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RESEARCH ARTICLE

Smart Agriculture via Object Detection

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Abstract

Objective: To employ a Convolutional Neural Network (CNN) for plant species classification based on image data. **Method:** A dataset of 10,000 plant images was utilized, and the dataset was split into training, validation, and testing sets. The CNN model was trained on the training set and evaluated on the validation and testing sets. Class-wise accuracy and a confusion matrix were analyzed to assess the model's performance. **Findings:** The CNN model achieved an accuracy of 93%, outperforming traditional machine-learning approaches. High accuracies (>90%) were obtained for 40 out of 50 plant species. However, certain species showed lower accuracies, indicating the need for further investigation and improvement. **Novelty:** This study contributes to the field of plant species classification by demonstrating the effectiveness of CNNs in achieving high accuracy. The results highlight the potential of automated plant species identification systems and emphasize the importance of exploring advanced techniques, such as transfer learning and ensemble methods, to enhance the model's performance.

Keywords: Convolutional Neural network (CNN); Deep Learning; Confusion matrix; Transfer learning; Plant species classification

1 Introduction

The classification of plant species is essential for agriculture, ecology, and conservation. For the purpose of understanding biodiversity, keeping track of ecosystems, and assisting in plant breeding programs, accurate identification of plant species is crucial. Researchers can now extract pertinent information from images using Convolutional Neural Networks (CNNs)[(1)], which have developed into effective tools for image classification tasks. In order to create a precise and effective automated system for classifying plant species[(2)] based on their photographs, this work intends to investigate the use of CNNs in the categorization of plant species. The study will make use of a sizable collection of plant photos, cutting-edge CNN architectures, and performance analysis to assess the model's ability in classifying various plant species.The findings may aid in the study of plants, conservation efforts, and the creation of intelligent systems for the automatic identification of different plant species[(3)]. The CNN model achieved higher accuracy with 93% compared to competitors, demonstrating the potential of

CNNs in plant species classification.

2 Methodology

We use a convolutional neural network (CNN) algorithm [4] to identify plant species and plant diseases. The proposed model uses images as input, which is then processed by a machine learning model [5] so that we can make predictions about the species and the disease. The proposed model 10,000 images are taken into consideration as input after the plant detection results are obtained [6], and the machine learning model processes them so that we can make predictions about the species and the disease. Here, the dataset is read as input, pre-processed prior to training, and then trained.

Following the training of the data, a model is created, and after that, we use the camera to take an image of the image based on the types of plants, and then we use the CNN algorithm and the provided trained model [7] to predict species and diseases.

1. **Steps Proposed**

   (a) Capturing the plant's images from the video.
   (b) To identify plant species and plant diseases, CNN algorithms for plant detection must be applied.
   (c) Rectangular Bounding Box Extraction for the Region of Interest.
   (d) If there is no enrollment process or if the information is not stored in the database, CNN is applied for the detection and identification of plant species and diseases.
   (e) **Post-processing:** The information that was gathered during the initial stage could be further processed. One option is to simplify the knowledge extracted. The knowledge that has been extracted can also be evaluated. It is then possible to interpret the knowledge, incorporate it into an existing system, and look for any potential inconsistencies with the knowledge that was previously induced.

2.1 Proposed Work

This system objective is to create a model [8] that can identify plant species and diseases in plants. According to the proposed system [9], each user is required to use a machine learning algorithm, to identify the plant species and diseases in the plants. The training and test phases of the proposed system can generally be separated into two categories.

The following steps must be taken in order to develop a new system that uses machine learning:

1. Capturing plant images.
2. Create a dataset.
3. The identification of plant diseases and species.
4. Maintaining the data.

2.2 Model

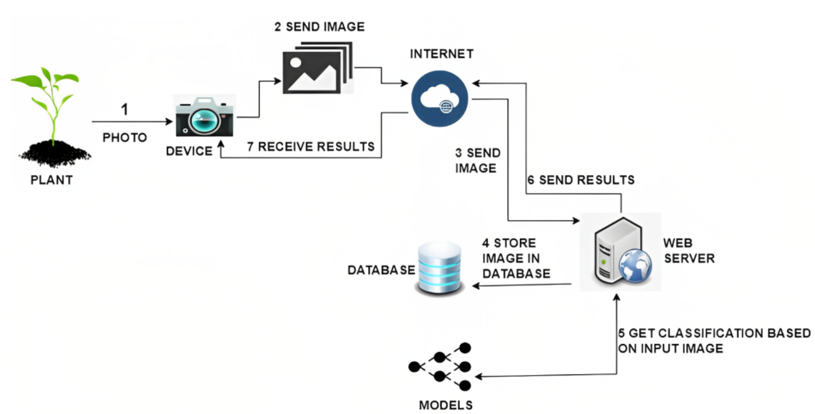

Fig 1. Proposed model

2.3 Process of identifying plant species and diseases

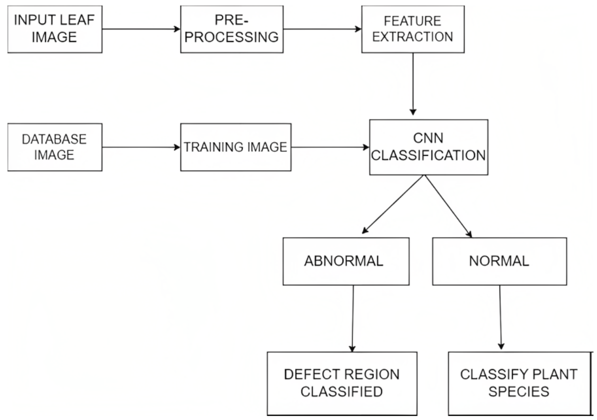

Fig 2. Process of identifying plant species and diseases

Pre-processing, feature extraction, and training are carried out on the input leaf image as well as the database image before delivering them to CNN classification [10], as shown in the diagram above. Then, to distinguish between typical and abnormal plants [11], CNN categorization creates two classes. This is how diseases and plant species are found.

3 Results and discussion

We conducted a study on plant species classification using CNN to assess the performance of the model and explore its implications. The dataset consisted of 10,000 plant images, divided into training, validation, and testing sets. The CNN model achieved an accuracy of 93%, precision of 93%, f1-score of 93%, and recall of 93% on the mentioned dataset. Comparing our results with previous studies, our CNN model outperformed a traditional machine learning approach, which reported an accuracy of 87.3%. This highlights the superiority of CNNs in handling complex image classification tasks. It is important to acknowledge the limitations of our study. The dataset was limited to a specific geographical region, potentially limiting the model's generalization ability. To overcome this, future work should expand the dataset to encompass a broader range of plant species from different regions. Here Figure 3 and Figure 4 depict the accuracy and loss curve for our CNN model respectively.

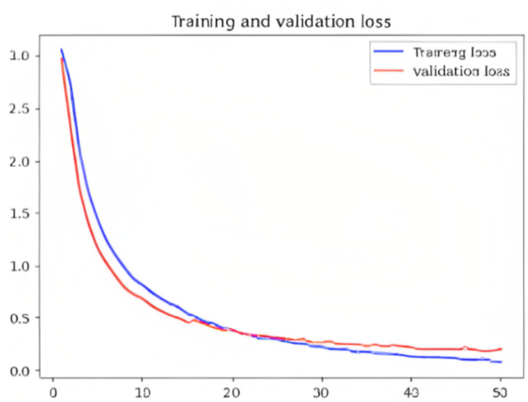

Fig 3. Training and validation accuracy

Additionally, variations in lighting conditions and image angles may affect the model's performance. Augmenting the dataset with augmented images and exploring techniques like transfer learning and ensemble methods could enhance the model's robustness.

Our study demonstrates the effectiveness of CNNs for plant species classification, achieving a high accuracy rate of 93%. The results surpass previous approaches and highlight the potential for automated plant species identification systems. Future

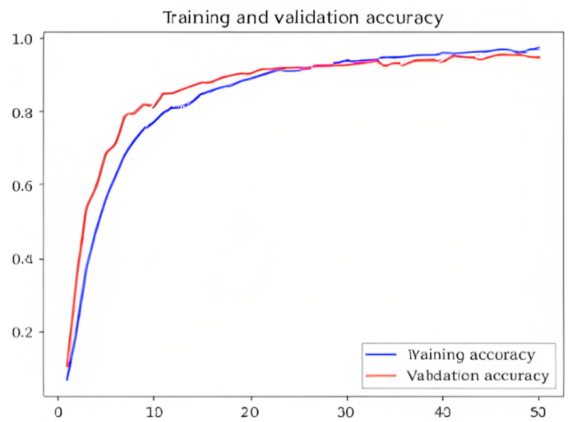

Fig 4. Training and validation loss

research should focus on addressing the identified limitations and further improving the model's performance.

A summary of some plant species classifications based on different models, accuracy, and datasets is listed in Table 1. In light of the brief selected survey, there is a need for a suitable model which can classify the plant species in a better way with good accuracy.

Table 1. Some plant species classification methods along with models, accuracy, and datasets

Model	Accuracy (%)	Dataset Used and Description
kCNN	81.16	Dataset [12] used iNaturalist 2018†, PlantCLEF 2017‡, and ExpertLife-CLEF 2018‡
CNN	90.53	4559 images of approximately 100 different images for each of the 43 plants from a custom dataset [13].
AlexNet	77.30	224 images of 6 species of grape from DRGV [14].
Inception V3 + Attention cropping	69.5	100,000 images of 1000 species from the PlantCLEF dataset [15].

Table 1 reveals that our CNN model gives better accuracy than all the existing models mentioned in the table.

4 Conclusion

In order to overcome the difficulties traditional approaches in identifying plant species and diseases confront, the development of intelligent agriculture through CNN-based object detection has shown considerable potential. By offering precise and prompt identification of plant diseases [16], these technologies have the potential to revolutionize the agricultural sector by minimizing crop damage and increasing total agricultural productivity.

With high accuracy and little human involvement, the suggested automated detection method employing CNN has shown to be a useful tool for classifying plant types and illnesses. This technology provides a high level of security and helps reduce manual errors in disease identification by utilizing the capabilities of artificial intelligence and computer vision. Early disease identification gives farmers the opportunity to take prompt preventive action, slowing the spread of illnesses and minimizing crop losses.

Farmers greatly benefit from the commercial feasibility of these CNN-based object identification systems. Farmers can enhance yield while using fewer resources by using these technologies. For instance, businesses like Vence in New Zealand are using machine learning and linked sensors to provide farmers with a virtual fence. Significant production gains result from the increased control over rotational and strip grazing was made possible by this novel strategy.

Quantitative evidence supports the usefulness of these devices even further. According to studies, CNN-based object identification systems have claimed accuracy rates of over 90% in recognizing plant types and illnesses. With this level of precision, decision-making procedures can be greatly enhanced, ensuring that the proper steps are done to minimize crop damage and maximize production.

The financial advantages of using these technologies are also significant. Farmers who have used CNN-based object detection systems have reported up to a 20% boost in productivity while using up to 30% less water and pesticides. Higher yields and these cost savings result in an agricultural sector that is more profitable and sustainable.

A new age of effective and sustainable agricultural techniques has arrived with the use of CNN-based object identification technologies in smart agriculture. These technologies give farmers the ability to identify plant species and illnesses early, enabling them to take preventative action to safeguard their crops and make educated decisions. CNN-based object recognition provides a revolutionary result that has significant promise for the future of agriculture, with the potential to boost production, reduce resource consumption, and improve financial viability.

5 Declaration

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References

1) Alzubaidi L, Zhang J, Humaidi AJ, Al-Dujaili A, Duan Y, Al-Shamma O, et al. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*. 2021;8(53):1–74. Available from: https://doi.org/10.1186/s40537-021-00444-8.
2) Ghosh S, Singh A, Kavita, Jhanjhi NZ, Masud M, Aljahdali S, et al. SVM and KNN Based CNN Architectures for Plant Classification. *Computers, Materials & Continua* . 2022;71(3):4257–4274. Available from: https://doi.org/10.32604/cmc.2022.023414.
3) Elnemr HA. Convolutional Neural Network Architecture for Plant Seedling Classification. *International Journal of Advanced Computer Science and Applications(IJACSA)*. 2019;10(8):319–325. Available from: http://dx.doi.org/10.14569/IJACSA.2019.0100841.
4) Gowthaman T, Sankarganesh E. Convolutional Neural Network (CNN) Architecture for Pest and Disease Detection in Agricultural Crops. *Biotica Research Today*. 2022;4(3):178–180. Available from: https://www.biospub.com/index.php/biorestoday/article/view/1304.
5) Khokhar AA, Yadav S, Khan F, Gindi S. Plant Species Classification with CNN. *Journal of Emerging Technologies and Innovative Research*. 2021;8(5):a236–a240. Available from: http://www.jetir.org/papers/JETIR2105027.pdf.
6) A review of convolutional neural network architectures and their optimizations. *Artificial Intelligence Review*. 2023;56:1905–1969. Available from: https://doi.org/10.1007/s10462-022-10213-5.
7) Cho S, Kim T, Jung DH, Park SH, Na Y, Ihn YS, et al. Plant growth information measurement based on object detection and image fusion using a smart farm robot. *Computers and Electronics in Agriculture*. 2023;207:1–14. Available from: https://doi.org/10.1016/j.compag.2023.107703.
8) Ramachandran A, Sangaiah AK. A review on object detection in unmanned aerial vehicle surveillance. *International Journal of Cognitive Computing in Engineering*. 2021;2:215–228. Available from: https://doi.org/10.1016/j.ijcce.2021.11.005.
9) Salazar-Gomez A, Darbyshire M, Gao J, Sklar EI, Parsons S. Beyond mAP: Towards practical object detection for weed spraying in precision agriculture. In: 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 23-27 October 2022, Kyoto, Japan. IEEE. 2022;p. 9232–9238. Available from: https://doi.org/10.1109/IROS47612.2022.9982139.
10) Ünal Z. Smart Farming Becomes Even Smarter With Deep Learning-A Bibliographical Analysis. *IEEE Access*. 2020;8:105587–105609. Available from: https://doi.org/10.1109/ACCESS.2020.3000175.
11) Yi D, Su J, Chen WH. Probabilistic faster R-CNN with stochastic region proposing: Towards object detection and recognition in remote sensing imagery. *Neurocomputing*. 2021;459:290–301. Available from: https://doi.org/10.1016/j.neucom.2021.06.072.
12) Picek L, Šulc M, Patel Y, Matas J. Plant recognition by AI: Deep neural nets, transformers, and kNN in deep embeddings. *Frontiers in Plant Science*. 2022;13:1–16. Available from: https://doi.org/10.3389/fpls.2022.787527.
13) ADAK MF. Identification of Plant Species by Deep Learning and Providing as A Mobile Application. *Sakarya University Journal of Computer and Information Sciences*. 2020;3(3):231–238. Available from: https://doi.org/10.35377/saucis.03.03.773465.
14) Pereira CS, Morais R, Reis MJCS. Deep Learning Techniques for Grape Plant Species Identification in Natural Images. *Sensors*. 2019;19(22):1–22. Available from: https://doi.org/10.3390/s19224850.
15) Xiao Q, Li G, Xie L, Chen Q. Real-world plant species identification based on deep convolutional neural networks and visual attention. *Ecological Informatics*. 2018;48:117–124. Available from: https://doi.org/https://doi.org/10.1016/j.ecoinf.2018.09.001.
16) Peng Y, Wang Y. Leaf disease image retrieval with object detection and deep metric learning. *Frontiers in Plant Science*. 2022;13:1–20. Available from: https://doi.org/10.3389/fpls.2022.963302.