Research on Maize Leaf Counting Based on Target Detection  
The maize Maize is a widely cultivated cereal crop around the world, and its productivity is highly dependent on the number of leaves it produces. Leaf counting is a crucial step in the growth and yield estimation of maize. Traditional methods of manual leaf counting are time-consuming and labor-intensive, which can lead to inaccurate results. To overcome these limitations, research on maize leaf counting based on target detection has been carried out. In this essay, we will discuss the research on maize leaf counting based on target detection and its significance in the field of agriculture.  
  
Target detection is a method of identifying and locating a specific object within an image or video. The technique involves analyzing the visual features of the object, such as its shape, color, and texture, and comparing them to the features of the background. In the case of maize leaf counting, target detection involves identifying and counting the number of leaves present in an image of a maize plant.  
  
Several methods have been proposed for maize leaf counting based on target detection. One such method is the use of machine learning algorithms such as convolutional neural networks (CNNs) and support vector machines (SVMs). These algorithms are trained on a large dataset of maize leaf images, which allows them to accurately identify and count the number of leaves in an image.  
  
Another method is the use of computer vision techniques such as edge detection and image segmentation. Edge detection involves identifying the boundaries of the leaves in an image, while image segmentation involves separating the image into different regions based on their visual features. These techniques can be used to accurately count the number of leaves in an image of a maize plant.  
  
The significance of research on maize leaf counting based on target detection lies in its potential to revolutionize the way maize productivity is estimated. By automating the leaf counting process, farmers and researchers can obtain more accurate and timely information on the growth and development of maize plants. This information can be used to optimize crop management practices such as fertilization, irrigation, and pest control, which can ultimately lead to increased yields and profits for farmers.  
  
Furthermore, the use of target detection in maize leaf counting can help to address the labor shortage in agriculture. With the increasing scarcity of labor in the agricultural sector, automated technologies such as target detection can help to reduce the burden on farmers and make agriculture more attractive to young people.  
  
In conclusion, research on maize leaf counting based on target detection has significant potential to revolutionize the way maize productivity is estimated. By automating the leaf counting process, farmers and researchers can obtain more accurate and timely information on the growth and development of maize plants, leading to increased yields and profits for farmers. The use of target detection in maize leaf counting can also help to address the labor shortage in agriculture and make agriculture more attractive to young people.

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Abstract

This paper proposes an enhanced YOLOv5n model, named CTR\_YOLOv5n, that incorporates a Coordinate Attention (CA) mechanism and a Swin Transformer (STR) detection head to identify common maize diseases, such as leaf spot, gray spot, and rust, in mobile applications. Maize diseases are known to occur frequently and are complicated and difficult to control, which can have a significant impact on maize yield and quality. By building upon the lightweight YOLOv5n model, the accuracy of the CTR\_YOLOv5n model is improved through the addition of a CA attention module, which enhances the model's global information acquisition capabilities by using TR2 as the detection head. The algorithm model achieves an average recognition accuracy of 95.2%, which is 2.8% higher than the original model, and the memory size is significantly reduced to 5.1MB compared to 92.9MB of YOLOv5l, which meets the requirement of being lightweight. Compared with mainstream attention mechanisms like SE, CBAM, and ECA, the CA mechanism used in this model provides better recognition results and higher accuracy, enabling fast and accurate recognition of maize leaf diseases with fewer computational resources. These findings provide new insights and methods for real-time recognition of maize and other crop spots in mobile applications.

Keywords: Maize-Leaf Anomaly; Object Detection; Deep-Learning ; Digital Agriculture

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References

1. Cao, T.; Zhang, X.; Chen, X.; Peng, X.; Lin, J. Maize Disease Classification Method Based on Spatial Attention Mechanism and DenseNet. *Radio Eng.* **2022**, *52*, 1710–1717.
2. Fan, X.; Zhou, J.; Xu, Y.; Peng, X. Maize Disease Recognition under Complicated Background Based on Improved Convolutional Neural Network. *Trans. Chin. Soc. Agric. Mach.* **2021**, *52*, 210–217.
3. Bao, W.; Huang, X.; Hu, G.; Liang, D. Identification of maize leaf diseases using improved convolutional neural network. *Trans.* *Chin. Soc. Agric. Eng.* **2021**, *37*, 160–167.
4. Wang, Y.; Wu, J.; Lan, P.; Li, F.; Ge, C.; Sun, F. Apple disease identification using improved Faster R-CNN. *J. For. Eng.* **2022**, *7*, 153–159. [[CrossRef](http://doi.org/10.13360/j.issn.2096-1359.202104028)]
5. Huang, Y.; Ai, X. Research on Classification of Corn Leaf Disease Image by Improved Residual Network. *Comput. Eng. Appl.*

**2021**, *57*, 178–184. [[CrossRef](http://doi.org/10.3778/j.issn.1002-8331.2105-0321)]

1. Wu, Y. Identification of Maize Leaf Diseases Based on Convolutional Neural Network. *J. Phys. Conf. Ser.* **2021**, *1748*, 032004. [[CrossRef](http://doi.org/10.1088/1742-6596/1748/3/032004)]
2. Wang, C.; Wang, C.; Liu, J. Identification of Maize Leaf Diseases based on Deep Learning. *Mod. Agric. Res.* **2022**, *28*, 102–106. [[CrossRef](http://doi.org/10.19704/j.cnki.xdnyyj.2022.06.020)]
3. Azlah, M.A.F.; Chua, L.S.; Rahmad, F.R.; Abdullah, F.I.; Wan Alwi, S.R. Review on Techniques for Plant Leaf Classification and Recognition. *Computers* **2019**, *8*, 77. [[CrossRef](http://doi.org/10.3390/computers8040077)]
4. Koklu, M.; Unlersen, M.F.; Ozkan, I.A.; Aslan, M.F.; Sabanci, K. A CNN-SVM Study Based on Selected Deep Features for Grapevine Leaves Classification. *Measurement* **2022**, *188*, 110425. [[CrossRef](http://doi.org/10.1016/j.measurement.2021.110425)]
5. Argüeso, D.; Picon, A.; Irusta, U.; Medela, A.; San-Emeterio, M.G.; Bereciartua, A.; Alvarez-Gila, A. Few-Shot Learning Approach for Plant Disease Classification Using Images Taken in the Field. *Comput. Electron. Agric.* **2020**, *175*, 105542. [[CrossRef](http://doi.org/10.1016/j.compag.2020.105542)]

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