Matrik: Jurnal Manajemen, Teknik Informatika, dan Rekayasa Komputer
Vol. 24, No. 2, March 2025, pp. 371∼380
ISSN: 2476-9843, accredited by Kemenristekdikti, Decree No: 200/M/KPT/2020
DOI: 10.30812/matrik.v24i2.4284

Image Classification of Poisonous Plants Using the MobileNetV2 Convolutional Neural Network Model Method

Muhammad Furqan Nazuli[1], **Muhammad Fachrurrozi**[1], **Muhammad Qurhanul Rizqie**[1], **Abdiansah**[1], **Muhammad Ikhsan**[2]
[1]Universitas Sriwijaya, Palembang Indonesia
[2]WU Vienna University, Wien, Austria

Article Info

Article history:

Received July 21, 2024
Revised October 29, 2024
Accepted March 15, 2025

Keywords:

Accuracy;
Convolutional Neural Network;
Image Classification;
MobileNetV2;
Poisonous Plants.

ABSTRACT

Poisonous plants can be dangerous for many people, but some can be used as medicines or as pest killers. Some people, especially those in environments with a wide variety of plants, can take advantage of this poisonous plant. Lack of knowledge and information causes the use of this poisonous plant to be inappropriate. This research aims to develop software to classify images of poisonous plants using the Convolutional Neural Network method with the MobileNetV2 model and to compare the accuracy of classification results with various dataset configurations and varying parameters. The research method used is a Convolutional Neural Network, which has relatively high accuracy in classifying various digital images. The data used in this research consists of eight poisonous plants and several non-poisonous plants. The research results on 153 test data show that the accuracy value was 99.34%, precision was 99%, recall was 99%, and F1-Score was 99%. This research contributes to developing software that can quickly provide information and knowledge about poisonous plants, offering a high-accuracy solution for classifying poisonous plants using image data. Furthermore, implementing MobileNetV2 provides an efficient and lightweight model suitable for deployment on mobile devices, enhancing accessibility and usability in the field. The potential applications of this software extend beyond individual use, potentially benefiting agricultural, medical, and educational sectors. Future work will expand the dataset to include more plant species and refine the model to improve its robustness against diverse environmental conditions and image qualities.

Corresponding Author:

Muhammad Furqan Nazuli, +6281366844647,
Information Engineering Study Program, Faculty of Computer Science,
Universitas Sriwijaya, Palembang, Indonesian,
Email: mfnazuli@gmail.com.

How to Cite:
M. Nazuli, M. Fachrurrozi, M. Rizqie, A. Abdiansah, and M. Ikhsan, "Image Classification of Poisonous Plants Using the MobileNetV2 Convolutional Neural Network Model Method", *MATRIK: Jurnal Manajemen, Teknik Informatika, dan Rekayasa Komputer*, Vol.24, No.2, pp. 371-380, March, 2025.

1. INTRODUCTION

Poisonous plants that grow in nature can pose significant dangers to humans and animals [1]. However, certain poisonous plants have medicinal properties or can be used as natural pesticides. Understanding these plants is crucial for both safety and potential benefits. Despite their abundance, many people lack the necessary knowledge to identify and utilize them, leading to unintended harm correctly. This challenge highlights the need for an accurate and efficient method to classify poisonous plants, ensuring their proper identification and usage [2]. To address this challenge of identifying poisonous plants accurately and safely, image processing technology offers a promising solution that can help people recognize these plants without direct contact [3]. Image processing involves identifying objects by matching certain image characteristics to images that have been trained [4]. Image classification is the process of identifying images based on certain features so that they can be grouped into several classes so that each class can describe an entity that has recognizable characteristics [5].

Research related to plant image classification has been carried out previously, classification of poisonous plants based on leaf images using the Backpropagation method shows an accuracy percentage of 95% using four types of datasets and 188 image data [6]. Other research, namely the application of the Principal Component Analysis (PCA) and K-Nearest Neighbors (KNN) algorithms in the classification of poisonous and non-toxic mushroom types, produces an accuracy percentage of 92% using 25 test data [7]. However, both studies only used a few datasets. Some of the following studies used similar datasets but used other machine learning methods [8, 9].

Deep learning is an image classification algorithm that is very popular today [10]. Deep learning is a part of machine learning that is related to algorithms where the way this algorithm works imitates the structure and function of the brain, which is called an artificial neural network [11]. One of the deep learning methods widely used in classification is the convolutional neural network. Research that uses this method is Classification of Plant Types Based on Leaf Images Using the Convolutional Neural Network Method [12] This research proves that the CNN method is capable of classifying plant genera well. The classification results, using 50 new image data to test the model, show that the software's success accuracy is 92%.

CNN is one of the methods that is often used to solve problems related to image classification [13]. Several models are used in the CNN method. The research was carried out with the title disease identification on tomato leaves and cassava leaves based on leaf images using the Android-based Convolutional Neural Network method in the testing process using 3 models on CNN, namely VGG16, InceptionV3, and MobileNet. The results show that the MobileNet model has higher accuracy, namely 95.33%, the InceptionV3 model is 92.67%, and the VGG16 model is 76.67% [14].

The MobileNetV2 model has faster computing speeds. Based on research on face mask image detection using CNN and transfer learning, MobileNetV2 has the fastest computing time, 4081 seconds. It has an accuracy of 0.981 or only a difference of 0.007 compared to the Xception architecture. MobileNetV2 has very good time to performance because its computing time is 4.03 times faster than Xception with an accuracy difference of 0.007 [15].

Based on the explanation above, this research builds software that can classify images of poisonous plants using the Convolutional Neural Network method with the website-based MobileNetV2 model. It aims to develop software for classifying images of poisonous plants and compare the accuracy of results from classifying images of poisonous plants with varying dataset configurations and parameters.

The difference between this research and the previous one is that we focus on classifying images of poisonous plants using the Convolutional Neural Network (CNN) method with the MobileNetV2 model, which previous researchers have not utilized in this context. Research related to plant image classification has been carried out previously, such as the classification of poisonous plants based on leaf images using the Backpropagation method, which showed an accuracy percentage of 95% using 4 types of datasets and 188 image data. Other research, namely applying the Principal Component Analysis (PCA) and K-Nearest Neighbors (KNN) algorithms in classifying poisonous and non-toxic mushroom types, produced an accuracy percentage of 92% using 25 test data. However, both studies only used a few datasets.

This research aims to develop software for classifying images of poisonous plants using the Convolutional Neural Network method with the MobileNetV2 model and to compare the accuracy of results from classifying images of poisonous plants with varying dataset configurations and parameters. A dataset consisting of eight types of poisonous plants and several non-poisonous plants was used to ensure reliable results, with some test data used for accuracy evaluation. The classification performance results show the accuracy magnitude discussed in the following discussion.

2. RESEARCH METHOD

The research method is a process flow carried out to conduct research and as evaluation material in classifying images of poisonous plants using the Convolutional Neural Network method, MobileNetV2 model. The process flow includes collecting data in the form of images of poisonous plants and then pre-processing the data on the images of poisonous plants. Next, a dataset configuration process was carried out by dividing the data into 3 parts to simplify the model training and testing process. Then model training and model testing are carried out to produce the actual level of accuracy.

2.1. Data collection

The data used in this research is secondary data, namely poisonous plants and herbal plants obtained from a website on the Internet. Data on poisonous plants and herbal plants was taken from the Kaggle dataset, which contains several types of poisonous plants and herbal plants taken using several image capture techniques, such as distance, lighting, angle, and background of the object. Images of sample datasets of poisonous plants and herbal plants can be seen in Figure 1.

Figure 1. Example datasets

The two datasets are first combined into one and then carried out pre-processing. This research did not use the entire dataset of raw data, so it only used 495 images. Nine classes result from the pre-processing process with different data divisions according to the specified dataset configuration. After the data sharing was successful, the next step was to increase variations in the amount of data so that the model training process was better, an augmentation process was added with the technique used, namely rotation of 30 degrees. After the augmentation process, the dataset is ready for the model training and testing process. The distribution of the dataset can be seen in Table 1.

Table 1. Dataset Distribution

Data Tanaman	Jumlah Data	Augmentasi
Beracun	440	5.280
Tidak Beracun	55	660
Total	495	5.940

2.2. Pre-Process Data

This process aims to process the dataset into a form that can be used to train the model. There are two stages, namely image resizing and grayscaling. At the image resizing stage, all images with different sizes are reduced and equalized to 224×224 pixels. The next stage is converting the data into grayscaling with an intensity value range between 0-225. From the technical side of image processing, the grayscaling process aims to reduce channels in the image to speed up the image processing process. The data is then divided into classes. There are eight classes of poisonous plants, namely Castor (Castrol Oil), Happy Leaves (Dieffenbachia), Digitalis (Foxglove), Lilies (Lilies), Lily of the Valley, Jepun Flower (Oleander), Rhubarb, Wisteria, and one non-toxic plant class. The data used in this research uses images in jpg format.

2.3. Dataset Configuration

This research compares dataset configurations to get the best accuracy results. This differs from previous research, which used tuning parameters as a differentiator to get the best accuracy. The data is divided into several configurations to see which configuration comparison can produce a better model. Data is divided into training data and test data. The configuration values are used by dividing the two data into three divisions, namely 80:20, 70:30, and 60:40. The training data is divided into two parts, namely training data and validation data, with each data configuration 75:25.

2.4. CNN Architecture

This research uses a new architecture of the CNN method with the MobileNetV2 model to classify poisonous plant images. Figure 2 shows the architecture of the method used. The architecture used in this research uses one convolution layer. The first layer is the input with 224×224 and three color dimensions. The first layer receives input data in the form of an array according to the length of the data after going through data pre-processing. The results of the first convolution create 7×7 pixels with a number of filters 1280. Dropout is added to remove unneeded information features. This results in feature reduction. Dropout is a tuning technique in neural networks where several neurons are selected randomly, and the training process is not used [16]. Dropout has a function to prevent overfitting and speed up the model learning process.

Flatten is added to this architecture. Flatten is a layer used to flatten the data produced by the previous stages into 1 column [17]. Flatten has a function to change image features from three dimensions to one dimension to carry out the classification process. The last layer is fully connected. Fully connected is a layer where all active neurons in the previous layer are connected to neurons in the next layer. Fully connected layers can only be implemented at the end of the network [18]. This layer is built using a softmax activation function to calculate probability values for the output results. The CNN architecture's result is nine neurons. This architecture is expected to be able to carry out classification quickly with better accuracy values than other architectures.

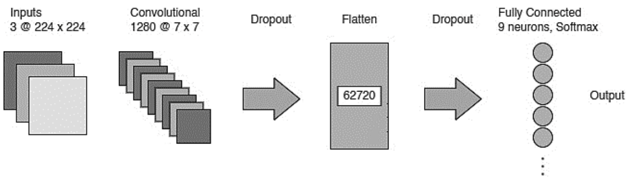

Figure 2. Configuration of the CNN architecture used

2.5. Model Training

The data used to train the MobileNetV2 model is training data containing 8 classes of poisonous plants and 1 class of non-poisonous plants. The MobileNetV2 model learns features from train data and tries to guess the label of each image. The better the classification results, the greater the accuracy value and the smaller the loss value of the model. After obtaining the best results from the training process, the model will be tested, and the final classification results will be obtained.

2.6. Model Testing

In this process, the MobileNetV2 model, which has undergone a training process, is then tested using new data, namely test data for eight classes of poisonous plants and one class of non-toxic plants. The process of testing this model is carried out with predictions and calculated using a confusion matrix so that the actual level of accuracy of the previously trained model can be known. The criteria chosen for testing the model are accuracy, precision, recall, and F1-Score calculations.

Accuracy is the total correct classification carried out by the model as a whole. Accuracy is carried out by comparing data that has been successfully classified correctly with the entire existing data[19]. Precision calculates how often the model makes a positive prediction and how often the prediction is correct. Precision is described by the amount of data in the positive category that is correctly classified and then divided by the total data that is classified as positive [20]. Recall calculates when the actual class produces a positive value and how often the model predicts positive. Recall is also called sensitivity and is described by what percentage of data in the positive category is classified correctly by the model [21]. F1-Score is the harmonic average value of precision and recall. F1-Score is used as a reference if the existing dataset does not approach the number of False Negatives (FN) and False Positives (FP) [22].

3. RESULT AND ANALYSIS

ISeveral experiments in the testing phase use varying dataset configurations. Tests were carried out using test data from 8 classes of poisonous plants and 1 class of non-toxic plants. Table 2 summarizes the configuration information of the dataset used in the research. This research uses the same tunning parameters between the models being trained. The first parameter is a learning rate of 0.0004, and the second parameter is a batch size of 64. The same tunning parameters are used because, in this research, the focus is on finding the best accuracy in the variations in the dataset configuration used.

Table 2. Dataset Configuration Variations

Name	Data Ratio Configuration (Train:Test)
Model 1	60 : 40 (223:74:198)
Model 2	70 : 30 (257:85:153)
Model 3	80 : 20 (297:99:99)

3.1. Model 1 Configuration Results Data

Figure 3 shows the best performance of the model seen from the convergent graph obtained at the 10th epoch with accuracy results for training data of 98.65% and for validation data of 98.99%, Then in the loss graph for each training data and validation data, the results were 0.0242 and 0.0285. the performance results of model 1 on test data with each model performance evaluation measurement metric obtained an accuracy result of 98.99%. For precision, get a value of 0.99. Recall gets a value of 0.99. F1-Score gets a value of 0.99.

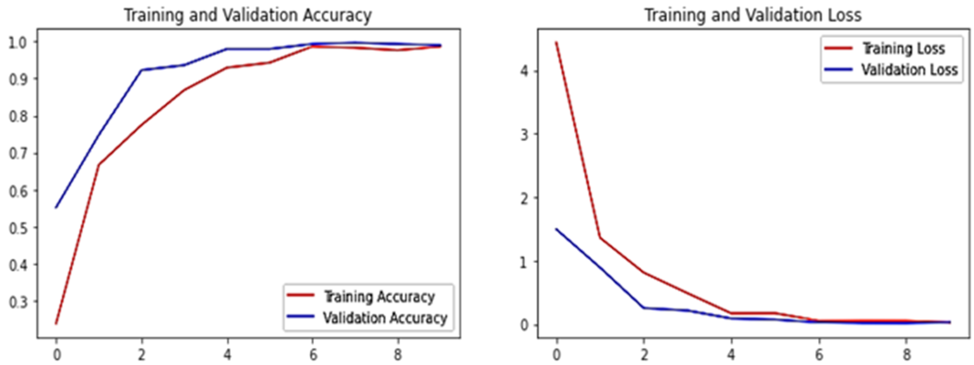

Figure 3. Accuracy measurement results in model 1

3.2. Model 1 Configuration Results Data

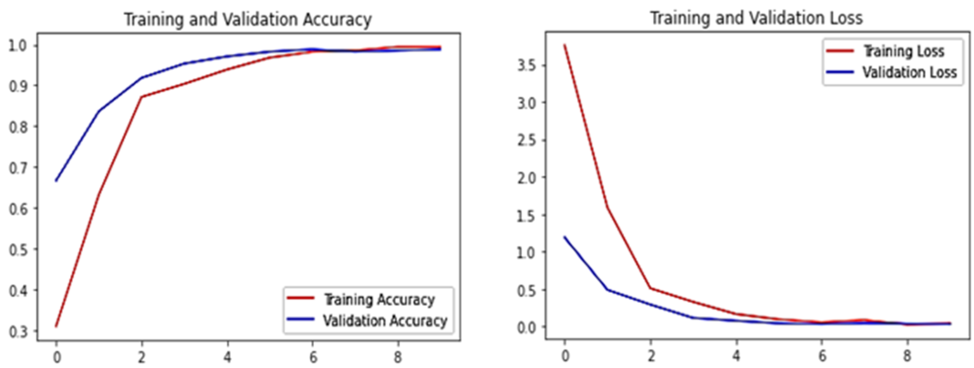

Figure 4. Accuracy measurement results in model 2

Figure 4 shows the best performance of the model seen from the convergent graph obtained at the 10th epoch with an accuracy result of training data of 99.42% and validation data of 98.83%. Then, in the loss graph for each training data and validation data, the results were 0.0395 and 0.0317; the performance results of model 2 on test data with each model performance evaluation measurement metric obtained an accuracy of 99.34%. For precision, get a value of 0.99. Recall gets a value of 0.99. F1-Score gets a value of 0.99.

3.3. Model 3 Configuration Results Data

Figure 5 shows that the best performance of the model, which can be seen from the convergent graph, was obtained at the 10th epoch with accuracy results for training data of 98.74% and for validation data of 99.75%. Then, in the loss graph for each training and validation data, the results were 0.0368 and 0.0065. The performance results of model 3 on test data with each model performance evaluation measurement metric obtained an accuracy result of 98.99%. For precision, get a value of 0.99. Recall gets a value of 0.99. F1-Score gets a value of 0.99.

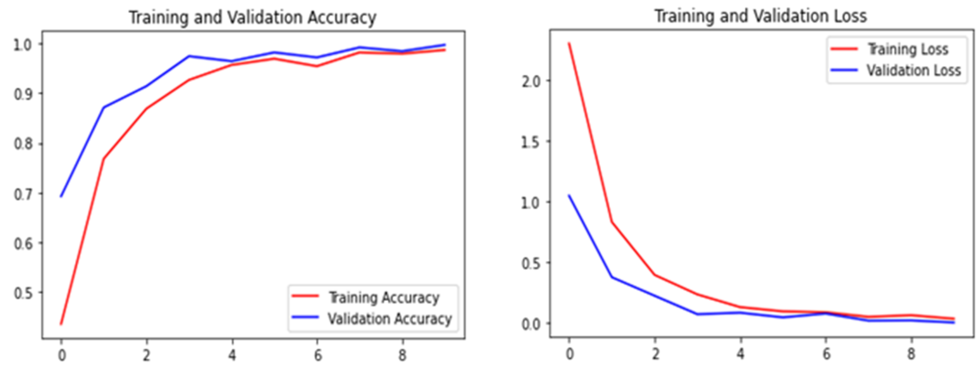

Figure 5. Accuracy measurement results in model 3

3.4. Analysis of Research Results

Several variations of each dataset configuration that were trained, validated, and tested using the MobileNetV2 CNN model method performed differently in classifying poisonous plants. To find the model configuration with the best performance, the average value of the model performance evaluation measurement metrics is measured. The results of the comparison of model performance based on training data and validation data are shown in Table 3.

Table 3. Comparison of Training and Validation Results on The Model

Model	Train_Acc	Val_Acc	Train_Loss	Val_Loss
Model 1	98.65%	98.99%	0.0242	0.0285
Model 2	**99.42%**	**98.83%**	**0.0395**	**0.0317**
Model 3	98.74%	99.75%	0.0368	0.0065

Table 3 shows the variation data from each dataset configuration which has different training and validation performance in the poisonous plant classification process. Model 2 is the best model of several models used. Model 2 has better training data accuracy values even though the validation data accuracy is lower than the other models. The parameters used as a reference for whether the model in this research is good or not are based on the accuracy value of the training data. Model 2 has a training data accuracy of 0.68% greater than the second-best model, namely Model 3. A 0.58% accuracy value cannot be classified by Model 2.

Table 4. Comparison of Test Results on The Model

Model	Accuracy	Precision	Recall	F1-Score
Model 1	98.99%	0.99	0.99	0.99
Model 2	**99.34%**	**0.99**	**0.99**	**0.99**
Model 3	98.99%	0.99	0.99	0.99

Table 4 shows the performance evaluation measurement metrics data. Based on the table results, Model 2 performs better than other models using test data. Model 2 has a stable and higher value compared to the other models. The test accuracy using the test data obtained in Model 2 is 99.34%, outperforming previous state-of-the-art studies in this domain. In comparison, a study by Azadnia et al. [6] reported an accuracy of 95% using four types of datasets and 188 images. Another study by Yan et al. [7] reported an accuracy of 92% using 25 test data. This shows that our approach improves classification performance. However, 0.66% of the models failed to classify because of the 153 images for test data; 1 image data could not be classified correctly by the model, namely the Wisteria class, which was classified into the Foxglove class. This happens because the two classes are similar in shape, and when training the model using grayscale data, the model can only extract features from the shape, not the color. Wisteria and Foxglove have a group shape, so the model fails to carry out 1 classification of image data.

4. CONCLUSION

Based on the results described in the results and discussion section, it can be concluded that applying the Convolutional Neural Network method with the MobileNetV2 model in classifying poisonous plants works quite well. This is proven by the results of the model accuracy percentage of 99.34%. The MobileNetV2 model impacts faster total computing time based on previous research. The model scenario with a 70:30 dataset configuration produces the best accuracy, namely 99.34%. Of the 153 test data images, 0.66% or one image failed to be classified correctly. This is because during pre-processing, the dataset is made into grayscale. At the same time, the characteristics of the failed image are predominantly taken from color, but the shape is almost the same as other types. In measuring the model's success level, a precision value of 0.99, recall of 0.99, and F1-Score of 0.99 were obtained, so it can be concluded that the method and model used in the case study of pictures of poisonous plants can work well. In further research development, more and larger datasets from various sources can be used so that the MobileNetV2 model Convolutional Neural Network method can learn more features, and in using the software, it can be disseminated more widely. However, this study has some limitations. The model's classification performance is highly dependent on grayscale image preprocessing, which reduces the ability to differentiate plants based on color. This could lead to misclassification in cases where shape similarity is high. Additionally, the dataset used in this study may not fully represent the diversity of poisonous and non-poisonous plants in real-world conditions. To keep the accuracy value high and further improve it, future research should consider increasing the dataset size and employing more advanced pre-processing techniques, including color-based feature extraction. Furthermore, future research can create a more balanced dataset of poisonous and non-poisonous plants to enhance model generalization and accuracy when classifying unseen input images.

5. ACKNOWLEDGEMENTS

The author would like to thank the supervisor of the Sriwijaya University Campus, especially the Faculty of Computer Science, Informatics Engineering Study Program, for providing the opportunity and support to carry out this research smoothly. The author also thanks all parties involved in this research.

6. DECLARATIONS

AUTHOR CONTRIBUTION

Muhammad Furqan Nazuli: Conceptualization, Methodology, Analysis, Modeling, Software, Writing - Original Draft M Fachrurrozi: Validation, Review & Editing, Supervision M Qurhanul Rizqie: Validation, Writing - Review & Editing, Supervision Abdiansah: Validation, Review & Editing, Supervision

FUNDING STATEMENT

This research and scientific article were conducted using independent funding from the researchers and the faculty. No external grants or sponsorships were received during the study. The internal resources of the research team and the academic institution fully supported all expenses related to data collection, model development, and publication.

COMPETING INTEREST

This research uses data obtained from an online data center, model comparison, and 3 data configurations to produce an accurate and good model. There is no funding during data collection and processing. Funding for data processing uses independent funds from researchers and the Faculty of Computer Science, Sriwijaya University. All authors contributed to the research and writing of the article following authority and approval for manuscript submission.

REFERENCES

[1] J. Huixian, "The Analysis of Plants Image Recognition Based on Deep Learning and Artificial Neural Network," *IEEE Access*, vol. 8, no. 2, pp. 68 828–68 841, 2020, https://doi.org/10.1109/ACCESS.2020.2986946.

[2] D. Sinaga, C. Jatmoko, and N. Hendriyanto, "Multi-Layer Convolutional Neural Networks for Batik Image Classification," *Scientific Journal of Informatics*, vol. 11, no. 2, pp. 477–484, 2024, https://doi.org/10.15294/sji.v11i2.3309.

[3] S. Manoharan J, "Flawless Detection of Herbal Plant Leaf by Machine Learning Classifier Through Two Stage Authentication Procedure," *Journal of Artificial Intelligence and Capsule Networks*, vol. 3, no. 2, pp. 125–139, 2021, https://doi.org/10.36548/jaicn.2021.2.005.

[4] O. D. Nurhayati, "Pengolahan Citra untuk Identifikasi Jenis Telur Ayam Lehorn dan Omega-3 Menggunakan K-Mean Clustering dan Principal Component Analysis," *Jurnal Sistem Informasi Bisnis*, vol. 10, no. 1, pp. 84–93, 2020, https://doi.org/10.21456/vol10iss1pp84-93.

[5] M. H. IBRAHIM, "WBA-DNN: A hybrid weight bat algorithm with deep neural network for classification of poisonous and harmful wild plants," *Computers and Electronics in Agriculture*, vol. 190, no. 2, pp. 1–10, 2021, https://doi.org/10.1016/j.compag.2021.106478.

[6] R. Azadnia, F. Noei-Khodabadi, A. Moloudzadeh, A. Jahanbakhshi, and M. Omid, "Medicinal and poisonous plants classification from visual characteristics of leaves using computer vision and deep neural networks," *Ecological Informatics*, vol. 82, no. 1, pp. 1–12, 2024, https://doi.org/10.1016/j.ecoinf.2024.102683.

[7] X. Yan, X. Peng, Y. Qin, Z. Xu, B. Xu, C. Li, N. Zhao, J. Li, Q. Ma, and Q. Zhang, "Classification of plastics using laser-induced breakdown spectroscopy combined with principal component analysis and K nearest neighbor algorithm," *Results in Optics*, vol. 4, no. 2, pp. 1–9, 2021, https://doi.org/10.1016/j.rio.2021.100093.

[8] G. Batchuluun, S. H. Nam, and K. R. Park, "Deep learning-based plant classification and crop disease classification by thermal camera," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 10, pp. 10 474–10 486, 2022, https://doi.org/10.1016/j.jksuci.2022.11.003.

[9] T. S. Xian and R. Ngadiran, "Plant Diseases Classification using Machine Learning," *Journal of Physics: Conference Series*, vol. 2, no. 1, pp. 1–13, 2021, https://doi.org/10.1088/1742-6596/1962/1/012024.

[10] K. B. Obaid, S. R. M. Zeebaree, and O. M. Ahmed, "Deep Learning Models Based on Image Classification: A Review," *International Journal of Science and Business*, vol. 4, no. 11, pp. 75–81, 2020, https://doi.org/10.5281/zenodo.4108433.

[11] X. Cao, J. Yao, Z. Xu, and D. Meng, "Hyperspectral Image Classification with Convolutional Neural Network and Active Learning," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 58, no. 7, pp. 4604–4616, 2020, https://doi.org/10.1109/TGRS.2020.2964627.

[12] B. M. Quach, V. C. Dinh, N. Pham, D. Huynh, and B. T. Nguyen, "Leaf recognition using convolutional neural networks based features," *Multimedia Tools and Applications*, vol. 82, no. 1, pp. 777–801, 2023, https://doi.org/10.1007/s11042-022-13199-y.

[13] M. Billah, X. Wang, J. Yu, and Y. Jiang, "Real-time goat face recognition using convolutional neural network," *Computers and Electronics in Agriculture*, vol. 194, no. 5, pp. 1–6, 2022, https://doi.org/10.1016/j.compag.2022.106730.

[14] M. F. Naufal and S. F. Kusuma, "Pendeteksi Citra Masker Wajah Menggunakan CNN dan Transfer Learning," *Jurnal Teknologi Informasi dan Ilmu Komputer*, vol. 8, no. 6, p. 1293, 2021, https://doi.org/10.25126/jtiik.2021865201.

[15] T. Anandhakrishnan and S. M. Jaisakthi, "Deep Convolutional Neural Networks for image based tomato leaf disease detection," *Sustainable Chemistry and Pharmacy*, vol. 30, no. 2, pp. 1–11, 2022, https://doi.org/10.1016/j.scp.2022.100793.

[16] A. Kumar and N. Sachdeva, "Multimodal cyberbullying detection using capsule network with dynamic routing and deep convolutional neural network," *Multimedia Systems*, vol. 28, no. 6, pp. 2043–2052, 2022, https://doi.org/10.1007/s00530-020-00747-5.

[17] H. Ge, Z. Zhu, Y. Dai, B. Wang, and X. Wu, "Facial expression recognition based on deep learning," *Computer Methods and Programs in Biomedicine*, vol. 215, no. 2, pp. 1–9, 2022, https://doi.org/10.1016/j.cmpb.2022.106621.

[18] S. Roopashree, J. Anitha, T. R. Mahesh, V. Vinoth Kumar, W. Viriyasitavat, and A. Kaur, "An IoT based authentication system for therapeutic herbs measured by local descriptors using machine learning approach," *Measurement: Journal of the International Measurement Confederation*, vol. 200, no. 1, pp. 1–15, 2022, https://doi.org/10.1016/j.measurement.2022.111484.

[19] S. Naeem, A. Ali, C. Chesneau, M. H. Tahir, F. Jamal, R. A. K. Sherwani, and M. U. Hassan, "The classification of medicinal plant leaves based on multispectral and texture feature using machine learning approach," *Agronomy*, vol. 11, no. 2, pp. 1–15, 2021, https://doi.org/10.3390/agronomy11020263.

[20] H. Hendriyana and Yazid Hilman Maulana, "Identification of Types of Wood using Convolutional Neural Network with Mobilenet Architecture," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 4, no. 1, pp. 70–76, 2020, https://doi.org/10.29207/resti.v4i1.1445.

[21] N. Pandiangan, M. L. Buono, and S. H. Loppies, "Implementation of Decision Tree and Naïve Bayes Classification Method for Predicting Study Period," *Journal of Physics: Conference Series*, vol. 1569, no. 2, pp. 1–6, 2020, https://doi.org/10.1088/1742-6596/1569/2/022022.

[22] D. H. Parekh and V. Dahiya, "Predicting Breast Cancer using Machine Learning Classifiers and Enhancing the Output by Combining the Predictions to Generate Optimal F1-Score," *Biomedical and Biotechnology Research Journal (BBRJ)*, vol. 6, no. 1, pp. 331–334, 2022, https://doi.org/10.4103/bbrj.bbrj.

[This page intentionally left blank.]