JURNAL TEKNOINFO
Volume 20, Number 1, January 2026, Page 93-104
E-ISSN 2615-224X P-ISSN 1693-0010
https://publikasi.teknokrat.ac.id/index.php/teknoinfo/index
DOI: https://doi.org/10.33365/teknoinfo.v20i1.873

Development of a Plant Weed Detection Model Using the Mask R-CNN Algorithm for Smart Farming

Budi Prayitno[1], Pritasari Palupiningsih[2,*], Atam Rifai Sujiwanto[3]
[1,2,3] Teknik Informatika, Institut Teknologi PLN
[1]budiprayitno@itpln.ac.id, [2,*]pritasari@itpln.ac.id, [3]atam1931108@itpln.ac.id

Abstract

A more efficient and sustainable agricultural system is urgently needed during world population growth and global climate change. One of the main challenges is that ineffective weed management can significantly reduce crop yields. Conventional farming methods, such as large-scale herbicide application, also negatively impact the environment. Therefore, the development of smart farming technology based on artificial intelligence (AI) is a crucial innovative solution. This research is urgent in the context of developing AI-based systems that significantly contribute to agricultural technology. The urgency of this study is the creation of a plant weed detection model using deep learning to determine the readiness of planting land with high accuracy values. The importance of this research lies not only in the development of technology, but also in its contribution to the farmer economy and the progress of the agricultural sector in Indonesia. This research aims to build and develop a plant weed detection model using deep learning to determine the readiness of planting land, as well as evaluate the detection model built to produce high accuracy. The research method used follows a flow consisting of problem understanding, data understanding, data preprocessing, modelling, and evaluation. The deep learning method used is object detection by applying the Mask R-CNN algorithm with the ResNet-50 architecture as the backbone. The evaluation of model performance was carried out using Mean Average Precision (MAP). The results of this study demonstrated the development of a deep learning-based weed detection model using the Mask R-CNN algorithm, which achieved a MAP of 37.32 and was able to overcome the challenges of varying weed types, lighting conditions, and complex field conditions.

Keywords: Deep learning; Mask R-CNN; Object detection; Smart farming; Weeds.

1. INTRODUCING

Population growth and global climate change are increasing the need for efficient agriculture, with the main challenge being weed management to maintain crop productivity. Agriculture with the massive use of herbicides, is not only less effective but also has a negative impact on the environment [1], [2]. Smart farming is a promising solution by integrating Internet of Things (IoT) technology and artificial intelligence. This technology ebnables object detection to be used to detect plant weeds more accurately and efficiently[3], [4]. The development of an edge AI device for smart poultry farms exemplifies the potential of deep learning in livestock management, with the model achieving high accuracy in object detection and segmentation [5]. AI-based solutions, especially those that utilize image processing and advanced ML/DL algorithms, offer a transformative approach. This technology overcomes the shortcomings of conventional methods, leading to increased agricultural yields, increased sustainability, and greater food security [6]. However, the application of deep learning models in real-world field conditions faces challenges such as variability of weed types, lighting conditions, and complex

Pritasari Palupiningsih: *Corresponding Author

Volume 20, Number 1, January 2026, Page 93-104
E-ISSN 2615-224X P-ISSN 1693-0010
https://publikasi.teknokrat.ac.id/index.php/teknoinfo/index
DOI: https://doi.org/10.33365/teknoinfo.v20i1.873

backgrounds [7], [8]. Therefore, the development of a weed detection system based on Mask R-CNN needs to be developed more deeply to support the readiness of planting land in smart farming.

Based on the description above, the formulation of this research problem are (a) how to build and develop a plant weed detection model using deep learning to determine the readiness of planting land; (b) how the results of the accuracy of the plant weed detection model built using deep learning. The objectives of this research are (a) to build and develop a plant weed detection model using deep learning to determine the readiness of planting land; (b) evaluate the detection model to produce high accuracy.

This research is urgent in the context of developing artificial intelligence-based systems that make significant contributions to agricultural technology, including: (a) Encouraging precision agriculture automation based on artificial intelligence, (b) reducing the use of harmful herbicides, and (c) optimizing deep learning in smart farming to increase agricultural productivity and maintain environmental sustainability according to the needs of industry 4.0. The urgency of this research is to create an accurate weed detection model based on deep learning, which is further developed through validation, optimization, and integration into smart farming systems to improve agricultural productivity, efficiency, and sustainability.

The development of plant weed detection models using deep learning has become one of the solutions to improve efficiency and sustainability in agricultural systems. Deep learning facilitates early detection of plant diseases, which is important for preventing plant damage. An IoT-based framework using networks in an adaptive multi-scale has been developed to predict diseases, manage pests, and optimize irrigation, thereby improving crop yields and reducing resource use [9]. In this context, it is important to understand that accurate model of plant weed detection not only contributes to increased agricultural productivity but can also reduce dependence on excessive herbicides [10]. In recent years, the initial approach taken involved the use of Convolutional Neural Networks (CNN) algorithms for the classification of weeds and plants. The implementation of deep learning using CNN algorithms can be used to detect plant pests and diseases early and accurately [11]. However, these classification models have limitations, particularly in terms of spatial image segmentation, which limits their application in the field [12].

As object detection technology continues to advance, more complex models such as Faster R-CNN and YOLO have been introduced to improve detection speed and efficiency. While these algorithms demonstrate impressive performance in detecting large objects, their accuracy tends to decrease when encountering small objects, such as weeds, especially in open fields with complex backgrounds [7]. Therefore, to improve detection accuracy, U-Net-based approaches are starting to be in high demand. U-Net has proven to be highly effective in image segmentation, resulting in pixel-by-pixel segmentation, although its reliability is more noticeable in the context of medical imaging with a homogeneous background [8]. Mask R-CNN, especially with a ResNet-50 backbone, is effective for the precise detection of leaf and rust diseases in apple orchards, offering detailed pixel-level classification essential for smart spraying systems and sustainable agriculture [13]. A new approach to detecting hay coverage in agricultural fields. This method is based on an improved Mask Regional Convolutional Neural Network (Mask R-CNN) algorithm, which overcomes the limitations of conventional, time-consuming manual measurement techniques. The improved Mask R-CNN algorithm developed offers a highly accurate and efficient method for detecting hay coverage, providing a significant step forward from manual measurement and offering potential benefits for wider agricultural applications [14]. The Mask R-CNN algorithm, developed as an extension of Faster R-CNN, offers a more adaptive solution for instance segmentation. For example, the Mask R-CNN -based system shows demonstrated performance in detecting and measuring table olives, with strong localization capabilities. While the accuracy of maturity and defect classifications is promising, they present areas for further refinement, especially through

Pritasari Palupiningsih: *Corresponding Author

JURNAL TEKNOINFO
Volume 20, Number 1, January 2026, Page 93-104
E-ISSN 2615-224X P-ISSN 1693-0010
https://publikasi.teknokrat.ac.id/index.php/teknoinfo/index
DOI: https://doi.org/10.33365/teknoinfo.v20i1.873

advanced classification techniques and optimization for embedded hardware [15]. By adding segmentation branches for each proposed object, the Mask R-CNN can generate bounding boxes and masks simultaneously, making it particularly suitable for plant weed detection applications. Research shows that Mask R-CNN can achieve higher accuracy than YOLOv5 in the context of UAV imagery [16]. However, the effectiveness of the Mask R-CNN is highly dependent on the quality of the dataset used, the augmentation process applied, as well as the proper hyperparameter settings [17]. The creation of a much-needed dataset for the segmentation of strawberry disease samples and the successful application of the Mask R-CNN -based model that achieved high accuracy in identifying and segmenting these diseases in complex environments [18]. In the evaluation of the weed detection model, the use of Mean Average Precision (MAP) is a method to assess the detection performance of objects. Adaptive augmented data as well as precise backbone selection, such as ResNet-50, can significantly improve detection accuracy, especially in varying lighting and background conditions [19]. The novelty in this study lies in the development of specific datasets for weed imagery of water spinach plants in Indonesia, the development of a detection model using the Mask R-CNN algorithm with a ResNet-50 backbone, and the evaluation of model performance using mAP under various real conditions. It aims to create an accurate weed detection model with a variety of complex field conditions [20].

2. METHODOLOGY

This study uses a structured methodological approach to solve the existing research problems. This study uses an experimental research method with a deep learning model development approach for weed detection in kale plants. The experimental method was chosen because it allows hypothesis testing through systematic control of variables and measurement of outcomes in a controlled environment[21]. Experimental research in deep learning requires a design that accommodates the iterative process of model development, validation, and performance evaluation [22]. The research design follows the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, which has been proven effective in developing machine learning models for agricultural applications [23]. This framework consists of five phases: problem understanding, data understanding, data preprocessing, modeling, and evaluation. The intended application of deep learning is to apply the Mask R-CNN algorithm. This research uses a structured methodological approach to solve existing research problems. The intended application of deep learning involves the Mask R-CNN algorithm. In this study, the ResNet50 architecture will also be used to obtain an optimal detection model. The plant object used in this study is the water spinach plant. The following image is a research flow diagram compiled.

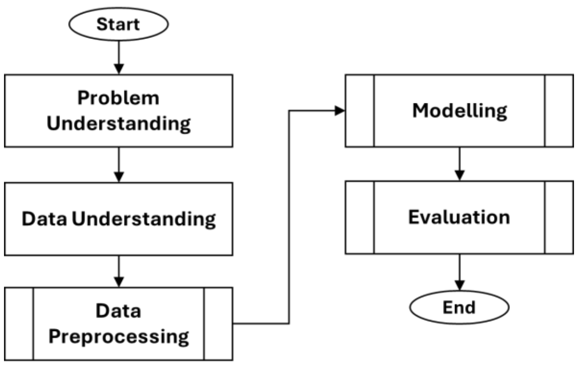

Figure 1. Research Methods

Pritasari Palupiningsih: *Corresponding Author

Volume 20, Number 1, January 2026, Page 93-104
E-ISSN 2615-224X P-ISSN 1693-0010
https://publikasi.teknokrat.ac.id/index.php/teknoinfo/index
DOI: https://doi.org/10.33365/teknoinfo.v20i1.873

The flow diagram consists of 5 stages, including *problem understanding, data understanding, data preprocessing, modeling*, and *evaluation*.

1. *Problem Understanding*

   At this stage, context and problems related to plant weed detection are identified. This refers to the application of *deep learning* in the creation of object detection models using the Mask R-CNN algorithm. In addition, a literature analysis related to the application of deep learning for object detection based on images with high accuracy results was also carried out.

2. *Data Understanding*

   The data understanding stage begins with collecting data on the weed imagery used and studying the data to improve the quality of the data. The data used is data on weed image of water spinach plants, with the following samples.

Figure 2. Weed Image

The data collected in the form of images or images that have a .jpg format and later in the detection process will be classified into 3, namely flat-leaved weeds (*Cyperus rotundus*), broad-leaved weeds (*Physalis longifolia*), and compound-leaved weeds (*Phyllanthus urinaria* and *Raphanus sp*).

3. Data Preprocessing

   At this stage, the process of image data selection, image data division, and image augmentation is carried out to expand the data set, as follows.

   a. Image selection

      Image selection is used to ensure the validity and relevance of the image data used. The weed images taken in this data set are only data sets that appear on water spinach plants and the selection of data that has good quality from the results of data collection independently.

   b. Resize an image

      At this stage, the total processed data is 250 *datasets*, with sizes of 512x600 *pixels*, 1080x1900 pixels, and 800x600 *pixels*. All the data is resizing to 512x512 *pixels* with the aim of making the training process easier and speeding up the model training time by reducing the complexity of the model.

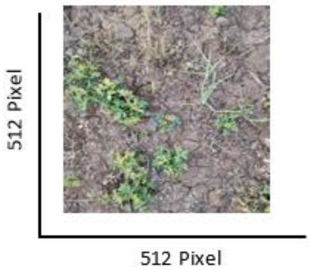

Figure 3. Image pixel size 512 x 512

Pritasari Palupiningsih: *Corresponding Author

JURNAL TEKNOINFO
Volume 20, Number 1, January 2026, Page 93-104
E-ISSN 2615-224X P-ISSN 1693-0010
https://publikasi.teknokrat.ac.id/index.php/teknoinfo/index
DOI: https://doi.org/10.33365/teknoinfo.v20i1.873

The total after performing the image augmentation process is 486 image data and there are 1472 objects obtained.

c. Data labeling

This stage is data labeling because it is to tell the position of the image by adding *masking, bounding boxes* and labels to each weed object.

d. *Data Splitting* /Image data splitting

The image data division stage was carried out by dividing *486 datasets* into three parts, namely *data validation* (5%), *testing data* (15%), and *training data* (80%).

e. Data Augmentation

This stage is carried out by multiplying image data by manipulating data on the image such as, rotating the image, enlarging the image, flipping the image, mirroring the image, giving a *shread* to the image, rotating the image, cropping the image and adjusting the exposure level on the image.

4. Modelling

This stage involved creating a model from Mask R-CNN object detection to detect water spinach weeds. The stages are as follows.

a. Input *hyperameter*

This stage begins with entering hyperparameters into the model. Parameters in the model are needed to set the boundaries of the function during the model training process. This will cause the model to fit, so that it will perform at its best during the training process.

b. Model Development Process

The process begins with image input, entering the model for the process of object detection and segmentation. Next, feature extraction was carried out using the ResNet-50 architecture. Then, going into *the Region Proposal Network* (RPN) process to generate a proposal for a region that might contain an object, which is the beginning of object detection, resulting in rough bounding boxes containing potential objects.

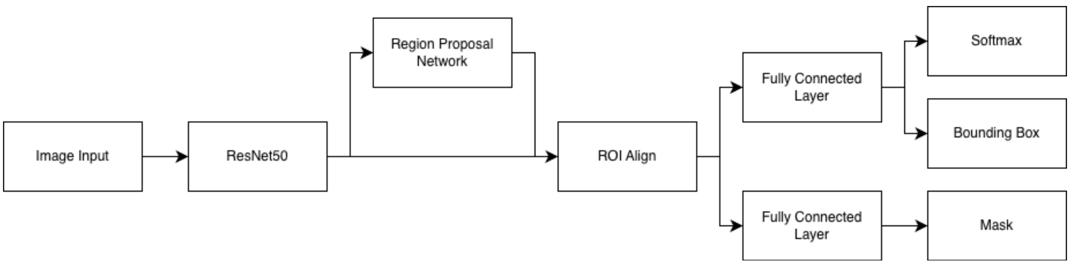

Figure 4. Mask-RCNN Algorithm

Then, Region of Interest Align (ROI Align) performs the process of cutting and adjusting features correlated with the region proposal, so that the features of the region proposal can have a fixed size and are suitable for the next step. Next, Fully Connected Layer is the process of taking the features obtained from ROI Align and processing them further. Then, *Softmax* is used to classify objects in the region proposal into appropriate classes. Then, *the Bounding Box* is a model that predicts the right wrapping box for the object in the region proposal. Finally, *Mask* is modeled to predict pixel-by-pixel masks that identify areas of objects in the proposed region.

c. Model training process

At this stage, the model will perform repeated learning using predetermined iterations. The number of model training processes greatly affects the training

Pritasari Palupiningsih: *Corresponding Author

JURNAL TEKNOINFO
Volume 20, Number 1, January 2026, Page 93-104
E-ISSN 2615-224X P-ISSN 1693-0010
https://publikasi.teknokrat.ac.id/index.php/teknoinfo/index
DOI: https://doi.org/10.33365/teknoinfo.v20i1.873

results, allowing the model to perform at its best. In addition, adequate hardware resources are required to train the model.

5. *Evaluation*

At this stage, the results of the training process will be described in detail based on the model's performance. This evaluation is carried out by observing each iteration of the model training process.

a. Converting training results into curves

This stage tries to visualize the results of the model learning process from each iteration with saveral parameters that have been determined in the hyperparameter determination section of the model in the previous stage. The goal is to make it easier to observe the results of the model process that has been successfully trained using imagery in the training data group

b. Testing with *the Mean Average Precision* (MaP) model

This stage begins by comparing with the ground truth/background for each object class. Then, the precision-recall value is calculated for each class based on the comparison results. The final step is to calculate the average precision value across all recalls for all existing object classes. The higher the MaP value, the better the performance of the object detection model in detecting and positioning the object correctly.

3. RESULTS AND DISCUSSIONS

3.1. Data Collection

The data collected in the form of images included flat-leaved weeds, broad-leaved weeds, and weeds with jointed leaves. This data is a combination of primary data and data sets obtained from similar studies, total 255. Based on the data collection results, the data was categorized into three groups, namely flat-leaved weeds, broad-leaved weeds, and jointed-leaved weeds. After the augmentation process, the total number of images used in the study increased to the following:

Table 1. Categories and the amount of data after data augmentation process

Yes	Objects	Quantity
1	Flat-leaved weeds	487
2	Broad-leaved weeds	513
3	Jointed-leaved weeds	472
	Total	1472

Thus, images were obtained with groups of flat-leaved weeds having 487 objects, broad-leaved weeds having 513 objects, and jointed-leaved weeds having 472 objects. The total number of image object classes is 1472, with all data in *.jpg format. In this study, it should be noted that in one image there may be more than one object class, so that from a total of 486 object data, there are 1472 object data.

Pritasari Palupiningsih: *Corresponding Author

JURNAL TEKNOINFO
Volume 20, Number 1, January 2026, Page 93-104
E-ISSN 2615-224X P-ISSN 1693-0010
https://publikasi.teknokrat.ac.id/index.php/teknoinfo/index
DOI: https://doi.org/10.33365/teknoinfo.v20i1.873

Table 2. Sample data image

No	Categories	Image
1	Broad-leaved weeds	 
2	Flat-leaved weeds	 
3	Jointed-leaved weeds	 

The class of broad-leaved weeds is grouped based on the shape of the leaf that has a single branch with a single leaf, characterized by curved leaf bones. Meanwhile, in the flat-leaved weed class, grouping is carried out based on the shape of the leaves with the leaves that are parallel and tend to be elongated, although not wide. Furthermore, for the Jointed-leaved weeds class, images are grouped based on a single leaf stalk containing more than one leaf. In this experiment, 80% of the dataset was used for model training, consisting of 388 image data. The testing data used 5% of the entire dataset, consisting of 26 image data, while the validation data used 15% of the entire data, consisting of 72 image data.

3.2. Model Development

Model development is necessary to describe the model used. This stage is carried out by processing data using the Mask R-CNN algorithm with the Resedual Network 50 (ResNet-50) architecture. The results of the model development experiment conducted with the Mask R-CNN algorithm using a 512 x 512 x 3 image input. The Mask R-CNN algorithm used is as follows.

Pritasari Palupiningsih: *Corresponding Author

JURNAL TEKNOINFO
Volume 20, Number 1, January 2026, Page 93-104
E-ISSN 2615-224X P-ISSN 1693-0010
https://publikasi.teknokrat.ac.id/index.php/teknoinfo/index
DOI: https://doi.org/10.33365/teknoinfo.v20i1.873

Layer	Output Size	ResNet-50
Input image	750 x 600	-
conv1	375 x 300 x 64	7 x 7, 64, stride 2
conv2	188 x 150 x 256	3 x 3 max pool, stride 2 1x1, 64 [3x3, 64] x 24 1x1, 256
conv3	94 x 75 x 512	1x1, 128 [3x3, 128] x 46 1x1, 512
conv4	47 x 38 x 1024	1x1, 256 [3x3, 256] x 52 1x1, 1024
conv5	94 x 75 x 512	1x1, 128 [3x3, 128] x 46 1x1, 512
conv6	47 x 38 x 1024	1x1, 256 [3x3, 256] x 52 1x1, 1024

Figure 5. R-CNN Algorithm

From the above experiment it is created with hyperparameters like the table below. Hyperparameter determination is carried out by trial-and-error method to obtain the best hyperparameters.

Table 3. Hyperparameter

Yes	*Hyperparameter*	*Value*	Remarks
1	check_point	300	A pre-trained model that is used to continue training or inference.
2	data_loader_worker	2	Number of input functions used to load data during training
3	batch_size	2	Number of samples processed in a single iteration of training
4	learning_rate	0.00002	Step size that determines how much the model is updated during training
5	Epochs	7500	Number of training iterations across datasets
6	Batch_size_ROI	128	Number of regions of interest processed in a single iteration of training
7	Class_detection	4	Number of object classes detected by the model

3.3. Training Model

The training model using the Mask R-CNN algorithm was performed with 7500 epochs, as shown in the table below:

Table 4. Training

No	Epochs	Box_loss_train	Box_loss_validation
1	500	0.8363	0.7440
2	1000	0.7315	0.8268
3	1500	0.7061	0.7167

Pritasari Palupiningsih: *Corresponding Author

JURNAL TEKNOINFO
Volume 20, Number 1, January 2026, Page 93-104
E-ISSN 2615-224X P-ISSN 1693-0010
https://publikasi.teknokrat.ac.id/index.php/teknoinfo/index
DOI: https://doi.org/10.33365/teknoinfo.v20i1.873

No	Epochs	Box_loss_train	Box_loss_validation
4	2000	0.5160	0.586
5	2500	0.5169	0.4627
6	3000	0.3921	0.3728
7	3500	0.3387	0.3500
8	4000	0.3733	0.4159
9	4500	0.4018	0.3309
10	5000	0.3299	0.3347
11	5500	0.3891	0.3544
12	6000	0.3588	0.3448
13	6500	0.3246	0.4241
14	7000	0.2906	0.4153
15	7500	0.3487	0.4343

If plotted, it will produce the following graph:

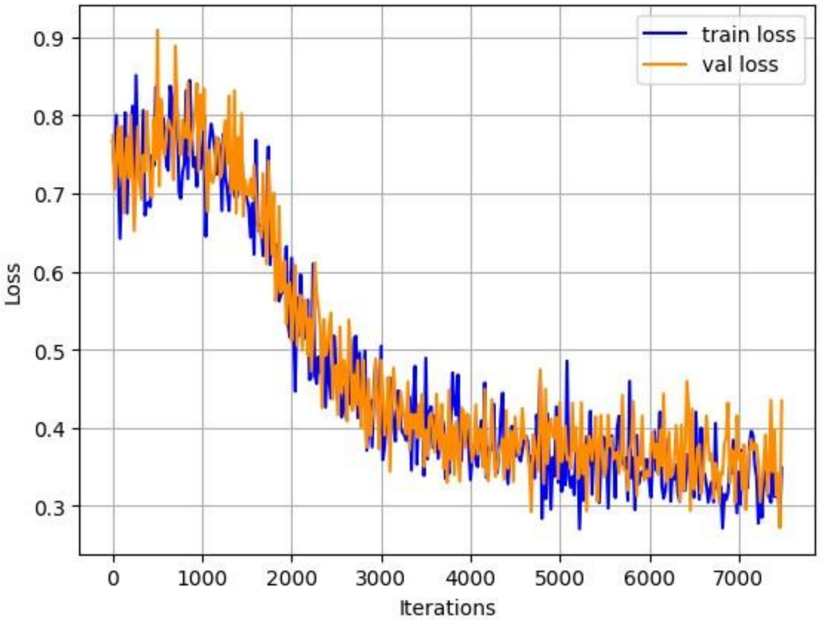

Figure 6. Results graph

The table above shows the training results of the Mask R-CNN model with the training box loss metric on the training and validation datasets for each different number of epochs. The model experienced an increase in performance along with an increase in the number of epochs at the beginning of training. However, after reaching a certain point, the increase in performance slowed down and the box loss on the validation data also showed greater variation. This indicates that the model may experience overfitting on the training data as the number of epochs increases. Therefore, in this model, to obtain optimal training results, the model was stopped at 4500 epochs. The Mask R-CNN training process took approximately 1 hour, 1 minute, and 10 seconds. During training, the model built using device resources consumed approximately 3.6 GB of the total 16 GB capacity on the dedicated GPU on the device used. These results show that Mask R-CNN model training can be carried out efficiently by utilizing available computing resources.

Pritasari Palupiningsih: *Corresponding Author

Volume 20, Number 1, January 2026, Page 93-104
E-ISSN 2615-224X P-ISSN 1693-0010
https://publikasi.teknokrat.ac.id/index.php/teknoinfo/index
DOI: https://doi.org/10.33365/teknoinfo.v20i1.873

3.4. Testing

During the testing process, a function from the detectron2 library was used. Model testing was conducted with variations in Intersection of Union (IoU), which was performed repeatedly to generate Average Precision (AP).

Table 5. Average Accuracy

	Category		
	Flat	**Broad**	**Jointed**
AP	20,358	46,338	45,302

$$MAP = \frac{AP_{(flat+broad+jointed)}}{3}$$

$$MAP = \frac{20{,}358 + 46{,}338 + 45{,}302}{3}$$

$$MAP = 37{,}32$$

The AP values for each identified category of objects for which AP is measured are: "flat," "broad," and "jointed." "Flat" has an AP value of 20,358, "broad" has the highest AP value of 46,338, and "jointed" has an AP value of 45,302. A high AP value indicates that the model performs well in detecting and recognizing objects in that category and segmenting objects appropriately. From the Avarage Precision data of the experiment above, it produced a MAP of 37.32.

4. CONCLUSION

This study aims to develop a weed-detection model for kale plants using the Mask R-CNN deep learning algorithm to assess the readiness of the planting land and evaluate the performance of the built model. The results show that the Mask R-CNN-based weed detection model with the ResNet-50 architecture was successfully developed and implemented to address the main challenges in weed management in conventional agriculture. The results of the weed detection model using Mask R-CNN showed that it was successfully built in 1 hour, 1 minute, and 10 seconds. When creating the model, the GPU memory used during training was 6.4 GB / 16 GB, and to obtain optimal training results, the model was stopped at 4500 epochs of training. The resulting MAP of this model was 37.32. The best performance was in the broadleaf weed category (46.338) and compound leaf weeds (45.302). However, it still faces challenges in detecting flat-leaf weeds that closely resemble kale plants. Optimal condition stopping at epoch 4500 successfully prevented overfitting, resulting in a more robust model under real-world conditions. The results of this study have significant implications for supporting the development of smart agricultural systems in Indonesia that are more efficient, sustainable, and environmentally friendly, while also potentially increasing agricultural productivity and farmer welfare by optimizing the use of agricultural resources.

5. ACKNOWLEDGMENT

The author would like to express his deepest gratitude to the Ministry of Research, Technology, and Higher Education of the Republic of Indonesia for its financial support through the Beginner Lecturer Research Grant (Penelitian Dosen Pemula 2025). This support has been essential in facilitating this research. Furthermore, the author would like to express his appreciation to the LPPM (Institute of Technology) of the PLN Institute of Technology for its support throughout the research

Pritasari Palupiningsih: *Corresponding Author

JURNAL TEKNOINFO
Volume 20, Number 1, January 2026, Page 93-104
E-ISSN 2615-224X P-ISSN 1693-0010
https://publikasi.teknokrat.ac.id/index.php/teknoinfo/index
DOI: https://doi.org/10.33365/teknoinfo.v20i1.873

6. REFERENCES

[1] R. Mathur, "Artificial Intelligence in Sustainable Agriculture," *IJRASET*, vol. 11, no. 6, pp. 4047–4052, Jun. 2023, doi: 10.22214/ijraset.2023.54360.

[2] O. B. Akintuyi, "The Role of Artificial Intelligence in U.S. Agriculture: A Review: Assessing advancements, challenges, and the potential impact on food production and sustainability," *Open Access Res. J. Eng. Technol.*, vol. 6, no. 2, pp. 023–032, Apr. 2024, doi: 10.53022/oarjet.2024.6.2.0017.

[3] P. R. Bhagat, F. Naz, and R. Magda, "Artificial intelligence solutions enabling sustainable agriculture: A bibliometric analysis," *PLoS ONE*, vol. 17, no. 6, p. e0268989, Jun. 2022, doi: 10.1371/journal.pone.0268989.

[4] N. Naman, J. T. G, J. K. Bhatia, N. Bhardwaj, and R. Rahul, "Utilizing artificial intelligence (AI) for sustainable agriculture: Precision farming as a catalyst for environmental conservation," *Int. J. Agric. Extension Social Dev.*, vol. 7, no. 3, pp. 405–409, Mar. 2024, doi: 10.33545/26180723.2024.v7.i3e.441.

[5] S. Cakic, T. Popovic, S. Krco, D. Nedic, D. Babic, and I. Jovovic, "Developing Edge AI Computer Vision for Smart Poultry Farms Using Deep Learning and HPC," *Sensors*, vol. 23, no. 6, p. 3002, Mar. 2023, doi: 10.3390/s23063002.

[6] A. Kaur *et al.*, "Artificial Intelligence Driven Smart Farming for Accurate Detection of Potato Diseases: A Systematic Review," *IEEE Access*, vol. 12, pp. 193902–193922, 2024, doi: 10.1109/ACCESS.2024.3510456.

[7] M. Nishio, S. Noguchi, and K. Fujimoto, "Automatic Pancreas Segmentation Using Coarse-Scaled 2D Model of Deep Learning: Usefulness of Data Augmentation and Deep U-Net," *Applied Sciences*, vol. 10, no. 10, p. 3360, May 2020, doi: 10.3390/app10103360.

[8] A. F. I. Osman, N. M. Tamam, and Y. A. M. Yousif, "A comparative study of deep learning-based knowledge-based planning methods for 3D dose distribution prediction of head and neck," *J Applied Clin Med Phys*, vol. 24, no. 9, p. e14015, Sep. 2023, doi: 10.1002/acm2.14015.

[9] B. Padmavathi, A. BhagyaLakshmi, G. Vishnupriya, and K. Datchanamoorthy, "IoT-based prediction and classification framework for smart farming using adaptive multi-scale deep networks," *Expert Systems with Applications*, vol. 254, p. 124318, Nov. 2024, doi: 10.1016/j.eswa.2024.124318.

[10] H. Ko *et al.*, "A Deep Residual U-Net Algorithm for Automatic Detection and Quantification of Ascites on Abdominopelvic Computed Tomography Images Acquired in the Emergency Department: Model Development and Validation," *J Med Internet Res*, vol. 24, no. 1, p. e34415, Jan. 2022, doi: 10.2196/34415.

[11] C. L. Nazalia, P. Palupiningsih, B. Prayitno, and Y. S. Purwanto, "Implementation of Convolutional Neural Network Algorithm to Pest Detection in Caisim," in *2023 International Conference on Computer Science, Information Technology and Engineering (ICCoSITE)*, Jakarta, Indonesia: IEEE, Feb. 2023, pp. 609–614. doi: 10.1109/ICCoSITE57641.2023.10127792.

[12] L. Zimmermann, E. Faustmann, C. Ramsl, D. Georg, and G. Heilemann, "Technical Note: Dose prediction for radiation therapy using feature-based losses and One Cycle Learning," *Medical Physics*, vol. 48, no. 9, pp. 5562–5566, Sep. 2021, doi: 10.1002/mp.14774.

[13] G. Storey, Q. Meng, and B. Li, "Leaf Disease Segmentation and Detection in Apple Orchards for Precise Smart Spraying in Sustainable Agriculture," *Sustainability*, vol. 14, no. 3, p. 1458, Jan. 2022, doi: 10.3390/su14031458.

[14] Y. Shao *et al.*, "Detection of Straw Coverage under Conservation Tillage Based on an Improved Mask Regional Convolutional Neural Network (Mask R-CNN)," *Agronomy*, vol. 14, no. 7, p. 1409, Jun. 2024, doi: 10.3390/agronomy14071409.

Pritasari Palupiningsih: *Corresponding Author

JURNAL TEKNOINFO
Volume 20, Number 1, January 2026, Page 93-104
E-ISSN 2615-224X P-ISSN 1693-0010
https://publikasi.teknokrat.ac.id/index.php/teknoinfo/index
DOI: https://doi.org/10.33365/teknoinfo.v20i1.873

[15] M. Macías-Macías, H. Sánchez-Santamaria, C. J. García Orellana, H. M. González-Velasco, R. Gallardo-Caballero, and A. García-Manso, "Mask R-CNN for quality control of table olives," *Multimed Tools Appl*, vol. 82, no. 14, pp. 21657–21671, Jun. 2023, doi: 10.1007/s11042-023-14668-8.
[16] J. S. Buatti *et al.*, "Standardizing and improving dose predictions for head and neck cancers using complete sets of OAR contours," *Medical Physics*, vol. 51, no. 2, pp. 898–909, Feb. 2024, doi: 10.1002/mp.16898.
[17] J. Pan, "Image Segmentation Based On U-Net and Adjusted U-Nets," *HSET*, vol. 85, pp. 316–327, Mar. 2024, doi: 10.54097/accm2w81.
[18] U. Afzaal, B. Bhattarai, Y. R. Pandeya, and J. Lee, "An Instance Segmentation Model for Strawberry Diseases Based on Mask R-CNN," *Sensors*, vol. 21, no. 19, p. 6565, Sep. 2021, doi: 10.3390/s21196565.
[19] D. Nguyen *et al.*, "3D radiotherapy dose prediction on head and neck cancer patients with a hierarchically densely connected U-net deep learning architecture," *Phys. Med. Biol.*, vol. 64, no. 6, p. 065020, Mar. 2019, doi: 10.1088/1361-6560/ab039b.
[20] S. Cai, Y. Tian, H. Lui, H. Zeng, Y. Wu, and G. Chen, "Dense-UNet: a novel multiphoton in vivo cellular image segmentation model based on a convolutional neural network," *Quant Imaging Med Surg*, vol. 10, no. 6, pp. 1275–1285, Jun. 2020, doi: 10.21037/qims-19-1090.
[21] N. Zhu *et al.*, "Deep learning for smart agriculture: Concepts, tools, applications, and opportunities," *International Journal of Agricultural and Biological Engineering*, vol. 11, no. 4, pp. 21–28, 2018, doi: 10.25165/j.ijabe.20181104.4475.
[22] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, Apr. 2018, doi: 10.1016/j.compag.2018.02.016.
[23] F. Martinez-Plumed *et al.*, "CRISP-DM Twenty Years Later: From Data Mining Processes to Data Science Trajectories," *IEEE Trans. Knowl. Data Eng.*, vol. 33, no. 8, pp. 3048–3061, Aug. 2021, doi: 10.1109/TKDE.2019.2962680.

Pritasari Palupiningsih: *Corresponding Author