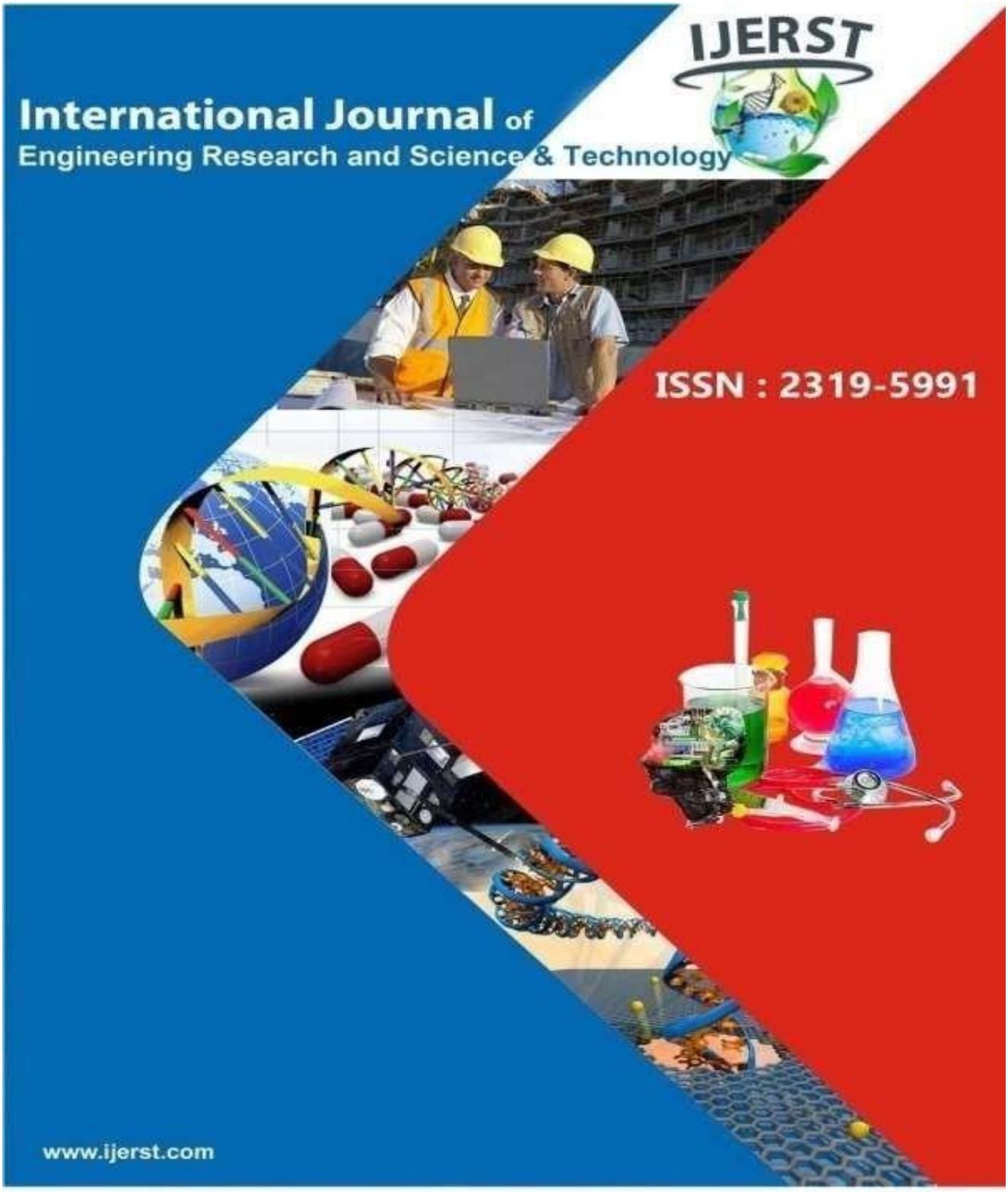



Email: editor@ijerst.com or editor.ijerst@gmail.com

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

Vol. 19, Issue 3, 2023

# RECOGNITION OF CROP DISEASE AND INSECT PESTS BASED ON DEEP LEARNING IN HARSH ENVIRONMENT

Maltesh Kamatar, Prashanth.K, Naveen Kumar. H

Asst. Professor, Asst. Professor, Asst. Professor

maltkpl@pdit.ac.in, prashanthkogali@gmail.com, pdit.naveen@gmail.com

Department of CSE, Proudhadevaraya Institute of Technology, Abheraj Baldota Rd, Indiranagar, Hosapete, Karnataka-583225

## ABSTRACT

Insect and disease pests in agriculture are among the most important factors that may drastically reduce crop yields. Identifying and detecting pests early on may eliminate economic losses caused by them. In this study, we provide a method for automatically diagnosing crop illnesses using convolutional neural networks. The dataset incorporates 10 different crops and contains twenty-seven images of illnesses. It was retrieved from the public data set of the 2018 AI Challenger Competition. This study trains the Inception-ResNet-v2 model. The cross-layer direct edge and the multi-layer convolution are two parts of the model's residual network. To activate it, the ReLu function is used after the combined convolution operation is completed. The results of the testing show that this model is helpful, with a total recognition accuracy of 86.1%. Following the training of this model, we developed a Wechat applet with the ability to detect agricultural diseases and insect pests. As a further step, we gave the test. The results prove that the system can accurately identify crop diseases and give suitable suggestions.

## I.INTRODUCTION

Agriculture serves as the backbone of many economies worldwide, providing sustenance and livelihoods for billions of people. However, crop diseases and insect pests pose significant threats to agricultural productivity, food security, and farmer incomes. Early detection and management of these threats are essential for mitigating losses and ensuring sustainable agricultural practices.

Traditional methods of disease and pest detection often rely on visual inspection by farmers, which can be time-consuming, subjective, and prone to human error. Furthermore, in harsh environments characterized by adverse weather conditions,

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

Vol. 19, Issue 3, 2023

limited resources, and remote locations, such as rural areas or developing countries, these challenges are exacerbated.

The "Recognition of Crop Disease and Insect Pests Based on Deep Learning in Harsh Environments" project aims to address these challenges by leveraging the power of deep learning techniques to automate and improve the detection of crop diseases and insect pests. Deep learning, a subset of machine learning, has demonstrated remarkable capabilities in image recognition and pattern detection, making it well-suited for this task.

## II. EXSISTING SYSTEM

According to statistics, the area of crops affected by pests and diseases in China is as high as 280 million km2 every year, and the direct yield loss is at least 25 billion kg [1]. In recent years, this problem is on the rise and seriously threatens the development of planting industry. Timely diagnosis and prevention of crop diseases has become particularly important. At present, agricultural workers often use books and network, contact local experts and use other methods to protect and manage crop diseases. But for various reasons, misjudgments and other problems often occur, resulting in agricultural production is deeply affected. At present, the research on crop diseases is mainly divided into two directions. The first one is the traditional physical method, which is mainly based on spectral detection to identify different diseases. Different types of diseases and insect pests cause different leaf damage, which leads to different spectral absorption and reflection of leaves eroded by diseases and healthy crops.

## III. PROPOSED SYSTEM

The central sever provide forecast service of weather condition and disease. Another kind of solution related of monitoring traps which are used to capture pest is with the help of image sensors [6]. In [6], he authors designed and implemented a low power consumed system which is based on wireless image sensors and powered by battery. The frequency of capturing and transferring trap images of sensors can be set and remote adjusted by trapping application. Acoustic sensors are also used in monitoring system. In [7], the authors give a solution to detect red palm weevil (abbr. RPW) with them. With the help of acoustic device sensor, the pest’s noise can be captured automatically. When the noise level of pest increases to some threshold, the system will notify the client that the infestation is occurring in the specific

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

Vol. 19, Issue 3, 2023

area. It helped farmers to be economical of time and energy to check every part of cropland by themselves and increase the labor efficiency. All acoustic sensors will be connected to base stations and each one will report the noise level if the predefined threshold value is surpassed [7]. Machine learning also had been applied in the agricultural field, such as investigation of plant disease and pests and so on. Plenty of techniques of machine learning had been widely used to solve the problem of plant disease diagnosis. In [8], a Neural Network based method of estimating the health of potato with leaf image datasets is proposed. Additionally, the experimental research in [9] was carried out, which aimed to implement a system of recognizing plant disease with images.

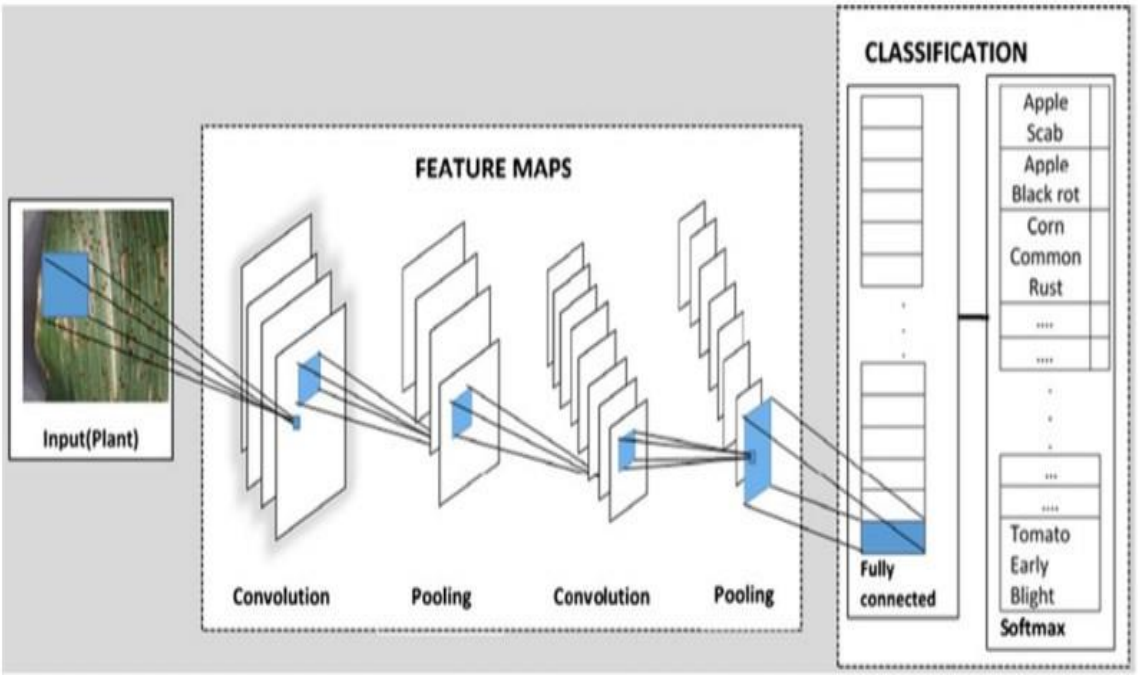



**Fig : System Design**

## IV. IMPLEMENTATION

- **Dataset Acquisition and Preprocessing Module:**

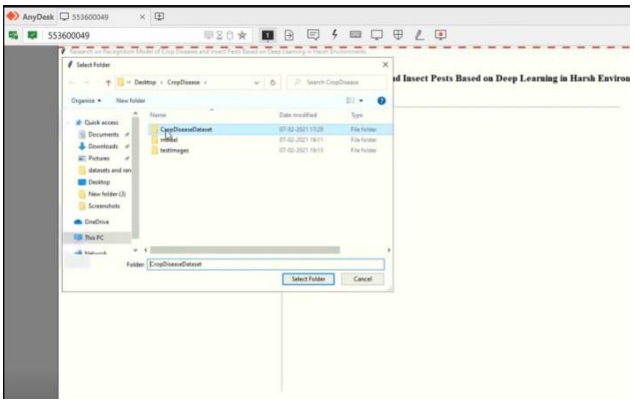
International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

Vol. 19, Issue 3, 2023

This module is responsible for acquiring a dataset of images containing crop samples affected by diseases and insect pests. It involves collecting images from various sources, annotating them with labels indicating the presence of diseases or pests, and preprocessing the images to ensure uniformity and quality.



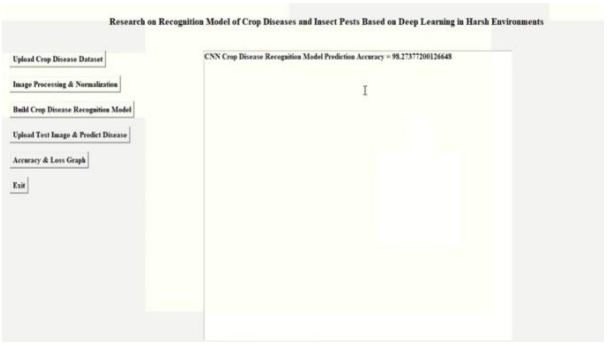




- **Image Processing and Normalization Module:**

This module focuses on standardizing and enhancing the quality of the acquired images. It includes tasks such as resizing images to a consistent resolution, adjusting brightness and contrast, removing noise, and applying transformations like rotation or cropping to improve model performance.

- **Model Building and Training Module:**

In this module, deep learning models are developed and trained using the preprocessed image dataset. Various deep learning architectures, such as convolutional neural networks (CNNs),

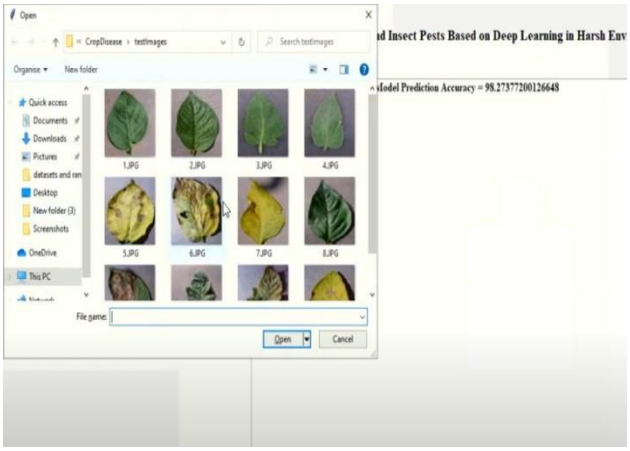



may be explored and optimized to achieve high accuracy in detecting crop diseases and insect pests.

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

Vol. 19, Issue 3, 2023




- **Model Evaluation and Validation Module:**

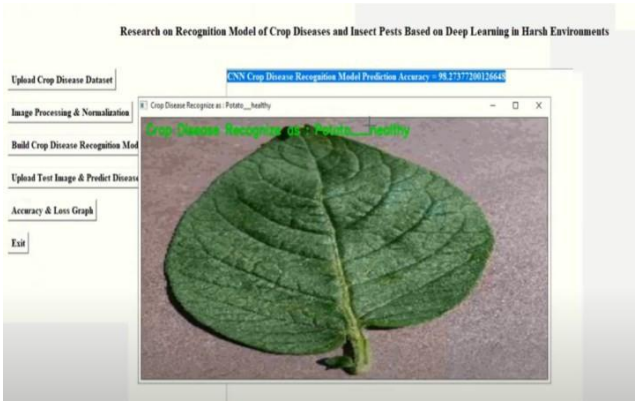
Once trained, the models need to be evaluated and validated to assess their performance and generalization ability. This module includes tasks such as splitting the dataset into training and testing sets, measuring metrics like accuracy and precision, and analyzing the model's behavior on unseen data.

- **Deployment and Integration Module:**

After successful evaluation, the trained models are deployed for practical use. This module involves integrating the models into a user-friendly application or platform accessible to farmers or agricultural extension workers. It includes tasks such as developing APIs for model inference, creating a user interface for uploading images and viewing predictions, and ensuring scalability and reliability of the deployed system.

- **Image Upload and Prediction Module:**

This module provides functionality for users to upload images of crop samples potentially affected by diseases or pests and receive predictions from the trained models. It includes components for image upload, preprocessing, model inference, and displaying prediction results to the user.




## V. CONCLUSION

In this study, we looked at 27 different approaches for identifying diseases in 10 distinct crop kinds. The Inception-ResNet-v2 model is built using deep learning theory and technology based on convolutional neural networks. The model clearly recognises the dataset, as the overall identification accuracy reaches 86.1% in the trials. Based on the results, this hybrid network model is a good alternative to the traditional model for identifying and detecting plant diseases and insect pests, as it achieves higher

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

Vol. 19, Issue 3, 2023

identification accuracy. In the future, it would be wise to improve two areas: 1) A dataset that tracks patients throughout time. This paper's study only covered 27 diseases out of 10, and it did not include other crop species or illnesses like wheat and rice. As a result, we need to take more pictures of crop species and illnesses so we can research them. 2) Improve the model. An example of a mixed network that has effectively absorbed the corresponding advantage is Inception-resnet-v2, as shown by the experimental findings presented in this research. Since this model has achieved excellent recognition accuracy, it merits more investigation and optimisation. Also, it would be great if we could train a network model to correctly identify cropped images.

## VI. REFERENCES

1. Barbedo, J. G. A. (2019). Factors influencing the use of deep learning for plant disease recognition. Biosystems Engineering, 180, 4-20.

2. Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Sensors, 17(9), 2022.

3. Ghosal, S., Blystone, D., Singh, A. K., Ganapathysubramanian, B., Singh, A., & Sarkar, S. (2018). An explainable deep machine vision framework for plant stress phenotyping. Proceedings of the National Academy of Sciences, 115(18), 4613-4618.

4. Islam, M. T., Yang, X., & Li, J. (2020). A deep learning model for identifying plant diseases using transfer learning. Computers and Electronics in Agriculture, 174, 105507.

5. Kassani, S. H., Soltani Arabshahi, S. K., Minaei, S., Kalantar, M., & Joolaei, R. (2017). Detection and classification of wheat leaf diseases using machine learning techniques. Computers and Electronics in Agriculture, 142, 369-379.

6. Lu, H., & Zhang, H. (2017). Integrated pest management for sustainable crop protection using machine learning. In 2017 IEEE 19th International Conference on High Performance Computing and Communications; IEEE 15th International Conference on Smart City; IEEE 3rd International Conference on Data Science and Systems (pp. 370-376). IEEE.

7. Picon, A., Yeguas-Bolivar, E., Marroquín-Graterol, M., de la Morena-de la Fuente, E., & Jiménez-Sáez, A. (2020). Review on deep

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

Vol. 19, Issue 3, 2023

learning in agricultural applications using remote sensing data. Remote Sensing, 12(11), 1841.

8. Reddy, M. R., & Chaudhary, P. (2020). Deep learning techniques for plant disease detection and classification: A review. Archives of Computational Methods in Engineering, 1-17.

9. Sa, I., Popović, A., Khanna, R., & Liebisch, F. (2020). DeepFruits: A fruit detection system using deep neural networks. Sensors, 20(18), 5133.

10. Sankaran, S., Mishra, A., Ehsani, R., & Davis, C. (2010). A review of advanced techniques for detecting plant diseases. Computers and Electronics in Agriculture, 72(1), 1-13.

11. Sharma, P., Dhanda, S. K., & Yadav, I. S. (2020). Identification and classification of cotton leaf diseases using deep learning techniques. SN Applied Sciences, 2(3), 1-12.

12. Singh, A. K., Ganapathysubramanian, B., Singh, A., & Sarkar, S. (2016). Machine learning for high-throughput stress phenotyping in plants. Trends in Plant Science, 21(2), 110-124.

13. Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. Computational Intelligence and Neuroscience, 2016.

14. Tsaftaris, S. A., Minervini, M., Scharr, H., & Nazare, T. S. (2016). Machine learning for plant phenotyping needs image processing. Trends in Plant Science, 21(12), 989-991.

15. Ubbens, J. R., & Stavness, I. (2017). Deep plant phenomics: A deep learning platform for complex plant phenotyping tasks. Frontiers in Plant Science, 8, 1190.