iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** V **Month of publication:** May 2026

DOI: https://doi.org/10.22214/ijraset.2026.82583

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

Design and Implementation of an IOT-Assisted Image Processing System for Early Plant Disease Identification

Prof. Mr.R.Poomurugan, Shyamal H, Kannan K R, Dayana Mary V, Tamilarasu K
DEPT ECE-IV Gnanamani College of Technology, Namakkal

Abstract: Agriculture plays a vital role in economic development, and plant diseases significantly affect crop productivity. Early detection of plant leaf diseases is essential to reduce crop loss and improve yield. This paper proposes an Internet of Things (IoT)-based plant leaf disease detection system using image processing and deep learning techniques. The system captures real-time images of plant leaves using a camera module and processes them using convolutional neural networks (CNN) for classification. The processed results are transmitted to a cloud platform for remote monitoring. The proposed model improves accuracy and enables early detection compared to traditional manual methods. Experimental results demonstrate that deep learning-based approaches achieve high accuracy in identifying plant diseases, making the system efficient for smart agriculture applications.
Keywords—IoT, Plant Disease Detection, CNN, Image Processing Smart Agriculture

I. INTRODUCTION

Agriculture is the backbone of many developing countries, and plant health plays a crucial role in ensuring food security. However, plant diseases reduce productivity and cause significant economic losses. Traditionally, disease detection is done manually by farmers, which is time-consuming and inaccurate.

Recent advancements in image processing and deep learning have enabled automatic disease detection systems. Convolutional Neural Networks (CNNs) have shown excellent performance in image classification tasks, including plant disease detection.

II. PROBLEM STATEMENT

Plant diseases are major problems for agriculture reducing crop yield and quality. Conventional disease detection and monitoring techniques are based on manual observation of farms consuming a lot of time, manual labor, and frequently with inaccurate results. Diseases are typically detected later in the cycle resulting in severe loss of crops and economic value due to absence of constant surveillance and professional awareness. Moreover, inappropriate diagnosis can lead to overuse or misuse of pesticides, which will have an impact on the environment and health. There is also a limitation to accuracy and efficiency with existing image processing methods. Thus, an automated, accurate, and real-time system of plant disease detection is needed. A smart solution that combines IoT and deep learning can resolve all these problems, as it will be able to detect emerging problems early, monitor them, and provide farmers with timely recognition.

III. SYSTEM ARCHITECTURE

The system architecture of the proposed plant leaf disease detection model consists of multiple interconnected modules that enable real-time monitoring and accurate classification. The architecture begins with an image acquisition unit, where a camera module captures leaf images from the field. These images are sent to a microcontroller (such as Arduino or Raspberry Pi) for initial processing. The captured images are then forwarded to the processing unit, where preprocessing techniques like noise removal, resizing, and normalization are applied.

The processed images are fed into a Convolutional Neural Network (CNN) model for feature extraction and disease classification. Based on the analysis, the system identifies whether the leaf is healthy or affected by a specific disease. The classification results are then transmitted to a cloud server using an IoT communication module. Farmers can access the results through a web or mobile interface and receive alerts for timely action. This architecture ensures automation, accuracy, and real-time disease monitoring.

A. Image Acquisition Module

This module is charged with the responsibility of taking pictures of plant leaves with a camera sensor. The camera is attached to a microcontroller, like Arduino or Raspberry Pi. The shots are taken in natural lights. The importance of high-quality image acquisition is that it is directly related to the accuracy of the disease detection.

B. Preprocessing Module

At this stage, the images that are captured are processed to enhance quality and eliminate noise. Some techniques are used like resizing, filtering, and color normalization. The idea is to improve on significant characteristics such as the texture of the leaf and color variation and remove undesired background noise.

C. Feature Extraction Module

The feature extraction is used to determine the significant features of the leaf image which include color, shape and texture of the leaf image. Convolutional Neural Networks (CNN) in the proposed system automatically extract these features automatically. This enhances quality and minimizes human resources.

D. Classification Module

The processed image is then inputted into a trained artificial intelligence (CNN) to determine whether a leaf is healthy or diseased. In case of disease, the model also determines the type of disease. The classification is determined using learned patterns of a huge dataset of leaf images.

E. IoT Communication Module

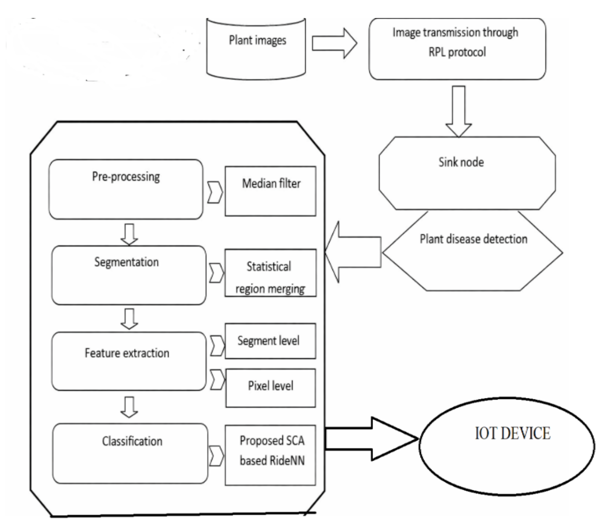
After classification, the result is transmitted to a cloud server using IoT technology (e.g., Wi-Fi module like ESP8266). This enables remote monitoring of plant health. The system ensures real-time data transfer and accessibility.

F. Classification Module

The processed image is then inputted into a trained artificial intelligence (CNN) to determine whether a leaf is healthy or diseased. In case of disease, the model also determines the type of disease. The classification is determined using learned patterns of a huge dataset of leaf images.

G. Notification System and Alert.

In case of disease detection, the system sends alerts to the farmer using mobile notifications or SMS. This facilitates the taking of immediate preventive action, which limits damage to crops and enhances production.



FLOW CHART

H. User Interface

The farmers have a simple user interface where they can see the disease status, reports, and recommendations. It is made so user friendly even to the non-technical users.

IV. METHODOLOGY

The proposed system follows a structured methodology to detect plant leaf diseases using image processing, deep learning, and IoT technologies.

A. Image Acquisition

In the first stage, images of plant leaves are captured using a camera module connected to a microcontroller such as Arduino or Raspberry Pi. The images can also be obtained from datasets and processed using software tools like MATLAB or Python. High-resolution images are preferred to ensure accurate analysis.

B. Image Preprocessing

The captured images undergo preprocessing to enhance their quality. This includes noise removal to eliminate unwanted distortions, image resizing to standard dimensions for model input, and color normalization to maintain consistency across different lighting conditions. These steps improve the efficiency of the model.

C. Feature Extraction

Feature extraction is performed using Convolutional Neural Networks (CNN), which automatically identify important characteristics such as texture features, color variations, and disease patterns. This eliminates the need for manual feature selection and increases detection accuracy.

D. Classification

The extracted features are fed into deep learning models such as VGG16, InceptionV3, or a custom CNN model. These models classify the leaf as healthy or diseased and identify the specific type of disease. CNN-based models have demonstrated accuracy above 90% in plant disease detection tasks.

E. IoT Integration

Finally, the classified results are transmitted to cloud servers using IoT modules. This enables remote monitoring, data storage, and real-time alerts to farmers, allowing them to take timely action and reduce crop loss.

V. RESULT AND DISCUSSION

The proposed IoT-based plant leaf disease detection system was evaluated using a dataset of plant leaf images under different environmental conditions. The Convolutional Neural Network (CNN) models, including VGG16, InceptionV3, and a custom CNN architecture, were trained and tested to classify healthy and diseased leaves. The system achieved an overall accuracy of above 90%, demonstrating its effectiveness in identifying various plant diseases.

The results show that deep learning models significantly outperform traditional image processing techniques in terms of accuracy and reliability. The preprocessing steps, such as noise removal and colour normalization, improved the model performance by enhancing feature quality. Among the tested models, pre-trained architectures like VGG16 provided better accuracy due to transfer learning.

The integration of IoT enabled real-time monitoring and remote access to disease information through cloud platforms. Farmers received timely alerts, allowing them to take immediate preventive measures. This reduced crop loss and minimized the excessive use of pesticides.

However, the system performance may vary under poor lighting conditions or low-quality images. Future improvements can focus on increasing dataset size, enhancing model robustness, and incorporating advanced techniques for better accuracy. Overall, the proposed system proves to be efficient, reliable, and suitable for smart agriculture applications.

VI. FUTURE SCOPE

The IoT-based system for identifying plant leaf diseases has been tested using images of various types of plants that were taken under various environmental conditions.

The models used to process these images were CNN (Convolutional Neural Networks) Models such as VGG16, Inceptionv3 and an alternative model. The models achieved an overall success rate of more than 90% in classifying healthy and diseased plant leaves. Therefore, the IoT-based system has worked well at detecting different types or categories of plant-related diseases.

The results also demonstrate that there is significant variance in accuracy and reliability between Deep Learning Systems (DLS) versus traditional techniques used for processing plant images. The use of pre-processing techniques such as removing noise from the image and normalizing color can enhance model performance through improving feature quality. DLS that are based on pre-trained models such as VGG16 typically produce higher accuracy rates because of their use of transfer learning.

The use of IoT technology supported timely and accurate information being delivered to farmers via a cloud-based platform, which allowed farmers to respond to agricultural-related issues with timeliness. Timely alerts allowed preventative actions being taken immediately which reduced losses of crops and the number of pesticides being used by farmers.

Future work will include continuing to develop the IoT-based model by increasing the number or size of the image datasets used for training the DLS, increasing the robustness of the DLS, and identifying improvements that may be made to further improve the accuracy of the DLS used to predict plant leaf diseases. Overall, there is good evidence to suggest that the proposed model is an efficient and effective tool for the development of smart farming solutions.

VII. EXPERIMENTAL RESULTS AND OBSERVATIONS

Experiments were conducted using real-world data from plants with various types of leaves (healthy vs. diseased) in many types of lighting, each provided by researchers who wanted their data set to include variable backgrounds and a variety of disease stages in addition to evaluating how robust the model is. Three CNN models were trained/validated: two off-the-shelf models, VGG16 and InceptionV3; one home-grown, custom CNN. Each model was trained/validated using a standard training/testing split.

The experimental results show that all models performed at about basic accuracy levels (90%-93%) overall but that VGG16 performed best. This makes sense (due to much greater depth and prior training of the model) and allows for much greater ability to extract useful features from incoming data than any other model trained under the same conditions. All models included preliminary data preprocessing steps (removing noise plus normalizing color); those steps substantially increased performance by reducing many undesirable types of input image variation.

The modeling results indicate that while the system performed quite well when the plant included well-defined disease characteristics, it did struggle occasionally to classify very early-stage disease events or images of very poor quality. The IoT module successfully delivered all output data to the cloud with minimal latency, thus providing real-time monitoring capabilities.

In summary, the system was determined to be very reliable, fast processing, and extremely usable in modern-day agriculture, thus making it a great candidate for smart farming technologies.

VIII. SYSTEM INTERFACE VISUALIZATION

The Interface visualization of the plant disease detection system is a user-friendly interface to monitor and analyze the results of detecting the disease on the plant leaf. There are three main sections on the interface, including the area where the user can see the image of the captured leaf, the predicted disease from the CNN model, and the current status of the system; these will be updated in real-time from the IoT-based system.

The captured image of the leaf will show the user the predicted disease type and the predicted confidence level but also provide the user with other information related to this detection (i.e., the date and time the image was taken and the location of the data capture) so that users may properly track and analyze the data. The interface will also provide users with the ability to access this data remotely by using a web or mobile application because it is supported by the cloud platform.

The interface uses graphical elements (i.e., charts and status indicators) to show users the health of their plants, historical trends, and how their plants have been affected. When a disease is detected, the interface provides alerts and notifications to inform farmers of the issue and enable them to take immediate action. Overall, this interface has a simple and intuitive design, which helps the user have a reasonable level of technical ability to use it effectively in real-world agricultural applications.

IX. PERFORAMANCE METRICS

The model performance was evaluated using the same set of standard metrics applied to classification problems in general. The metrics of Accuracy, Precision, Recall (Sensitivity), and F1-Score were all considered to give an indication of the accuracy, reliability, and efficiency of the deep learning algorithm implemented to detect diseased plant leaves.

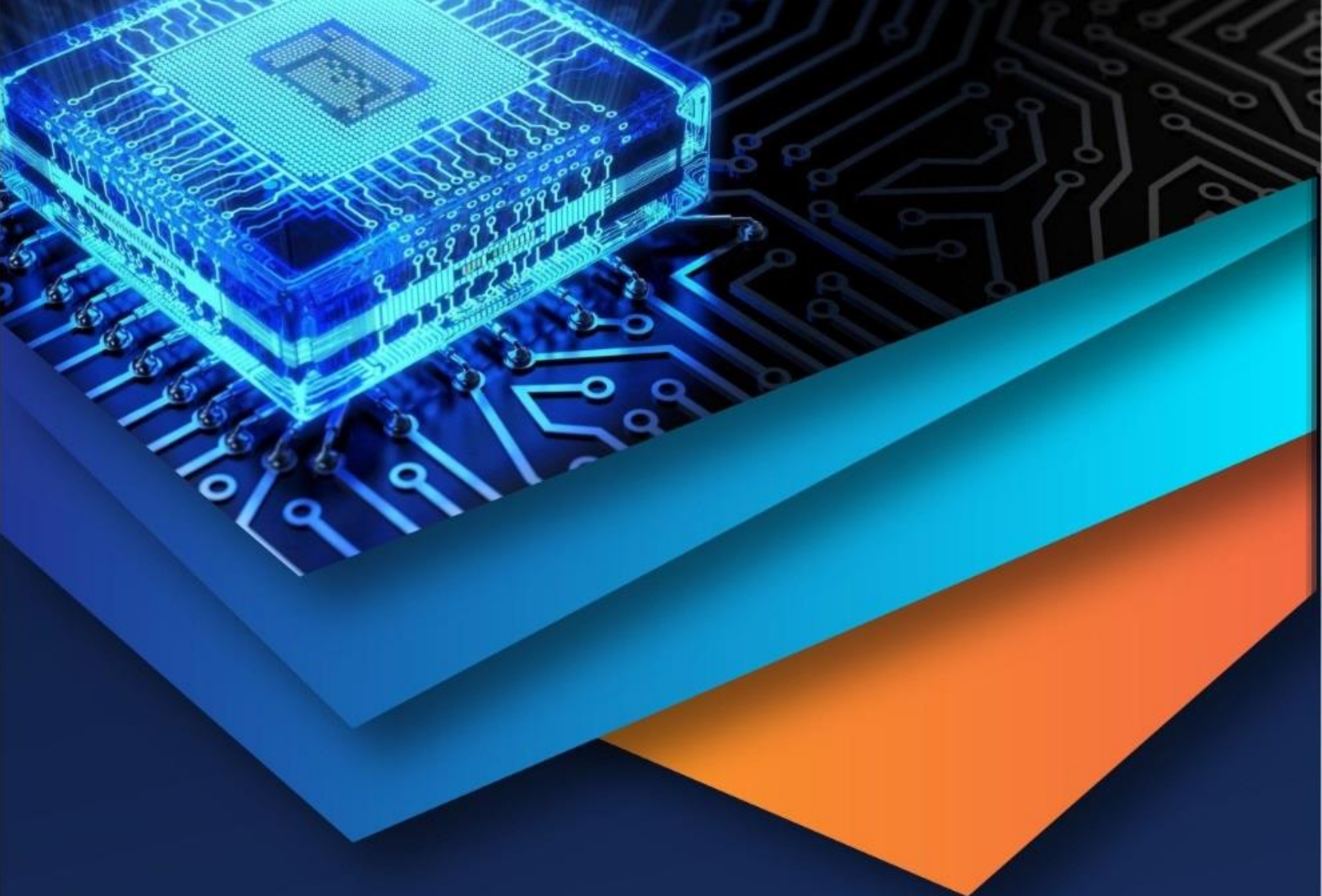
The primary metric used to evaluate model performance was Accuracy, which represents the ratio of image classifications that were processed correctly versus the total number of images in the dataset. The algorithm attained an accuracy greater than 90% which is a strong indication of its ability to detect disease.
Whereas Precision is defined as the ratio of correctly predicted positive cases (diseased leaves) divided by the total number of predicted positive cases, High levels of Precision would indicate that there will be less occurrences of false positive predictions.
Recall or (Sensitivity) is a measure of how well the model can detect correctly actual diseased leaves from actual examples of diseased leaves; therefore, higher values for Recall will be indicative of lesser occurrences of undetected diseased leaves.
The F1-Score is the harmonic meaning between Precision and Recall, providing a measure of the Model's performance that reflects on both aspects equally well.
Additionally, the Confusion Matrix will serve to illustrate the algorithm's performance through values of True Positive Counts; True Negative Counts; False Positive Counts; and False Negative Counts are all included in this method.
Taken Together, all of these metrics provide enough evidence to support the conclusion that this system can provide accurate and reliable results for real-time agricultural applications.

X. CONCLUSION

In conclusion, the paper discusses an innovative plant disease detection system based on IoT that uses images of leaves to identify and diagnose diseases through CNNs. With the addition of IoT technology, users can monitor their crops and detect diseases in real-time through cloud access.
Performance data from the experiments show that the proposed method has superior accuracy compared to currently utilized receipt-based methods. In addition to helping farmers detect disease early and prevent losses, the proposed method enables more intelligent planning for future crops based on the actual performance of detected diseases. The model is also reasonably priced, easy to use, and can be used for both small and large farms.
In summary, the proposed methodological principles present an opportunity for developing a smart agricultural system that utilizes 21st century technologies for efficient plant detection and disease management. Ultimately, the development of smart agriculture provides the foundation for increasing sustainable agricultural practices and providing farmers with tools to make better decisions in regard to the management of their plants and crops.

REFERENCES

[1] C. R. Rahman et al. (2020) - “Identification and recognition of rice diseases and pests using convolutional neural networks,” Biosystems Engineering, 194(1), 112-120.
[2] S. P. Mohanty et al. (2016) - "Using Deep Learning for image-based plant disease detection," Frontiers in Plant Science, 7, Article 1419.
[3] K. Simonyan et al. (2015) - "Very Deep Convolutional Networks for Large Scale Image Recognition," International Conference on Learning Representations (ICLR).
[4] Krizhevsky et al. (2012) - “ImageNet classification with deep convolutional neural networks," Advances in Neural Information Processing Systems, 25.
[5] S. Sladojevic et al. (2016) - "Deep Neural Networks based Recognition of Plant Disease by Leaf Image Classification", Computational Intelligence and Neuroscience.
[6] K. P. Ferentinos (2018) - “Deep Learning Models for Plant Disease Detection and Diagnosis,” Computers and Electronics in Agriculture, 145, 311-318.



10.22214/IJRASET

INDEX COPERNICUS
45.98

IMPACT FACTOR:
7.129

TOGETHER WE REACH THE GOAL
IMPACT FACTOR:
7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)