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Enhanced Plant Disease Detection System Using Thermal Imaging

Rajkumar L. Biradar*, Sruti Varanasi**, Srinayana Ragireddy***, Dhanalakshmi Badani****, Siri Kondapaka*****

**(Professor, Electronics and Telematics Engineering, G. Narayanamma Institute of Technology and Science, Hyderabad, India,*
Email: rajkumar_lb@gnits.ac.in)

***(Electronics and Telematics Engineering, G. Narayanamma Institute of Technology and Science, Hyderabad, India,*
Email: sruti.varanasi2005@gmail.com)

****(Electronics and Telematics Engineering, G. Narayanamma Institute of Technology and Science, Hyderabad, India,*
Email: ragireddysrinayana@gmail.com)

*****(Electronics and Telematics Engineering, G. Narayanamma Institute of Technology and Science, Hyderabad, India,*
Email: badanidhanalakshmi17@gmail.com)

******(Electronics and Telematics Engineering, G. Narayanamma Institute of Technology and Science, Hyderabad, India,*
Email: kondapakasiri2005@gmail.com)

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***Abstract*—Agriculture is essential and vital for global economy and ensuring food security. Indian economy is significantly agrarian and hence any decline in the yields of agriculture has a direct influence on the economy. Agricultural yields are influenced by many factors, out of which, crop diseases have a major impact and if we can monitor, predict and take preventive steps to limit disease progression, the crop yield loss can be minimized. Historically and traditionally, (crop) plant disease is primarily identified by visual inspection of the crop leaves; the leaves from plants provide early cues of infection in the form of changes in colour, shape, and texture of leaves; however this is time consuming and a tedious and arduous task if the crop area is large; it requires good knowledge and expertise of the crop disease onset and progression and the likely changes that happen on the plant's leaves at various stages of the disease. The goal of this project is to develop a system that analyses leaves using machine learning algorithms and Convolutional Neural Networks (CNN) in particular, to enhance the outcome by classifying whether the plant is healthy or unhealthy. Automating diagnosis process in this manner provides farmers with a fast, reliable and economical decision-making process, while also initiating timely diagnosis and reducing dependency on others to supervise the diagnosis. In future, it is proposed to use thermal imaging to capture the heat signature emitted by the leaves to identify temperature differences and heat variations which are not visible to the naked eye, to enrich the digital imaging step compared to what was adopted earlier. This approach gives us additional data and facilitates better accuracy in early detection than that of normal visual imaging.**

*Keywords— **Image pre-processing, Segmentation, Feature extraction, CNN, Detection, Machine learning.***

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I. INTRODUCTION

As the use of digital technologies and more precise farming methods is rapidly increasing, a timely and accurate diagnosis of plant diseases is more important as a guarantee of food security, sustainable production of crops, and economic stability. Nevertheless, the traditional techniques, like the manual visual checkup, tend to be time consuming and subjective and can easily be affected by the human factor. In areas that do not have much expertise and knowledge, these constraints make it difficult to monitor and control crops at a large scale.

Artificial intelligence (AI) and deep learning have made new opportunities available in recent years to automate the process of identifying plant diseases based on the analysis of images. Convolutional Neural Networks (CNNs) particularly have proven to be highly accurate in detecting patterns of diseases when leaf images are used and are thus efficient in delivering accurate diagnosis.

To meet the requirements of a stable, effective, and convenient solution, the current work presents a Plant Disease Detection System, based on CNN-based image classification. The objective of this system is to help farmers and agricultural researchers to automatically detect plant- based diseases based on the pictures of leaves collected and provide real-time feedback concerning the health of crops and to recommend potential preventive interventions. The model is easily scalable and simple to work with, thus making it easy to use and affordable.

The current study compares RGB images with infrared thermal images to assess the accuracy of detecting diseases in plants using thermal imaging. As part of the study, pictures of

Guava plant leaves are captured, over a time span of 2 weeks, to capture disease progression using normal RGB camera. Also infrared thermal camera images are captured on healthy and disease infested leaves using infrared camera; which are used as input dataset to establish the feasibility and validity of the proposed research, using CNN-based image classification. This study establishes that the health of crops can be monitored in a more comprehensive way using thermal imaging compared to RGB images, thus facilitating proactive management of diseases. This study establishes that adoption of smart technologies would help farmers to take timely decisions and become more productive and promote sustainable agriculture.

II. RELATED WORK

The latest trends in intelligent agriculture have been primarily focused on the automation of the process of detecting and diagnosing plant diseases with the help of artificial intelligence technology and image processing technologies. The conventional disease diagnosis methods based on expert observation and laboratory investigation were time-consuming and labour-intensive and subject to subjectivity. Therefore, scientists have attempted to substitute these manual methods with automated and information-driven solutions that are able to monitor plant diseases quickly, precisely and aid in large scale farming.

In this field, the main techniques that were used in the early years were the image processing methods to segment, analyse the colour, and extract the texture of the plant leaf to detect the diseased area. A framework of image processing was developed by Chen and Ullah [1], which involved usage of colour-based segmentation and genetic algorithms in identifying tomato leaf diseases as bacterial spots and early blight. Though the system decreased the amount of human labour and increased the pace of the diagnosis process, it was not as adaptable to the aspects of plant species and environmental conditions due to the reliance on the feature extraction that is performed by hand.

With the development of computational procedures, machine learning (ML) models started to be used in classification. The Support Vector Machines, K-Nearest Neighbours and the Random Forest algorithms were used on the feature sets based on digital leaf images. Waghmare and Kokare [2] proved that a multiclass SVM classifier with texture features can be effective in recognizing diseases on grapevines with a success of 96.6%. Nevertheless, these systems were preprocessing sensitive and depended on the good quality of the illumination, background and images, thus limiting their scaling to the real field situations.

Recently, the use of Deep Learning (DL) has become a significant change in the field of research on plant disease detection, especially Convolutional Neural Networks (CNNs). Ahmed and Yadav [3] provided a review of both machine learning and deep learning approaches for detecting plant diseases. Their study highlighted that CNN-based models are faster and more accurate compared to traditional ML methods, which points to the possibility of deep neural architecture being used in large- scale agriculture. Similarly, the study of Sladojevic et al. [4] showed that deep CNN constructs obtained accuracy levels of over 95 percent on varied crop datasets, which demonstrated that CNNs are the most promising paradigm for using automated leaf disease classification methods.

Hybrid and transfer learning models like VGG16, ResNet50 and GoogleNet have also been added to further make the models of detection more robust. Uguz and Uysal [5] used transfer learning to enhance the classification of olive leaf diseases to a maximum of 95% accuracy after augmentation. On the other hand, Fuentes et al. [6] combined the use of SSD, R-FCN and Faster R-CNN meta- models to identify disease-affected regions of complex field images, thus, allowing it to be used in near real-time.

With these developments, however, there are still challenges facing technology, some of which relate to the cost of computing, dependence on datasets, and the possibility of detecting symptoms at the early stage or stress-induced symptoms in varying lights and environments. CNN based Plant Disease Detection System proposed here intends to address some of the above shortcomings by incorporating thermal imaging and forming a simple and efficient basis for future plant disease detection system.

III. SCOPE OF THE WORK

The previous research successfully demonstrates the potential of image processing, machine learning, and deep learning for plant disease detection. However, limitations in cost, computational scalability, and real-time usability opens a dimension for further work.

To analyze these aspects and get a better understanding, a comparison of the existing methods and the proposed system is given below in TABLE I and TABLE II, based on the key performance parameters.

The proposed CNN- based Plant Disease Detection System addresses these challenges by emphasizing low-cost implementation, real- time classification, and modular expandability.

TABLE I

COMPARISON OF EXISTING METHODS WITH PROPOSED SYSTEM

Criteria	**Chen & Ullah [1]**	**Ahmed & Yadav [3]**	**Sladojevic et al. [4]**	**Proposed System**
Accuracy	Moderate	High	Very High	High
Method Type	Image Processing	ML + DL	Deep Learning (CNN)	CNN + Thermal
Complexity	Low	Moderate	High	Optimized (Low)
Cost	Low	Moderate	High	Low
Real-Time Capability	No	Limited	Limited	Yes
Early Detection	No	No	No	Yes
Applicability	Limited	Moderate	Lab-based	Real field

TABLE II

PLANT DISEASE DETECTION IN OTHER STUDIES

Criteria	**Spaner & Zhu [7]**	**Prince & Clarkson [8]**	**Kulkarni et al. [9]**	**Ahmed & Yadav [3]**
Methodology	ROI + Histogram	Multi-modal imaging	Image Processing + ML	ML & DL comparison
Algorithm / Model	Rule-based thermal analysis	MRSGM + SVM	Random Forest	CNN / SVM / ANN
Accuracy	High (not specified)	>90% precision	~93% accuracy	Up to 99% (CNN)
Advantages	Early detection (pre-visible)	High precision	Cost-effective	Very high accuracy, real-time capable
Disadvantages	Affected by temperature & humidity	Requires specialized hardware	May miss early lesions	Needs large dataset & high computation

IV. METHODOLOGY

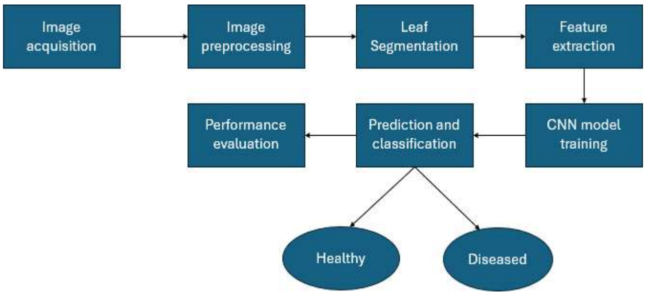

FIG. 1. BLOCK DIGRAM – RGB IMAGING

Fig. 1 shows the process followed for RGB Images. Input images acquired from the field are pre-processed, segmented and extracted and trained and classified, to infer whether the result prediction is normal or abnormal.

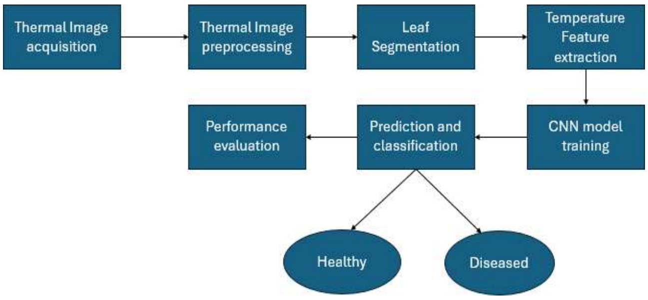

Fig. 2. BLOCK DIAGRAM – THERMAL IMAGING

Fig. 2 shows the process followed for Thermal Images. Input images acquired from the field are pre-processed, segmented and extracted and trained and classified, to infer whether the result prediction is normal or abnormal.

A. Data Acquisition and Pre-Processing

Data Acquisition is carried out in the initial phase; data quality is crucial and vital for the reliability of the entire system. Dataset of Guava plant images with special focus on the leaf physical characteristics are captured using normal mobile camera, to capture RGB Images and thermal images using Seek thermal camera attachment to mobile phone. The RGB images captured the healthy leaves and progression of white fungal disease (powdery mildew) over a span of 2 weeks. Thermal images are then pre-processed and then used in the study as input data.

This dataset consists of 104 images of healthy and diseased crop leaves which are used for training and testing purposes. Thermal images acquired from the field are pre-processed, segmented and extracted and compared with disease progression images obtained using RGB camera datasets to infer whether the result prediction by thermal imaging is accurate or not.

B. Image Segmentation

The thermal images are converted into Hue Saturation Values (HSV). HSV allows better separation of the leaf from the background based on thermal colour characteristics. A suitable threshold is applied to isolate and highlight the leaf region from the background using binary mask. Irrelevant surrounding information is thus suppressed. The images are resized to 224 x 224 pixels. Focusing on the segmented leaf ensures that the temperature values obtained from V channel in HSV accurately represents leaf's thermal properties; these segmented images are then used for further processing. This process is depicted in Fig. 3 below:

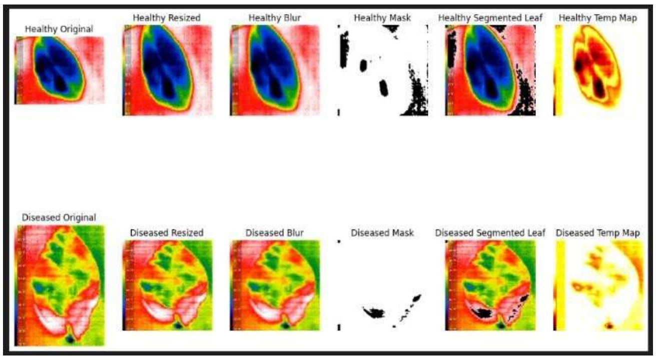

Fig. 3. SEGMENTATION

C. Feature Extraction

The V values in the segmented leaf represent the intensity variations which correspond to the heat patterns in the leaf. The temperature map is normalized and used as input to the CNN model. The features are automatically extracted by the convolutional and pooling layers, essentially learning the most discriminatory features (kernels) from the data itself, which is a major advantage over traditional, hand- crafted feature extraction.

D. Disease Classification

The extracted (or automatically learned) features are fed into a model to determine the ultimate result, the diagnosis which categorizes the leaf's condition as diseased or healthy by assigning a threshold and using statistical probability into a binary matrix of 0 and 1.

E. Outcome

Based on the analysis a prediction score is obtained which is used to classify the leaf as healthy or diseased. If the score is above threshold, the leaf is classified as diseased, else healthy. Fig. 4 depicts the prediction of a healthy leaf and Fig. 5 shows prediction of a diseased leaf.

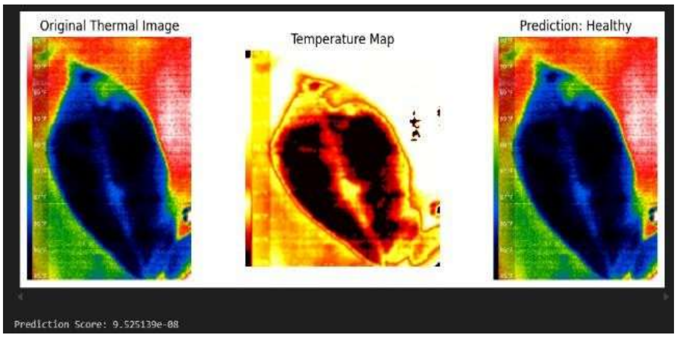

Fig. 4. OUTCOME PREDICTION- HEALTHY LEAF

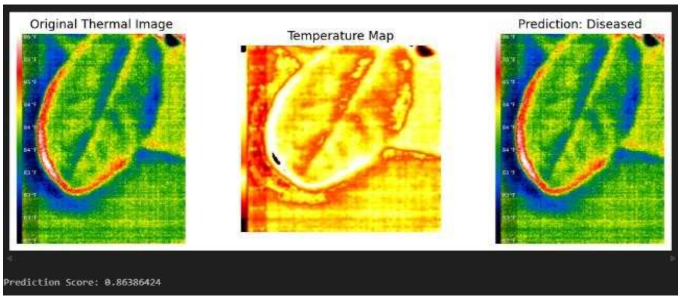

Fig.5. OUTCOME PREDICTION- DISEASED LEAF

TABLE III
PARAMETERS USED IN THE STUDY-RGB

Image resolution	224 x 224 pixels
Color code	RGB
Training validation split	80:20
Batch size & Epochs	batch size:8, Epochs:5

TABLE IV
PARAMETERS USED IN THE STUDY- THERMAL

Image resolution	224 x 224 pixels
Color code	Thermal
Training validation split	70:30
Batch size & Epochs	batch size:8, Epochs:20

The parameters used in the study are given in TABLE III and TABLE IV shown above.

V. RESULTS AND DISCUSSION

Sample output depicting the visual attribute-based prediction of the disease after processing the images from the field using thermal imaging against the RGB images is shown in Fig. 6 below:

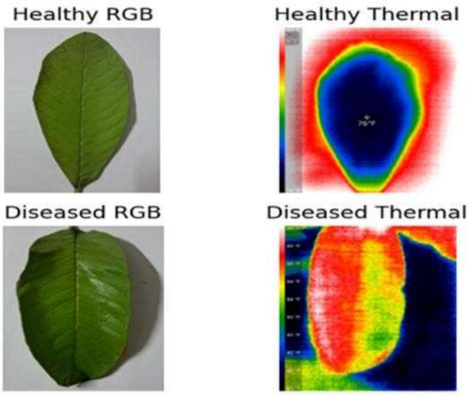

Fig. 6. COMPARISON OF RGB IMAGES WITH THERMAL IMAGES

The accuracy and losses in the model are shown in Fig. 7 and Fig. 8 below:

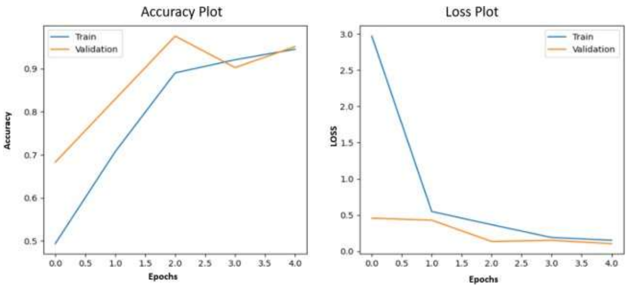

Fig. 7. ACCURACY AND LOSS OVER EPOCHS -RGB

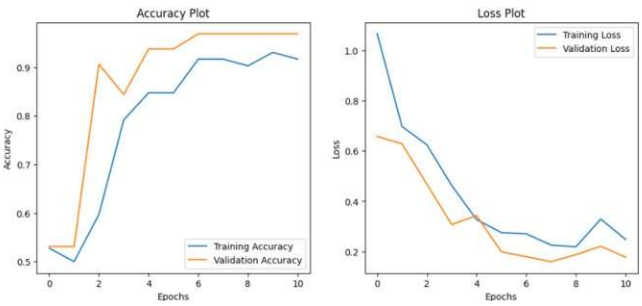

Fig. 8. ACCURACY AND LOSS OVER EPOCHS -THERMAL

From Fig. 7 and Fig. 8, we can infer that accuracy of both the training and validation models follow similar patterns. The divergence between the training and validation models is high when the number of epochs is more; In general, the validation accuracies are higher than the training accuracy.

From Fig. 7 and Fig. 8, losses observed in both the training and validation models follow similar patterns. The divergence between the training and validation models is high when the number of epochs is less. Losses in the validation model are always less than those of the training model.

These observations possibly point to the superior data processing capabilities of CNN.

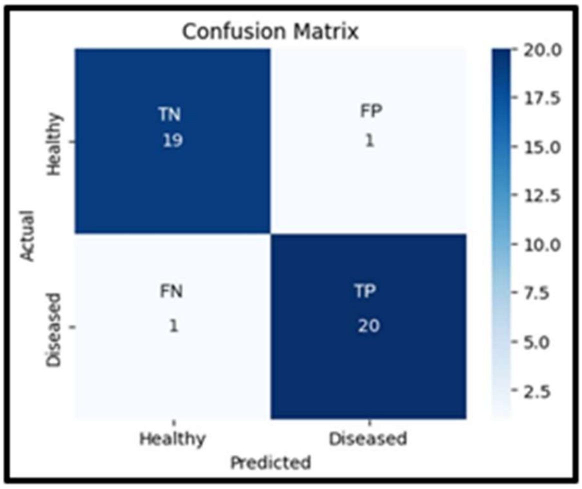

Fig. 9. CONFUSION MATRIX WITH LABELS – RGB

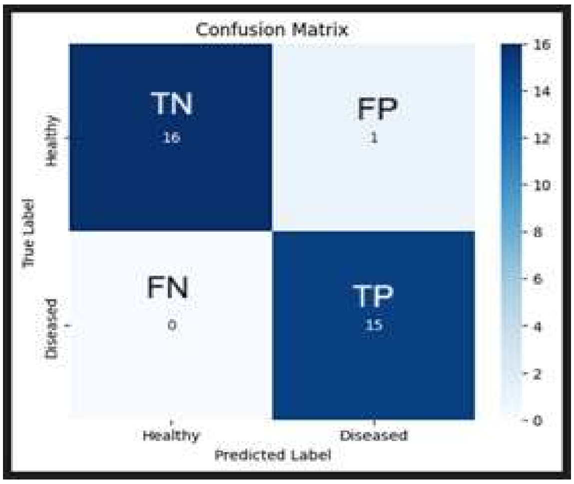

Fig. 10. CONFUSION MATRIX WITH LABELS – THERMAL

Another important inference observed from Fig. 9 and Fig. 10 is that the results in line with expected model behavior that prediction accuracy is more when True Negatives (TN) and True Positives (TP) are more.

	precision	recall	f1-score	support
0	0.95	0.95	0.95	20
1	0.95	0.95	0.95	21
accuracy			0.95	41
macro avg	0.95	0.95	0.95	41
weighted avg	0.95	0.95	0.95	41

CLASSIFICATION REPORT

Fig. 11. CLASSIFICATION REPORT -RGB

	precision	recall	f1-score	support
0	1.00	0.94	0.97	17
1	0.94	1.00	0.97	15
accuracy			0.97	32
macro avg	0.97	0.97	0.97	32
weighted avg	0.97	0.97	0.97	32

CLASSIFICATION REPORT

Fig. 12. CLASSIFICATION REPORT -THERMAL

From Fig. 11 the healthy and diseased leaves have 95% in precision of prediction, 5% of the leaves are missed (recall) for data recall and the combined harmonized indicator (f1-score) of the sampled data is 95%.

From Fig. 12 the healthy and diseased leaves have 100% and 94% respectively in precision of prediction, 6% and 0% of the leaves are missed (recall) respectively for data recall and the combined harmonized indicator (f1-score) of the sampled data is 97%.

The system using thermal imaging achieved an accuracy of 97%, while the system using RGB imaging achieved 95%, demonstrating improved early disease detection capability, before the appearance of visible symptoms.

VI. CONCLUSION AND FUTURE SCOPE

This system detects plant diseases early using image processing and machine learning. Within the constraints of limited dataset of the Guava leaves studied, it is observed that the Thermal imaging showed slightly better prediction accuracy (0.97) when compared to the RGB imaging (0.95). It provides fast and accurate results to help reduce crop damage. The approach lowers the need for manual inspection on large farms. Overall, it supports better crop management and improves agricultural productivity. Results can be further validated using a bigger dataset and the study can be extended to other plant species.

REFERENCES

[1] L. W. Chen and H. Ullah, "Plant disease detection using image processing," IOSR J. Electr. Electron. Eng., vol. 17, no. 6, pp. 6–16, Nov.–Dec. 2022.

[2] H. N. Waghmare and R. D. Kokare, "Detection and classification of diseases of grape plant using opposite colour local binary pattern feature and multiclass support vector machine," Int. J. Comput. Appl., vol. 71, no. 15, pp. 1–7, May 2013.

[3] I. Ahmed and P. K. Yadav, "A systematic analysis of machine learning and deep learning based approaches for identifying and diagnosing plant diseases," Sustain. Oper. Comput., vol. 4, pp. 96–104, 2023.

[4] S. Sladojevic, M. Arsenovic, A. Anderla, and D. Culibrk, "Deep neural networks based recognition of plant diseases by leaf image classification," Comput. Intell. Neurosci., vol. 2016, pp. 1–11, 2016.

[5] H. Uğuz and A. K. Uysal, "Classification of olive leaf diseases using deep convolutional neural networks," Neural Comput. Appl., vol. 33, no. 9, pp. 4885–4898, 2021.

[6] A. Fuentes, S. Yoon, S. Kim, and D. S. Park, "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition," Sensors, vol. 17, no. 9, pp. 1–20, 2017.

[7] W. Zhu, H. Chen, I. Ciechanowska, and D. Spaner, "Application of infrared thermal imaging for the rapid diagnosis of crop disease," Sensors, vol. 18, no. 12, Art. no. 4308, 2018.

[8] S.-A. Raza, G. Prince, J. P. Clarkson, and N. M. Rajpoot, "Automatic detection of diseased tomato plants using thermal and stereo visible light images," PLoS ONE, vol. 10, no. 4, p. e0123262, Apr. 2015, doi: 10.1371/journal.pone.0123262.

[9] P. Kulkarni, A. Karwande, T. Kolhe, S. Kamble, A. Joshi, and M. Wyawahare, "Plant disease detection using image processing and machine learning," Dept. of Electronics and Telecommunication