Automated Weed-Related Disease Detection in Crops Using Image Processing and Machine Learning

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Abstract: Effective management of crop diseases is thus necessary to assure food security and raise agricultural productivity. Weeds provide a regular and harmful threat to crop growth and complicate the diagnosis and management of diseases in a timely way, therefore promoting the spread of diseases. This work investigates the possibilities of image processing techniques for the identification of agricultural diseases connected to weed. Under various lighting conditions, we sort aerial images of crops and weeds taken by many cameras or drones using a deep learning model. Once significant qualities like texture, colour, and shape are taken from the images, image segmentation algorithms help to separate crops from weeds. Training a machine learning system, CNN, to identify and classify agricultural diseases connected to weeds comes next. We evaluate the accuracy parameters of the model to get knowledge on its possible use in real-time disease diagnosis. This work opens the path for automated crop disease monitoring systems that can help farmers in early detection and focussed treatment, therefore contributing to sustainable agricultural practices.

Keywords: CNN, Crop disease identification, Crop health monitoring, Image processing, Precision agriculture, Weed-based disease detection.

1 Introduction

One of the biggest challenges farmers face is crop disease management, which is significant since agriculture is the major source of food on a global scale. Some people think that weeds are the biggest threat to crops because of all the things that might cause illnesses. Weeds not only compete with crops for space, water, and nutrients, but they also harbour and spread several plant diseases, making crop disease outbreaks much worse. Identifying diseases early on is crucial for minimising crop loss and making the most of pesticides, especially when dealing with diseases caused by weeds. raditional methods of disease diagnosis include extensive physical inspection and chemical analysis, which may be laborious, error- prone, and time-consuming. In addition, these approaches do not provide results that are either accurate or scalable, nor do they deliv- er results in real time. Image processing has developed as a poten- tially useful tool for agricultural monitoring as a result of develop- ments in digital technology. This technology, which makes use of photos obtained from a variety of platforms, including drones, satel- lites, and ground-based cameras, makes it feasible to conduct a quick and accurate examination of the health of crops. Using image processing methods such as feature extraction, segmentation, and classification, it may be feasible to differentiate crop illnesses caused by weeds from those caused by other environmental condi- tions. A significant increase in the potential of image processing in agriculture has been brought about by the use of machine learning and deep learning algorithms. Through the use of these methodolo- gies, automated systems are able to identify and diagnose illnesses with a high degree of precision. Using image processing in conjunc- tion with sophisticated learning models, we may be able to design systems that are able to identify illnesses that are associated with weeds and categorise them according to their symptoms. Because of this, we will be able to choose the therapies that are the most suita- ble. These solutions support sustainable agricultural practices by significantly reducing the resources required for crop disease man-agement, such as time, money, and effort. This is accomplished by reducing the amount of resources that are required. The purpose of this project is to build a weed-based disease diagnosis system that is based on image processing. Additionally, the research will investi- gate the ability of machine learning models, namely deep learning, to identify and diagnose agricultural illnesses that are caused by weed infestations. What is required for contemporary agriculture is a disease management system that is not only effective but also scala- ble and automated. Several significant advancements in the fields of image processing and agriculture are driven by this study, including the following:

1. **Development of an Automated Disease Detection System:** The study describes the creation and implementation of an automated system able to identify agricultural diseases brought on by weeds, therefore reducing the labour-intensive human inspections. By use of image processing and deep learning approaches, the system offers rapid and accurate disease detection.
2. **Integration of Image Processing Techniques for Weed- Crop Differentiation:** This work uses modern segmentation techniques for precise crop/weed differentiation to enhance picture processing capacities. Crucially important for lowering false positives and negatives, this stage guarantees correct detection of diseases in weed infestations.
3. **Use of Deep Learning for Disease Classification:** This work aims to diagnose crop illnesses using CNNs trained using the properties gained from photos. Given the capabilities of the deep learning model to distinguish between various diseases, educated judgements and exact treatment plans may be derived.
4. **Real-time Disease Monitoring:** This paper provides the foundation for the direction of agricultural disease monitoring in real time going forward. By means of high- resolution images taken either by drones or cameras, the technology can quickly evaluate crop health and

alert farmers of any disease outbreaks. Early intervention made possible by this reduces crop losses.

5. **Contribution to Precision Agriculture:** This development improves farmers' capacity to monitor crop health, therefore supporting the fast growing sector of precision agriculture. Sustainable farming methods could be reinforced, pesticide use could be lowered, and resources could be more wisely distributed by including automated disease detecting systems.
6. **Potential for Broader Agricultural Application:** Since the proposed system may be tuned to fit various crops and environmental conditions, there is possibility for it to be used in large-scale agricultural activities. This approach has multiple possible uses in modern agriculture as it may be expanded to cover different plant diseases. Research offers a means of fast and accurate identification of weed- induced agricultural illnesses, therefore enhancing crop protection and guiding more environmentally friendly farming methods. It also encourages the use of machine learning and image processing technology for the purpose of preventing agricultural diseases. Therefore, in order to ensure that there is a sufficient supply of food and to boost agricultural production, it is necessary to have an effective management system in place for crop diseases. The presence of weeds presents a constant and negative danger to the growth of crops all during the growing season. Furthermore, they make it more difficult to detect and treat illnesses in a timely way, which in turn leads to the spread of diseases throughout the population. Agricultural diseases that are linked to waterweeds are the focus of this investigation, which aims to assess the possible uses of image processing techniques for the detection of these diseases. We sort aerial images of crops and weeds that were taken by a large number of cameras or drones under a range of lighting situations. This is accomplished with the assistance of a deep learning model. In order to help in the distinction of crops from weeds, image segmentation algorithms are used after the extraction of essential features from the photographs. These qualities include texture, colour, and shape. The next stage is to train a machine learning system known as CNN in order to identify and classify agricultural ailments that are related with weeds. This will determine the classification of these illnesses. In order to get insight into the potential applications of the model in real-time illness diagnosis, we conduct an analysis of the accuracy parameters of the model. This study paves the way for the development of automated crop disease monitoring systems, which may assist farmers in early disease identification and targeted treatment, hence helping to the implementation of sustainable agricultural practices at the farm level.

2 Literature review

Jin X, et al. (20211) studied vegetable garden weed detection using deep learning and image processing. They identified weeds in plantation contexts using convolutional neural networks on vegetable photos. The research found that deep learning models may improve crop-weed identification and farmed weed control.

Wang A, et al. reviewed ground-based machine vision and image processing for weed identification in 2019. The research included feature extraction, picture segmentation, and classification methods for agricultural weed detection. The research highlighted precision agriculture and automated weed identification using machine vision. Kumar et al. focused their 2019 photo segmentation study on agricultural disease detection. They recommended segmenting disease-damaged crop photos and classifying them to identify the illness. They found that image processing may speed up plant disease detection, reducing crop loss and intervention response times.

Wu Z, et al. (2021) examined numerous computer vision-based weed detectors. They examined everything from classical to deep learning-based methods to improve weed detection using image processing. The study prepared for multifaceted weed detection system improvements by thoroughly assessing and emphasising their pros and cons.

Hasan, et al. (2021) examined image-based deep learning weed detection systems. Additional DL models and CNNs were utilised to identify weeds. It also illuminated how to address weed-crop overlap, illumination difficulties, and the necessity for big annotated datasets for model training to improve real-world detection performance.

Ferentinos, et al. (2019) suggested a deep learning method to diagnose cannabis illnesses, nutritional deficits, and pests using photos. They correctly identified pest and disease infestations in cannabis plant photos using CNNs. Their investigation on a variety of plant types demonstrated that deep learning may assist diagnose plant diseases and offer a foundation for crop-specific models. Using region-based CNN for sesame crop weed identification and classification, Naik (2024) found Deep learning helps RCNNs detect and categorise sesame crop weeds better than other approaches. Regional CNN approaches provide potential for precision-sensitive agriculture, according to their findings.

Meena, et al. (2023) examined how weed, pest, and disease detection might boost agriculture. The research used image processing and machine learning to classify agricultural plant health concerns. Early agricultural problem detection improves crop yield and resource economy.

In 2023, Haq, et al. investigated wheat field weed detection using AI and image analysis. Their wheat field weed detection study used AI. The research showed that artificial intelligence and image processing can manage weeds in large-scale agriculture, where less pesticides and physical labour are needed.

ANNs for picture recognition helped Shah et al. (2021) create a robot that can distinguish plants from weeds. Precision agriculture was supported by a robotic device that independently identified weeds and plants in real time. The suggested technique may minimise weed identification effort by improving agricultural efficiency and sustainability.

CNN and UAV images were used to create an automated weed identification system by Haq MA (2022). This study found that UAVs with cameras can identify weeds over wide agricultural regions using high-resolution photos. CNNs might distinguish crops from weeds, providing an inexpensive and practical method for real- time weed monitoring in precision farming.

Table 1 Literature Review

Citation	**Author**	**Year**	**Objective**	**Methodology**	**Limitation**

1	Jin X, Che J, Chen Y	2021	To identify weeds in veg- etable planta- tions using deep learning and image processing.	Used CNN to process imag- es for weed identification in real-time.	Limited to veg- etable planta- tions; scalabil- ity issues.
2	Wang A, Zhang W, Wei X	2019	Reviewed ground-based machine vi- sion and im- age pro-cessing techniques for weed detec- tion.	Provided a comprehensive analysis of ex- isting tech- niques and their perfor- mance.	Lack of focus on scalability and real-time application.
3	Kumar KV, Jayasankar T	2019	To detect crop diseases using image seg- mentation techniques.	Applied image segmentation for extracting disease-specific re- gions in crop images.	Limited appli- cation to dis- ease detection; no emphasis on weed identifica- tion.
4	Wu Z, Chen Y, Zhao B	2021	Reviewed weed detec- tion methods using comput- er vision.	Analyzed var- ious computer vision-based weed detection approaches.	Lack of imple- mentation de- tails and real- world applica- tions.
5	Hasan AM et al.	2021	Surveyed deep learning techniques for weed detec- tion from im- ages.	Discussed var- ious deep learning mod- els like CNN, ResNet for weed detec- tion.	Limited to im- age-based ap- proaches; scalability con- cerns.
6	Ferentinos KP et al.	2019	To identify diseases, nu- trient defi- ciencies, and pests in can- nabis plants using deep learning.	Utilized a deep learning model for image- based analysis in cannabis plants.	Focused only on cannabis plants; lacks generalizability to other crops.

7	Naik NS, Chaubey HK	2024	To detect and classify weeds in sesame crops using RCNN.	Used Region- based CNN to identify and classify weeds in sesame crops.	Limited to ses- ame crops; computationally expensive.
8	Meena SD et al.	2023	To improve crop yield by detecting weeds, pests, and diseases.	Integrated weed, pest, and disease detection techniques for crop yield im- provement.	Lack of detailed analysis for in- dividual com- ponents (weeds, pests, diseases).
9	Haq SI et al.	2023	To detect weeds in wheat crops using AI and image analy- sis.	Implemented AI-based weed detection techniques in wheat fields.	Limited evalua- tion metrics for the model's per- formance.
10	Shah TM et al.	2021	To develop a robot for plant and weed identification as an agroeco- logical tool.	Used artificial neural net- works to ena- ble a robot for image-based identification of weeds and plants.	Restricted to experimental setups; real- world applica- tion challenges.

3 Problem Statement

There are different research in area of crop disease detection but there remains need to improve the flexibility as well as scalablity. CNN model used in conventional model where not eligible to provide better accuracy and performance. Thus proposed model is providing advance solution where image are compressed and processed by noise filter to improve the performance and accuracy during image classification for detection of weed based disease detection.

4 Proposed Work

The suggested model for weed-based crop disease diagnosis tackles the constraints of standard CNN models by boosting flexibility and scalability while simultaneously raising accuracy and performance. This model was developed from the ground up. The first step in the process is data collecting, which involves gathering high-resolution photographs of crops that have been impacted by weed-related ill- nesses from a variety of sources, including real-world farm data, ag- ricultural databases, or photos collected by drones. Preprocessing is performed on these pictures, which includes image compression to decrease size without losing important disease-related patterns and noise filtering to remove unnecessary artefacts and improve image quality for correct feature extraction. Both of these features are es- sential for effective feature extraction. In order to highlight disease- specific patterns and get the pictures ready for the classification pro- cess, feature enhancement methods are employed after prepro- cessing. These approaches include contrast normalisation and edge detection, among others. After the pictures have been processed, they are then fed into an enhanced Convolutional Neural Network (CNN) model. This model combines optimised preprocessing layers and innovative architectural characteristics to boost its capacity to successfully diagnose disorders. By overcoming the limitations of traditional CNN models and offering improved performance and us- ability, this all-encompassing process flow offers a cutting-edge so-lution for the diagnosis of agricultural diseases that are caused by weeds.

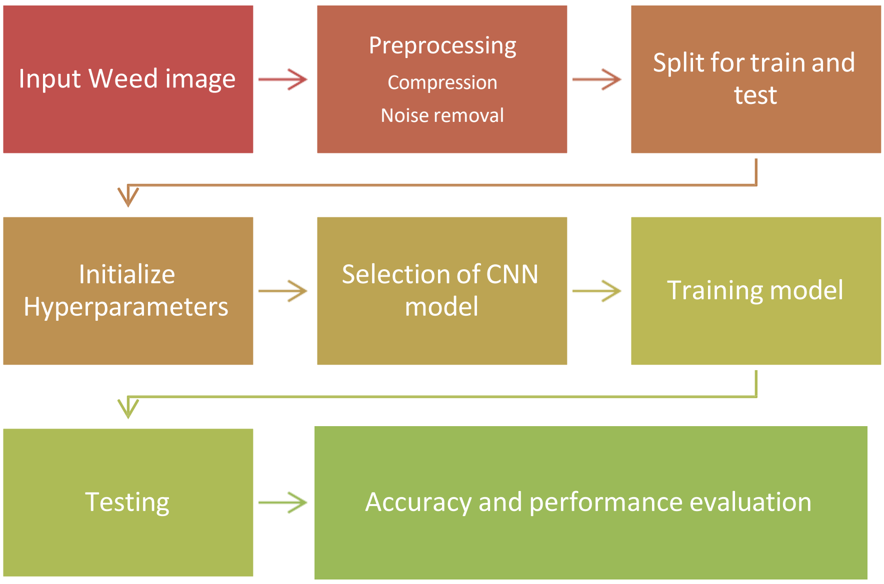

Fig 1 Process flow of work

In proposed work, different models have used hyperparameters such as learning rate, batch size, number of epoch, optimizer, and activation function and dropout layer.

Table 2 Hyper paramter configuration

Model	**Earning rate**	**Batch Size**	**Number of Epochs**	**Optimizer**	**Activation Funding**	**Dropout Rate**
CNN	0.001	32	50	Adam	ReLU	0.25
ResNet	0.001	32	50	Adam	ReLU	0.3
DenseNet	0.0005	32	50	RMSprop	ReLU	0.3
Hybrid	0.0001	64	100	Adam	ReLU	0.4

CNN					Softmax (output)	

Explanation of Parameters:

1. **Learning Rate**: Controls the step size during optimization.
2. **Batch Size**: Number of samples processed before updating the model.
3. **Number of Epochs**: Number of times the entire dataset passes through the model.
4. **Optimizer**: Optimization algorithm used to minimize the loss function.
5. **Activation Function**: Introduces non-linearity into the model.
6. **Dropout Rate**: Proportion of neurons randomly dropped to prevent overfitting.
7. **Loss Function**: Metric to evaluate model performance during training.

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5 Result and Discussion

In simulaiton training accuracy and training loss has been obtained for conventinal CNN, DenseNet, ResNet and Hybrid CNN model. The Hybrid CNN model shows the highest accuracy growth, surpassing the other models as epochs progress. DenseNet and ResNet also demonstrate strong performance, with DenseNet slightly outperforming ResNet. CNN achieves lower accuracy compared to the others, indicating its limitations for this task.

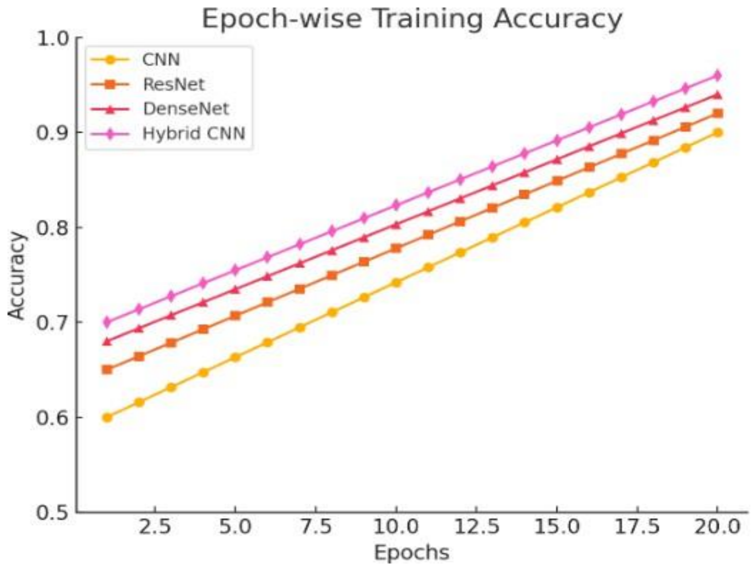

Fig 2 Comparative analysis of epoch wise training accuracy

The Hybrid CNN model has the fastest loss reduction, converging to the lowest loss value. DenseNet and ResNet exhibit steady reductions in loss, with DenseNet achieving slightly better results. CNN's loss decreases more slowly, reflecting its lower overall performance.

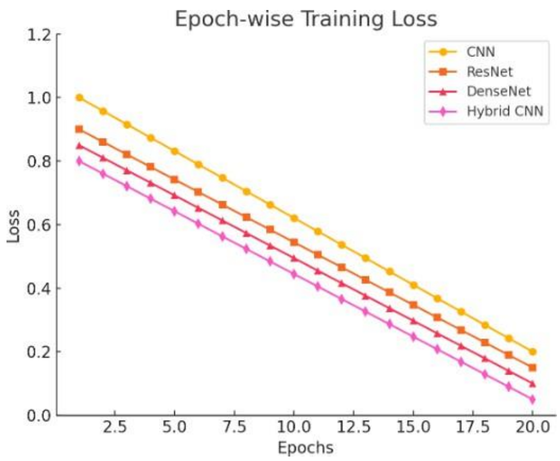

Fig 3 Epoch wise training loss

6 Conclusion

There is a variety of research being conducted in the field of agricultural disease detection; nevertheless, there is still a need to increase both the flexibility and the scalability of the system. The CNN model that was employed in the traditional model was not qualified to give greater accuracy and performance. As a result, the suggested model offers an advanced method in which images are compressed and processed by a noise filter in order to enhance the performance and accuracy of image classification for the purpose of weed-based disease diagnosis. It has been concluded that hybrid model is providing better accuracy as compared to conventional Resnet and Densenet model. Moreover, present work is less time and space consuming. When compared to the traditional Resnet and Densenet models, it has been shown that the hybrid model offers a higher level of accuracy. On top of that, the job that is being done now requires less time and space.

7 Future scope

In future, upcomming research would be capable to use better compression and noise removal. Moreover, those research might provide more flexible and scalable approach. For the foreseeable future, forthcoming studies will be able to make advantage of improved compression and noise reduction techniques. In addition, the study might potentially give a strategy that is more adaptable and scalable.

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