accuracy and successful qualitative deployment proves that the proposed system is a highly viable, scalable, and cost-effective tool for automated crop monitoring.

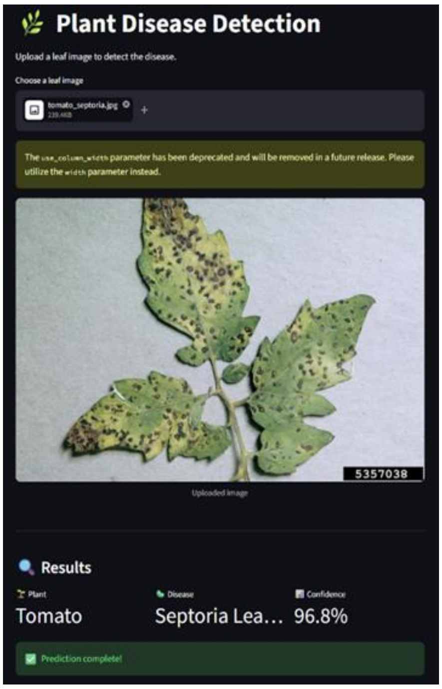

Fig. 3: Tomato leaf with septoria

Fig. 4 Healthy Pepper Bell

Fig. 5 Pepper Bell with Bacterial Spot

Table 1 Overall Classification Metrics

Metric	Score (%)
Accuracy	93.2%
Precision	94.5%
Recall (Sensitivity)	91.8%
F1-Score	93.1%

4. CONCLUSION

The idea behind this was simple – design a deep learning model that takes a leaf image as an input and produces a corresponding disease type label as an output. Based on the obtained results, this requirement is fulfilled. Instead of depending on a specialist who is prone to fatigue, mistakes, or may not be available at all, the tool performs an objective analysis of the leaf and produces a result instantly. With its performance being stable for various types of data, it is able to function reliably both on theoretical and practical data. Here are some notable aspects of the research conducted:

- Accuracy. The achieved prediction accuracy equals 93.2%. This figure isn't chosen to boast the result and fit in nicely into the required range.

- Data preprocessing. It may sound silly, but resizing and normalization turned out to be significant factors in terms of prediction improvement.
- Diseases classification. The best performance was observed for Tomato Septoria Leaf Spot, thanks to its clear visual features and successful recognition by the neural network. The problem with distinguishing between Septoria and Early Blight was not uncommon either since even professional agronomists sometimes confuse the two conditions due to very similar symptoms.
- Implementation. The whole process takes place within the GUI. An uneducated farmer will be able to use the program without difficulty – that was the primary goal of implementing this tool.
- Scalability. Using this solution will cost you a lot less than hiring professional field scouts, yet there's no architectural constraint on the possible application domains. We can simply scale this solution based on new sets of training data.

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