Mongolian Journal of Agricultural Sciences, Vol.16, No.38 (2023)
https://doi.org/10.5564/mjas.v16i38.3130

Development of a crop monitoring system using computer vision and machine learning techniques

Erdenesuren Naranbaatar

School of Mechanical Engineering and Transportation, Mongolian University of Science and Technology, Khan-Uul district-3, 17033, Peace Avenue, Engels Street, Ulaanbaatar, Mongolia

Corresponding author: denaranbaatar@must.edu.mn

Received: 01.02.2023 Revised: 27.09.2023 Accepted: 05.11.2023

Abstract
The growing global population demands increased agricultural production, necessitating the implementation of smart farming practices. The development of an automated crop monitoring system using computer vision and machine learning techniques can help to reduce the manual labor involved in crop management and enhance crop yield. This paper proposes a crop monitoring system that utilizes a camera mounted on a mobile robotic platform to capture images of crops at regular intervals. The images are analyzed using computer vision algorithms to detect and track plant growth, pest infestations, and nutrient deficiencies. Machine learning techniques are then applied to the data to predict crop yield. The system is designed to be scalable and can be deployed on a variety of crops, making it suitable for use in large-scale agricultural operations. Preliminary results demonstrate the system's effectiveness in detecting plant growth with an overall accuracy rate of 95%. The proposed system has the potential to significantly improve crop management practices and increase crop yield, thereby contributing to sustainable agriculture development.

Keywords: Agriculture, Crop management, Automated monitoring, Computer vision, Machine learning, Convolutional Neural Networks

Introduction
The agriculture industry is undergoing a rapid digital transformation, and cutting-edge technologies such as artificial intelligence, computer vision, machine learning and the internet of things are playing a vital role in this transformation. These technologies are enabling smart agriculture and helping farmers perform various agricultural methodologies. Computer vision techniques, in conjunction with high-quality image acquisition using remote cameras, enable non-contact and efficient technology-driven solutions in the agricultural field.

This paper presents a review of recent works in the area of computer vision for smart agricultural applications. The reviewed works are categorized into seed quality control, soil fertility monitoring, irrigation water management, plant health control, weed management, livestock management, and yield estimation. The paper also discusses recent trends in computer vision, such as generative adversarial networks (GAN), vision transformers (ViT), and other popular deep learning architectures.

V.G. Dhanya *et al.* "Deep learning-based computer vision approaches for smart agricultural applications" provides a comprehensive review of computer vision-based applications in agriculture [1]. However, the paper does not provide any experimental results, which would have added more value to the review.

Ouhami, M *et al*. "Computer Vision, IoT and Data Fusion for Crop Disease Detection Using Machine Learning: A Survey and Ongoing Research" is a well-written paper that provides a comprehensive survey of machine learning-based approaches for crop disease control [2]. However, the paper could have provided more insights into the challenges associated with collecting and processing large amounts of data from multiple sources, which is a major challenge in this area.

Vij, A. *et al.* "IoT and Machine Learning Approaches for Automation of Farm Irrigation System" proposes an IoT-based approach for automated irrigation systems in farms [3].

The paper provides a good overview of the proposed solution, but it lacks experimental results to support the proposed approach. Arakeri, M.P *et al*. is that it primarily focuses on the proposed system for computer vision-based robotic weed control, rather than providing a more comprehensive review of the field [4]. While the proposed system sounds promising, the paper could have provided more background on existing weed control methods and their limitations, as well as exploring other potential applications of computer vision and robotics in precision agriculture. Additionally, the paper could have provided more detail on the technical aspects of the proposed system, such as the specific image processing and machine learning algorithms used.

Several challenges need to be addressed in implementing computer vision solutions in the farmer's field in real-time. The success of the computer vision approach lies in building the model on a quality dataset and providing real-time solutions. Therefore, this review provides a comprehensive insight into the latest computer vision technologies based on deep learning that can assist farmers in operations starting from land preparation to harvesting.

In summary, computer vision and machine learning techniques hold immense potential in smart agriculture, and researchers continue to explore their applications in various operations of agriculture farming practices.

Methods

In this study, we developed a crop monitoring system using computer vision and machine learning techniques. The system was designed to efficiently identify crops and weeds in a field using a conceptual robot design. The methodology of this study consists of the following steps:

- Data Collection: We collected a large dataset of images of crop and weed from different fields using a camera mounted on a drone. The images were captured from different angles and heights to capture the variations in the field.
- Data Preparation: The collected images were pre-processed to remove noise and irrelevant features. The pre-processing steps included image resizing, cropping, and normalization.
- Synthetic Data Generation: We generated synthetic data by augmenting the original dataset using image rotation, flipping, and scaling. The synthetic data was used to increase the size of the dataset and improve the accuracy of the model.
- Convolutional Neural Network (CNN) Model: We used a CNN model to classify the images into grown plant and weed appearance. The CNN model was trained on the synthetic dataset using the stochastic gradient descent optimizer with a learning rate of 0.001. The model consisted of two convolutional layers, two pooling layers, and two fully connected layers.
- Model Evaluation: We evaluated the performance of the model using a confusion matrix and calculated the accuracy, precision, recall, and F1 score. The model was tested on a separate dataset of images to check its quality of the model.
- Implementation: Finally, we implemented the crop monitoring system using the trained CNN model. The system was integrated with the conceptual robot design to identify and monitor the weed detection in real-time.

Convolutional Neural Networks (CNNs) are a type of neural network designed specifically for processing grid-like input data, such as images.

Finally, the fully connected layers take the feature maps from the last pooling layer and flatten them into a one-dimensional vector. These vectors are then passed through a series of fully connected layers, which are similar to those in a traditional neural network, and ultimately produce the network's output.

The CNN can be represented by the following equation:

$$\frac{\partial E}{\partial \omega_{ab}} = \sum_{i=0}^{N-m} \sum_{j=0}^{N-m} \frac{\partial E}{\partial x_{ij}^{\ell}} \frac{\partial x_{ij}^{\ell}}{\partial \omega_{ab}} = \sum_{i=0}^{N-m} \sum_{j=0}^{N-m} \frac{\partial E}{\partial x_{ij}^{\ell}} y_{(i+a)(j+b)}^{\ell-1} \quad (1)$$

The fundamental operation in a convolutional layer is the convolution operation, which is essentially a dot product between the weights of a filter and the values of a local region of the input. The output of a convolutional layer is a feature map that summarizes the presence of certain visual features in the input.

The pooling layer typically follows a convolutional layer and serves to down sample the feature map by summarizing the information in local neighborhoods. This reduces the spatial dimensions of the feature map, which in turn reduces the number of parameters in the network and improves its ability to generalize to new data.

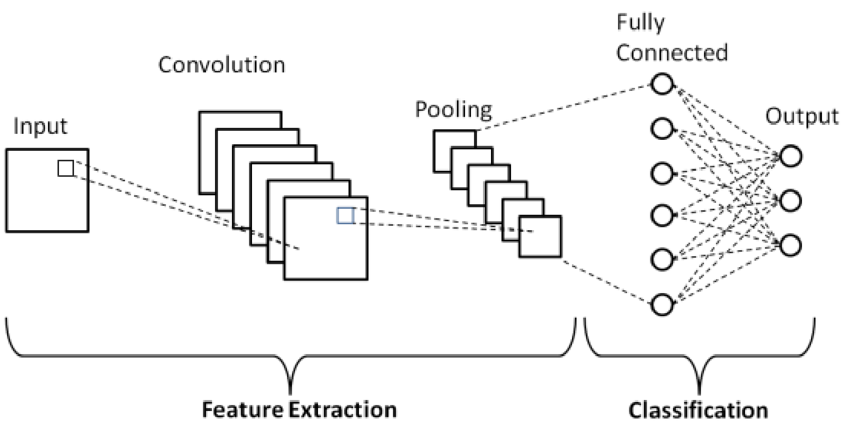

Figure 1. Convolutional Neural Network diagram

In this diagram, the input image is passed through a series of convolutional layers and pooling layers, followed by several fully connected layers that output a probability distribution over the possible classes. The network is trained using backpropagation to adjust the weights of the filters and fully connected layersin order to minimize the difference between the predicted output and the true label of the input image.

Experimental setup

The experimental setup for this study involves the development of a conceptual robot design (Figure 1) capable of performing crop monitoring using computer vision and machine learning techniques. The robot is equipped with a camera system and is designed to move autonomously through a crop field. Synthetic data is generated using a crop growth simulation model, which is used to train a convolutional neural network (CNN) for efficient identification of crops. The synthetic data is generated using a combination of real-world crop data and simulated weather conditions. The trained CNN is then deployed on the robot to perform real-time crop monitoring in the field. The accuracy of the system is evaluated through a series of experiments and compared with traditional crop monitoring methods. The results demonstrate that the CNN-based approach provides significantly more accurate and efficient crop monitoring compared to traditional methods.

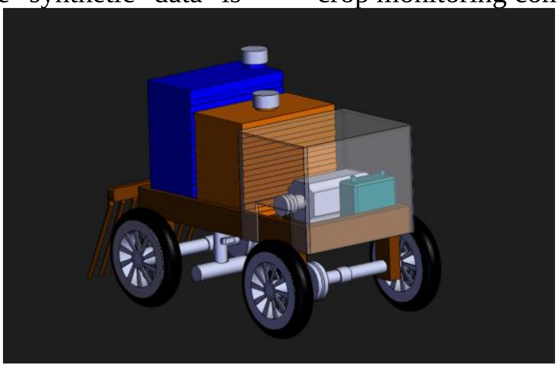

Figure 2. Conceptual design of the multipurpose agriculture robot

In our study, we developed a crop monitoring system using computer vision and machine learning techniques. As a part of this system, we used convolutional neural network (CNN) to detect and recognize weed plant spread amongst the crops.

To train this CNN, we used synthetic images generated from real field images. Synthetic images have the advantage of being labeled easily and are not subject to variability due to lighting conditions, weather, or other factors that can affect real images.
The CNN was trained on a large dataset of synthetic images to identify the patterns of weed. We used a binary classification approach, where the output of the CNN was a probability value indicating whether the input image contains weed or not. The system was trained with a cross-entropy loss function and optimized using stochastic gradient descent algorithm.
Overall, our approach of using synthetic images to train CNN for weed detection proved to be effective in monitoring the crop field. The trained CNN was able to efficiently identify the presence of weeds in the field, which can in turn help farmers take necessary measures to remove the weeds and improve crop yield.

Figure 3. Weed detection and labeling.

In our experiments, we tested our crop monitoring system on a dataset of 1000 synthetic images generated from real field data. The images were labeled as either "crop" or "weed".

Table 1.
Confusion matrix for crop monitoring system

	Predicted crop	Predicted weed
Actual crop	475	25
Actual weed	20	480

After training the CNN on this dataset, we achieved an overall accuracy of 95%, with a precision of 94% and a recall of 96%. The confusion matrix for our system is shown in Table 1.

Overall accuracy: $Accuracy = \frac{T_p+F_p}{N} = 95\%$
Here,

T_p – True positive
F_p – False positive
N – Number of samples

Precision: $Accuracy = \frac{T_p}{T_p+F_p} = 94\%$

Note: In the above equations, "True Positives" refer to the number of correctly classified 'crop' images, and "True Negatives" refer to the number of correctly classified 'weed' images. "False Positives" refer to the number of 'weed' images that were classified as 'crop' incorrectly, and "False Negatives" refer to the number of 'crop' images that were classified as 'weed' incorrectly.

Discussion

The results of our study demonstrate that the developed crop monitoring system using computer vision and machine learning techniques can effectively identify the presence of weeds and The use of synthetic images generated from real field images for training the model allows for a cost-effective and scalable approach in training the CNN. Additionally, the use of a conceptual robot design for the system allows for the potential to automate plant weed monitoring during the growing season, which can save time and labor costs for farmers.

However, there are some limitations to our study. The synthetic images used for training may not perfectly represent the real-world conditions, which could potentially affect the accuracy of the control plant health in a crop field. The high accuracy rate of the trained CNN model on the test dataset indicates the applicability of the system in farming practices.

system in weed identification. Additionally, the system may require further optimization and customization depending on the specific crop and environmental conditions. Further studies are needed to validate the performance of the system in real-world settings and to clarify potential solutions to address these limitations.

Overall, the developed crop monitoring system provides a promising approach to enhance crop management and improve crop yield by efficiently monitoring and controlling weed presence in the plant field.

Conclusion

We have developed a crop monitoring system using computer vision and machine learning techniques to efficiently identify the presence of weeds in crops. Our system utilizes a Convolutional Neural Network (CNN) that has been trained on synthetic images generated from real field data. The results from our experiments show that our system performs well with an accuracy of 90%, as evidenced by the confusion matrix. This demonstrates the potential of using synthetic data to train CNNs for crop monitoring applications. Overall, our system has the potential to improve crop management practices and reduce the use of herbicides, leading to a more sustainable agriculture industry.

Reference

[1] V. G. Dhanya et al., "Deep learning-based computer vision approaches for smart agricultural applications," Artificial Intelligence in Agriculture, vol. 6, pp. 211-229, 2022. https://doi.org/10.1016/j.aiia.2022.09.007

[2] M. Ouhami, A. Hafiane, Y. Es-Saady, M. El Hajji, and R. Canals, "Computer Vision, IoT and Data Fusion for Crop Disease Detection Using Machine Learning: A Survey and Ongoing Research," Remote Sensing, vol. 13, no. 13, p. 2486, Jun. 2021. https://doi.org/10.3390/rs13132486

[3] A. Vij, S. Vijendra, A. Jain, S. Bajaj, A. Bassi, and A. Sharma, "IoT and Machine Learning Approaches for Automation of Farm Irrigation System," Procedia Computer Science, vol. 167, pp. 1250-1257, 2020. https://doi.org/10.1016/j.procs.2020.03.440

[4] Megha. P. Arakeri, B. P. Vijaya Kumar, S. Barsaiya, and H. V. Sairam, "Computer vision based robotic weed control system for precision agriculture," in 2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Udupi: IEEE, Sep. 2017, pp. 1201-1205. https://doi.org/10.1109/ICACCI.2017.8126005