Transfer Learning for Medicinal Plant Leaves Recognition: A Comparison with and without a Fine-Tuning Strategy

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***Abstract*—Plant leaves are another common source of information for determining plant species. According to the dataset that has been collected, we propose transfer learning models VGG16, VGG19, and MobileNetV2 to examine the distinguishing features to identify medicinal plant leaves. We also improved algorithm using fine-tuning strategy and analyzed a comparison with and without a fine-tuning strategy to transfer learning models performance. Several protocols or steps were used to conduct this study, including data collection, data preparation, feature extraction, classification, and evaluation. The distribution of training and validation data is 80% for training data and 20% for validation data, with 1500 images of thirty species. The testing data consisted of a total of 43 images of 30 species. Each species class consists of 1-3 images. With a validation accuracy of 96.02 percent, MobileNetV2 with fine-tuning had the best validation accuracy. MobileNetV2 with fine-tuning also had the best testing accuracy of 81.82%.**

Keywords*—*Medicinal leaf plant; transfer learning; deep learning; phytomedicine

I. Introduction

Leaves have characteristics such as shape and texture to be identified with the help of image processing technology and deep learning. An object sees identification as geometric information with boundaries [1]–[10]. The identified leaf object is limited to the boundary identified as leaf size and leaf shape, while the leaf texture or pattern is seen from the leaf surface [11]. Generally, the size of the leaves can be different, but the surface pattern of the leaves does not differ from one another [12]–[15]. This study aims to identify medicinal or phytomedicine plant species by processing leaf imagery using image processing and deep learning [15]–[21].

Research on the identification of phytomedicine plant leaves has been carried out by several previous studies, for example Naresh and Nagendraswamy in 2015 [22], Mukherjee and his team in 2016 [23], Venkataraman & Mangayarkarasi in 2017 [24], Gao & Lin in 2018 [25], Sivaranjani et al. in 2019 [26], Pechebovicz et al. in 2020 [27], Bhuiyan et al. in 2021 [28].

In a study by Naresh and Nagendraswamy in 2015, the authors employed local binary patterns (LBP) to classify medicinal leaf plants. In a study conducted in 2016 by Mukherjee and his team, the classification of medicinal plants was accomplished with the use of Back Propagation Multi-Layer Perceptron (BP-MLP) [22], [29].

A study on the classification of medicinal plants also was carried out by Venkataraman and Mangayarkarasi (2017). They utilized the Histogram of Oriented Gradient (HoG)-Support Vector Machine for their research (SVM) [24]. Moreover, Gao and Lin (2018) used the OTSU approach in their classification of leaf plants for medicinal purposes. The OTSU approach involves using each manually marked edge point of the leaf to precisely detect the following outside points of the leaf located next to it [25]. The ExG-ExR index and the Logistic Regression (LR) classifier were utilized by Sivaranjani et al. to classify medicinal plants, and the researchers discovered that this method was successful. Based on each extracted leaf's color and texture characteristics, the Logistic Regression (LR) classifier is utilized to classify the various plant species [26].

In this study, we propose transfer learning models VGG16, VGG19, and MobileNetV2 to study the distinguishing features to identify medicinal plant leaves according to the dataset that has been collected. We also improved algorithm using fine-tuning strategy and analysed a comparison with and without a fine-tuning strategy to transfer learning model's performance.

II. Related Works

Research on leaf image classification has been carried out for the last few years. To see the development of research in this field, we conducted a literature study on leaf image classification research from 2015 to 2021. The overview of related works is depicted in Fig. 1.

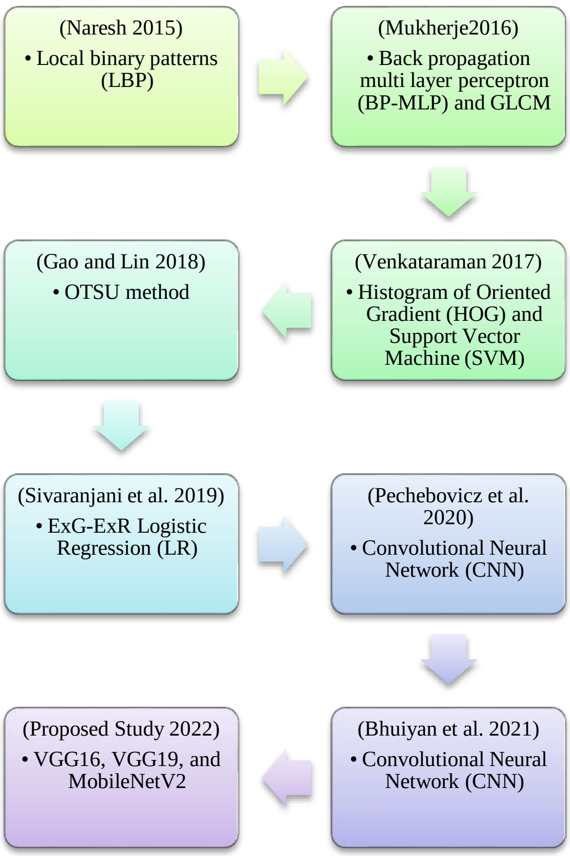

Fig. 1. Related Works

Local binary patterns (LBP) were used to classify medicinal leaf plants in a study by Naresh and Nagendraswamy in 2015 [22]. Back Propagation Multi-Layer Perceptron (BP-MLP) and Gray Level Co-occurrence Matrix (GLCM) were used to classify medicinal plants in a study by Mukherjee and his team in 2016. Results show that combined GLCM features can classify things better than basic single GLCM features. [23].

Venkataraman & Mangayarkarasi (2017) conducted a study for classification of medicinal plants using the Histogram of Oriented Gradient (*HoG*)-Support Vector Machine (SVM) [24]. Gao & Lin (2018) used the OTSU method to classify leaf plants that are used for medicine. OTSU method is to use each manually marked edge point of the leaf to accurately detect the next outer points of the leaf next to it [25].

Sivaranjani et al. (2019) used the ExG-ExR index and the Logistic Regression (LR) classifier to classify medicinal plants, and they found that this worked well. The Logistic Regression classifier is used to classify the plant species based on the color and texture features of each extracted leaf. This classifier has a 93.3 percent accuracy rate [26]. Convolutional Neural Networks were used in a study by Pechebovicz et al. (2020) to classify medicinal plants [27]. Bhuiyan et al. (2021) used Convolutional Neural Networks to conduct research for the identification of medicinal plants (CNN) [28].

III. Research Methodology

This research was conducted by applying several protocols or stages, including data collection, data preparation, feature extraction, classification, testing, and evaluation, as shown in the Fig. 2.

The first phase is data collection. The dataset used in this research is a public dataset called Medicinal Leaf Dataset. This dataset will be made public by Roopashree & Anitha in 2020 [30], [31]. The dataset collected is the result of photos using the Samsung s9+ Model Camera and Canon Inkjet Printer. Leaf photos are from leaves picked from different plants of the same species available at the study site. Healthy and mature leaves were selected for the dataset. The dataset consists of 1500 images of thirty species. Each species consists of 60 to 100 high quality images. An example of a dataset can be seen in the Fig. 3.

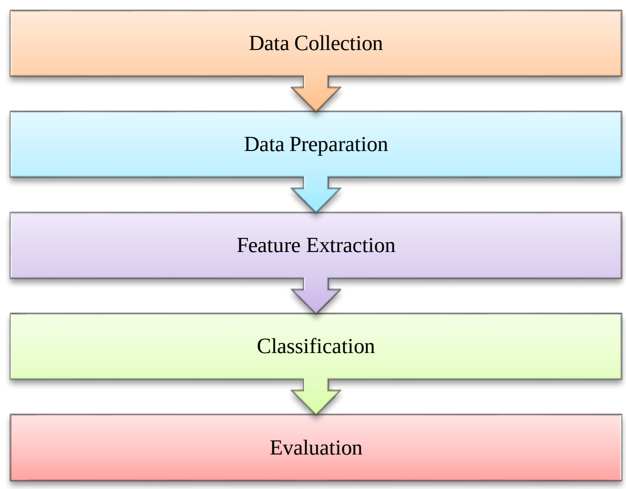

Fig. 2. Research Phases.

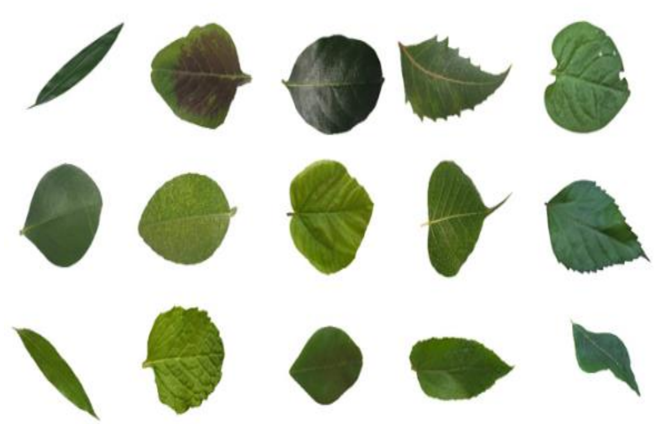

Fig. 3. Example of Dataset.

The dataset consists of 30 species of healthy medicinal plants such as Alpinia Galanga (Galanga Leaves), Amaranthus Viridis (Green Spinach Leaves), Artocarpus Heterophyllus (Jackfruit), Azadirachta Indica (Neem), Santalum Album (Sandalwood), Muntingia Calabura (Jamaica cherry), Plectranthus amboinicus (Indian Mint), Brassica Juncea (Oriental mustard), and many more.

The next stage is data preparation. The first sub-phase of data preparation is image normalization. This process is done by multiplying each pixel value by 1./255. The second data preparation stage is image augmentation. This stage is carried out by applying several image augmentation techniques to obtain additional synthetic data [32], [33]. The augmentations performed are horizontal_flip, vertical_flip, width_shift, height_shift, rotation, fill_mode = 'reflect', zoom brightness_range = [0.5, 1.5], featurewise_std_normalization = True, shear and featurewise_ center [34]–[37]. There are two stages of feature extraction carried out, as shown in the Fig. 4.

In data preparation phase, the dataset folder is named according to the scientific name of the species. The dataset is broken down for data training, validation, and testing. The entire dataset has been segmented to free from the background. The distribution of training and validation data is 80% for training data and 20% for validation data, with 1500 images of thirty species. The 80/20 dataset composition is based on previous research [38]–[45]. Data testing uses new data outside the dataset for training and validation. The testing data consisted of a total of 43 images of 30 species. Each species class consists of 1-3 images.

The third phase is feature extraction. This study conducted experiments to compare three pre-trained models for feature extraction on medicinal plant image datasets, namely VGG16, VGG19, and MobileNetV2.

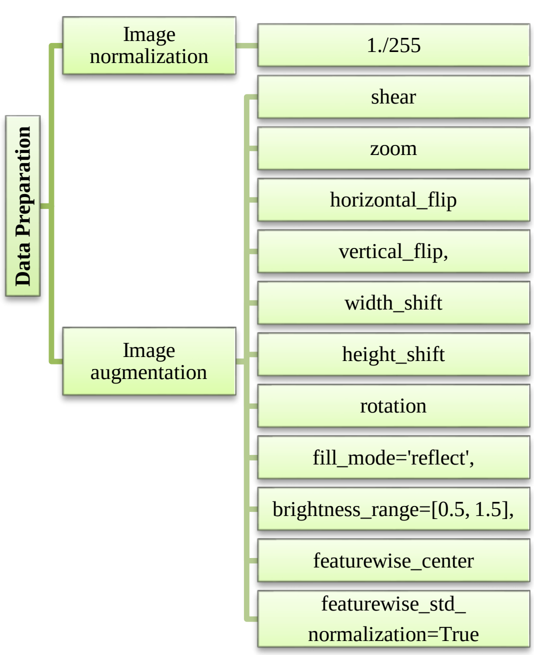

Fig. 4. Feature Extraction Methods.

The fourth phase is classification. The data that has been extracted features a pre-trained model, then training and model validation is carried out using training and validation data. In order to obtain better accuracy results, experiments were also conducted to compare the model with fine-tuning and without fine-tuning. The VGG16, VGG19, and MobileNetV2 model architectures study leaf shape information to differentiate different plant species. The input leaf size and color channel used are adjusted for the VGG16, VGG19, and MobileNetV2 models.

The fifth phase is testing that is done using new data outside the dataset. The testing data obtained by searching through Google using the keyword species name of plant. The data selected on Google is only focused the leaves object, if there is a background in the image, only the leaves are taken (cropped). The testing data consisted of a total of 43 images of 30 species. Each species class consists of 1-3 images. The following Fig. 5 is an example of testing data.

The final phase is evaluation. The evaluation is carried out by comparing the experimental results to find the best suitable model in the dataset. We evaluated the VGG16, VGG19, and MobileNetV2 models for leaf identification on medicinal plant leaves by conducting experiments on the collected datasets. The evaluation method used is the accuracy method. The evaluation was carried out in two stages: evaluation at the training stage and evaluation at the validation stage.

Fig. 5. Example of Data Testing.

IV. Result and Discussion

This study used the VGG16, VGG19, and MobileNetV2 classification models for leaf identification on medicinal plant leaves. Two different processes are carried out on the same classification model and dataset, namely with and without fine-tuning implementation. From the implementation results, we want to know how the effect of implementation on the accuracy results during the training, validation, and testing processes using the same dataset and classification model.

The first stage is the training process. The training process is carried out by conducting experiments on 80% of the data from the dataset as a whole. The dataset consists of 1500 images (for 30 classes), meaning that there are about 1200 data used in this experiment. The experimental results can be seen in the Table I.

TABLE I. ACCURACY RESULTS ON TRAINING DATA

Model	Training Experiment	
	Without Fine Tuning	With Fine Tuning
VGG16	99.24%	95.72%
VGG19	93.85%	95.51%
MobileNetV2	98.89%	98.41%

Based on the data in Table I, the model without fine-tuning obtains an accuracy of 99.24% for the VGG16 model, 93.85% for the VGG19 model, and 98.89% for the MobileNetV2 model. In contrast, the models with fine-tuning get 95.72% accuracy for the VGG16 model, 95.51% for the VGG19 model, and 98.41% for the MobileNetV2 model. Moreover, the difference Value of training experiment of model implementation using the fine-tuning and without fine-tuning is depicted in the Fig. 6.

Based on the data in Table II, the model without fine-tuning obtains an accuracy of 95.17% for the VGG16 model, 89.49% for the VGG19 model, and 87.50% for the MobileNetV2 model. While the models with fine-tuning get 93.75% accuracy for the VGG16 model, 92.90% for the VGG19 model, and 96.02% for the MobileNetV2 model. Moreover, difference value of validation experiment of model implementation by using fine tuning and without tuning is depicted Fig. 7.

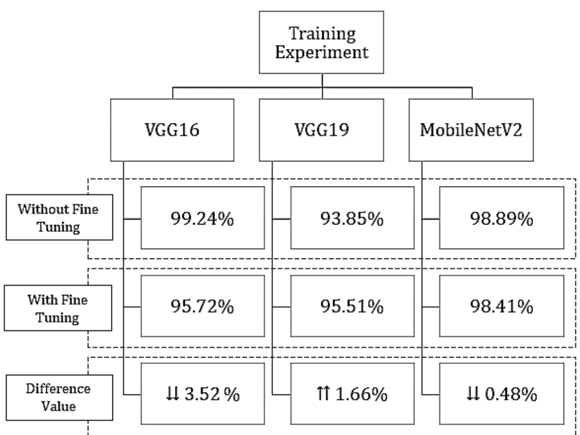

Fig. 6. Difference Value of Training Experiment.

The second stage is the validation process. The validation process is carried out by conducting experiments on 20% of the data from the dataset as a whole. The dataset consists of 1500 images (for 30 classes), meaning that about 300 pieces of data are used in this experiment. The experimental results can be seen in the Table II.

TABLE II. DATA ACCURACY RESULTS ON DATA VALIDATION

Model	Validation Experiment	
	Without Fine Tuning	With Fine Tuning
VGG16	95.17%	93.75%
VGG19	89.49%	92.90%
MobileNetV2	87.50%	96.02%

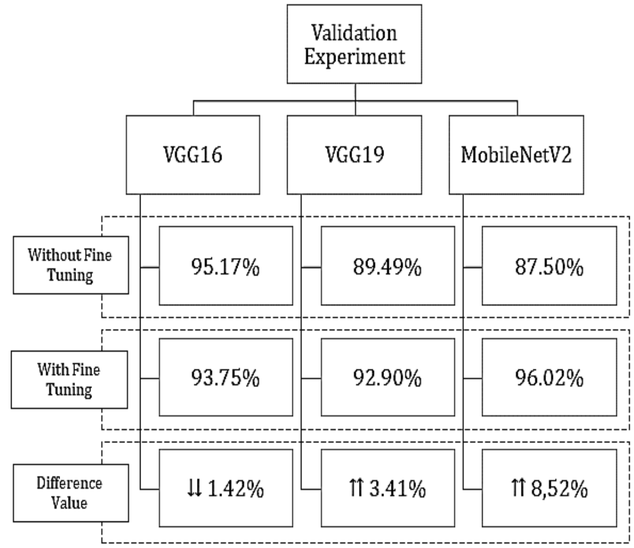

Fig. 7. Difference Value of Validation Experiment.

Based on the Fig. 7, MobileNetV2 and VGG19 with fine-tuning can significantly increase the validation accuracy, while in VGG16 with fine-tuning, it reduces validation accuracy. The third stage is the testing process. Testing data is new data that the model has never processed. After the model is obtained, then testing is carried out on the model using data testing and the result can be seen in Table III.

TABLE III. ACCURACY RESULTS ON TESTING DATA

Model	Testing Experiment	
	Without Fine Tuning	With Fine Tuning
VGG16	22.73%	36.36%
VGG19	15.91%	31.82%
MobileNetV2	43.18%	81.82%

From the experiment results, the models with fine-tuning both VGG16, VGG19, and MobileNetV2 experienced an increase in testing accuracy compared to the model before fine-tuning and the result can be seen in Table IV.

MobileNetV2 obtained the best model by fine-tuning with 96.02% validation accuracy, 81.82% testing accuracy, precision, recall, and f1-score values 0.73, 0.82, and 0.76. The following Fig. 8 is a classification report and confusion matrix obtained by the MobileNetV2 model by fine-tuning.

Overall, VGG16 obtained the highest accuracy compared to other models during the experiment of training without fine tuning (99.24%) and validation without fine tuning (95.17%). While in other experiments the MobileNetV2 model is superior to other models, as shown in the Table V.

Based on the experiment result, we recommended MobileNetV2 model to identify medicinal plant leaves according to the dataset that has been collected. MobileNetV2 was chosen for further research because it got the best accuracy and shorter computation time in recognizing the image of medicinal plant leaves [46]–[48].

TABLE IV. DETAIL OF RESULTS ON TESTING DATA

Class	Precision	Recall	F1-Score
Alpinia Galanga	1.00	1.00	1.00
Amaranthus Viridis	0.67	1.00	0.80
Artocarpus Heterophyllus	1.00	1.00	1.00
Azadirachta Indica	1.00	1.00	1.00
Basella Alba	1.00	1.00	1.00
Brassica Juncea	1.00	1.00	1.00
Carissa Carandas	0.00	0.00	0.00
Citrus Limon	1.00	1.00	1.00
Ficus Auriculata	1.00	1.00	1.00
Ficus Religiosa	1.00	1.00	1.00
Hibiscus Rosa-Sinesis	1.00	1.00	1.00
Jasminum	0.60	1.00	0.75
Mangifera Indica	0.67	1.00	0.80
Mentha	1.00	1.00	1.00
Moringa Oleifera	0.00	0.00	0.00
Muntingia Calabura	0.33	1.00	0.50
Muraya Koenigii	0.00	0.00	0.00
Nerium Oleander	0.00	0.00	0.00
Nyctanthes Arbor-tristis	1.00	1.00	1.00
Ocimum Tenuiflorum	0.00	0.00	0.00
Piper Betle	1.00	1.00	1.00
Plectranthus Ambonicus	0.00	0.00	0.00
Pongamis Pinnata	1.00	1.00	1.00
Psidium Guajava	1.00	1.00	1.00
Punica Granatum	1.00	1.00	1.00
Santalum Album	1.00	1.00	1.00
Syzygium Cumini	0.50	1.00	0.67
Syzygium Jambos	0.00	0.00	0.00
Tabernaemontana Divaricata	1.00	1.00	1.00
Trigonella Foenum-graecum	0.00	0.00	0.00
Macro avg	**0.66**	**0.66**	**0.66**
Weighted avg	**0.73**	**0.73**	**0.73**

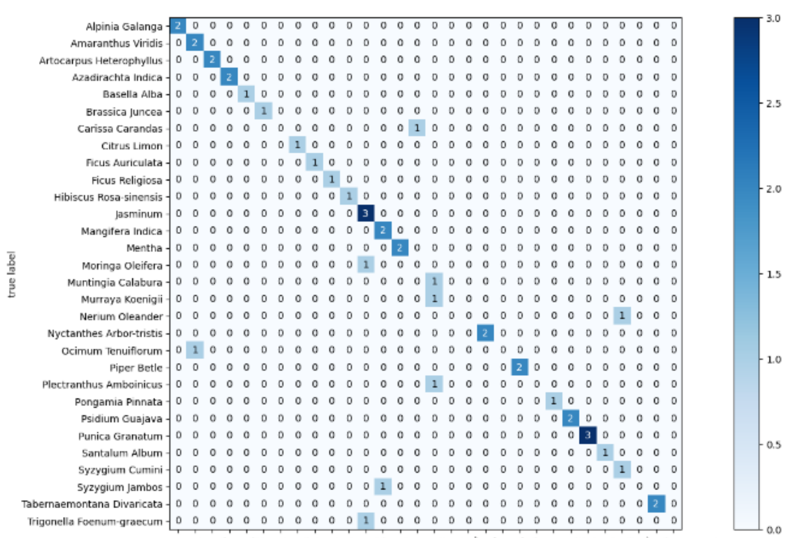

Fig. 8. Confusion Matrix.

TABLE V. OVERALL RESULT OF EXPERIMENT

Phase	**Method**	**VGG16**	**VGG19**	**MobileNet**
TR	WFT	99.24%	93.85%	98.89%
TR	FT	95.72%	95.51%	98.41%
VA	WFT	95.17%	89.49%	87.50%
VA	FT	93.75%	92.90%	96.02%
TE	WFT	22.73%	15.91%	43.18%
TE	FT	36.36%	31.82%	81.82%

*WFT = without fine tuning, FT = with fine tuning, TR=training, VA=validation, TE=testing

V. CONCLUSION

MobileNetV2 obtained the best validation accuracy with fine-tuning with a validation accuracy of 96.02%. MobileNetV2 also obtained the best testing accuracy with fine-tuning of 81.82%. In other models, the testing accuracy obtained is far below MobileNetV2. This condition is likely to happen because the dataset for training and validation used is less diverse and general to build a good model, so the resulting model overfits the dataset. In this case, MobileNetV2 with fine-tuning is quite able to overcome the weaknesses of the dataset used so that when new testing data is given, the accuracy results obtained are quite good. In addition, based on the experiment results, fine-tuning the model can improve the accuracy of the validation and testing produced.

The limitation of this study is that it ignores the background problem of the leaf image. Further research will be carried out using a dataset with a complex background by adding a segmentation method before being processed by the MobileNetV2 model.

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REFERENCES

[1] X.-F. Wang, D.-S. Huang, J.-X. Du, H. Xu, and L. Heutte, “Classification of plant leaf images with complicated background,” Appl. Math. Comput., vol. 205, no. 2, pp. 916–926, Nov. 2008.

[2] K. Yang, W. Zhong, and F. Li, “Leaf Segmentation and Classification with a Complicated Background Using Deep Learning,” Agronomy, vol. 10, no. 11, p. 1721, Nov. 2020.

[3] I. Ranggadara, Y. S. Sari, S. Dwiasnati, and I. Prihandi, “A Review of Implementation and Obstacles in Predictive Machine Learning Model at Educational Institutions,” in Journal of Physics: Conference Series, 2020, vol. 1477, p. 32019.

[4] Y. Jumaryadi, D. Firdaus, B. Priambodo, and Z. P. Putra, “Determining the Best Graduation Using Fuzzy AHP,” in 2020 2nd International Conference on Broadband Communications, Wireless Sensors and Powering (BCWSP), 2020, pp. 59–63.

[5] E. M. Jawad, H. G. Daway, and H. J. Mohamad, “Quantum-dot Cellular Automata Based Lossless CFA Image Compression Using Improved and Extended Golomb-rice Entropy Coder,” Int. J. Intell. Eng. Syst., vol. 15, no. 2, pp. 12–25, Apr. 2022.

[6] V. Ayumi, “Pose-based human action recognition with Extreme Gradient Boosting,” in 2016 IEEE Student Conference on Research and Development (SCOReD), 2016, pp. 1–5.

[7] V. Ayumi, “Mobile Application for Monitoring of Addition of Drugs to Infusion Fluids,” Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol., pp. 48–56, Nov. 2019.

[8] V. Ayumi, “Pose-based human action recognition with Extreme Gradient Boosting,” in Proceedings - 14th IEEE Student Conference on Research and Development: Advancing Technology for Humanity, SCOReD, 2017.

[9] V. Ayumi, “Application of Machine Learning for SARS-CoV-2 Outbreak,” Int. J. Sci. Res. Sci. Eng. Technol., vol. 7, no. 5, pp. 241–248, Oct. 2021.

[10] V. Ayumi, “Performance Evaluation of Support Vector Machine Algorithm for Human Gesture Recognition,” Int. J. Sci. Res. Sci. Eng. Technol., vol. 7, no. 6, pp. 204–210, 2020.

[11] J. Arun Pandian, G. Geetharamani, and B. Annette, “Data Augmentation on Plant Leaf Disease Image Dataset Using Image Manipulation and Deep Learning Techniques,” in 2019 IEEE 9th International Conference on Advanced Computing (IACC), 2019, pp. 199–204.

[12] J. S. Cope, D. Corney, J. Y. Clark, P. Remagnino, and P. Wilkin, “Plant species identification using digital morphometrics: A review,” Expert Syst. Appl., vol. 39, no. 8, pp. 7562–7573, Jun. 2012.

[13] Y. A. Putri, E. C. Djamal, and R. Ilyas, “Identification of Medicinal Plant Leaves Using Convolutional Neural Network,” J. Phys. Conf. Ser., vol. 1845, no. 1, p. 012026, Mar. 2021.

[14] M. A. F. Azlah, L. S. Chua, F. R. Rahmad, F. I. Abdullah, and S. R. Wan Alwi, “Review on Techniques for Plant Leaf Classification and Recognition,” Computers, vol. 8, no. 4, p. 77, Oct. 2019.

[15] F. Ghouse, K. Paranjothi, and R. Vaithiyanathan, “Dysgraphia Classification based on the Non-Discrimination Regularization in Rotational Region Convolutional Neural Network,” Int. J. Intell. Eng. Syst., vol. 15, no. 1, Feb. 2022.

[16] J. Lu, L. Tan, and H. Jiang, “Review on Convolutional Neural Network (CNN) Applied to Plant Leaf Disease Classification,” Agriculture, vol. 11, no. 8, p. 707, Jul. 2021.

[17] E. Korot et al., “Code-free deep learning for multi-modality medical image classification,” Nat. Mach. Intell., vol. 3, no. 4, pp. 288–298, Apr. 2021.

[18] V. Ayumi, E. Ermatita, A. Abdiansah, H. Noprisson, M. Purba, and M. Utami, “A Study on Medicinal Plant Leaf Recognition Using Artificial Intelligence,” in 2021 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS, 2021, pp. 40–45.

[19] E. Hidayat, Lukman, H. Noprisson, D. I. Sensuse, Y. G. Sucahyo, and E. D. Putra, “Development of mobile application for documenting traditional knowledge in Indonesia: A Case Study of Traditional Knowledge in Using Medicinal Plant,” in Proceedings - 14th IEEE Student Conference on Research and Development: Advancing Technology for Humanity, SCOReD 2016, 2017.

[20] H. Noprisson, D. I. Sensuse, Y. G. Sucahyo, and Lukman, “Metadata Development for Ethnophytomedicine Resources Using Metadata Analysis Approach,” in The 2016 8th International Conference on Information Technology and Electrical Engineering (ICITEE 2016), 2016.

[21] D. I. Sensuse, H. Noprisson, Y. G. Sucahyo, and L. Lukman, “Metadata Schema for Traditional Knowledge,” Int. J. Adv. Sci. Eng. Inf. Technol., vol. 7, no. 6, 2017.

[22] Y. G. Naresh and H. S. Nagendraswamy, “A novel fuzzy LBP based symbolic representation technique for classification of medicinal plants,” in 2015 3rd IAPR Asian Conference on Pattern Recognition (ACPR), 2015, pp. 524–528.

[23] G. Mukherjee, A. Chatterjee, and B. Tudu, “Study on the potential of combined GLCM features towards medicinal plant classification,” in 2016 2nd International Conference on Control, Instrumentation, Energy & Communication (CIEC), 2016, pp. 98–102.

[24] D. Venkataraman and N. Mangayarkarasi, “Support vector machine based classification of medicinal plants using leaf features,” in 2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI), 2017, pp. 793–798.

[25] L. Gao and X. Lin, “A method for accurately segmenting images of medicinal plant leaves with complex backgrounds,” Comput. Electron. Agric., vol. 155, pp. 426–445, 2018.

[26] C. Sivaranjani, L. Kalinathan, R. Amutha, R. S. Kathavarayan, and K. J. Jegadish Kumar, “Real-Time Identification of Medicinal Plants using

Machine Learning Techniques," in 2019 International Conference on Computational Intelligence in Data Science (ICCIDS), 2019, pp. 1–4.

[27] D. Pechebovicz et al., "Plants recognition using embedded Convolutional Neural Networks on Mobile devices," in 2020 IEEE International Conference on Industrial Technology (ICIT), 2020, pp. 674–679.

[28] M. R. Bhuiyan, M. Abdullahil-Oaphy, R. S. Khanam, and M. S. Islam, "MediNET: A Deep Learning Approach to Recognize Bangladeshi Ordinary Medicinal Plants Using CNN," in Soft Computing Techniques and Applications, Springer, 2021, pp. 371–380.

[29] S. Bhattacharya, A. Mukherjee, and S. Phadikar, "A deep learning approach for the classification of rice leaf diseases," in Intelligence enabled research, Springer, 2020, pp. 61–69.

[30] S. Roopashree and J. Anitha, "Medicinal leaf dataset," Mendeley Data, vol. 1, 2020.

[31] R. Shailendra et al., "An IoT and Machine Learning Based Intelligent System for the Classification of Therapeutic Plants," Neural Process. Lett., pp. 1–29, 2022.

[32] M. Defriani and I. Jaelani, "Recognition of Regional Traditional House in Indonesia Using Convolutional Neural Network (CNN) Method," J. Comput. Networks, Archit. High Perform. Comput., vol. 4, no. 2, pp. 104–115, 2022.

[33] R. M. Rao and M. K. Arora, "Overview of image processing," in Advanced image processing techniques for remotely sensed hyperspectral data, Springer, 2004, pp. 51–85.

[34] S. Mishra, D. Koner, L. Jena, and P. Ranjan, "Leaves shape categorization using convolution neural network model," in Intelligent and cloud computing, Springer, 2021, pp. 375–383.

[35] V. Maslej-Krešňáková, K. El Bouchefry, and P. Butka, "Morphological classification of compact and extended radio galaxies using convolutional neural networks and data augmentation techniques," Mon. Not. R. Astron. Soc., vol. 505, no. 1, pp. 1464–1475, 2021.

[36] I. Bhakta, S. Phadikar, and K. Majumder, "Thermal Image Augmentation with Generative Adversarial Network for Agricultural Disease Prediction," in International Conference on Computational Intelligence in Pattern Recognition, 2022, pp. 345–354.

[37] R. Karothia and M. K. Chattopadhyay MIEEE, "Vigorous Deep Learning Models for Identifying Tomato Leaf Diseases," in Proceedings of International Conference on Data Science and Applications, 2022, pp. 131–152.

[38] S. Widiyanto, R. Fitrianto, and D. T. Wardani, "Implementation of Convolutional Neural Network Method for Classification of Diseases in Tomato Leaves," in 2019 Fourth International Conference on Informatics and Computing (ICIC), 2019, pp. 1–5.

[39] P. Bharali, C. Bhuyan, and A. Boruah, "Plant disease detection by leaf image classification using convolutional neural network," in International conference on information, communication and computing technology, 2019, pp. 194–205.

[40] M. M. Ghazi, B. Yanikoglu, and E. Aptoula, "Plant identification using deep neural networks via optimization of transfer learning parameters," Neurocomputing, vol. 235, pp. 228–235, 2017.

[41] M. S. H. Kalathingal, S. Basak, and J. Mitra, "Artificial neural network modeling and genetic algorithm optimization of process parameters in fluidized bed drying of green tea leaves," J. Food Process Eng., vol. 43, no. 1, p. e13128, 2020.

[42] M. Syarief and W. Setiawan, "Convolutional neural network for maize leaf disease image classification," Telkomnika (Telecommunication Comput. Electron. Control., vol. 18, no. 3, pp. 1376–1381, 2020.

[43] R. Thangaraj, S. Anandamurugan, and V. K. Kaliappan, "Automated tomato leaf disease classification using transfer learning-based deep convolution neural network," J. Plant Dis. Prot., vol. 128, no. 1, pp. 73–86, 2021.

[44] M. Ji, L. Zhang, and Q. Wu, "Automatic grape leaf diseases identification via UnitedModel based on multiple convolutional neural networks," Inf. Process. Agric., vol. 7, no. 3, pp. 418–426, 2020.

[45] S. A. Wagle, R. Harikrishnan, S. H. M. Ali, and M. Faseehuddin, "Classification of plant leaves using new compact convolutional neural network models," Plants, vol. 11, no. 1, p. 24, 2021.

[46] H.-H. Yen et al., "Performance comparison of the deep learning and the human endoscopist for bleeding peptic ulcer disease," J. Med. Biol. Eng., vol. 41, no. 4, pp. 504–513, 2021.

[47] C. H. Karadal, M. C. Kaya, T. Tuncer, S. Dogan, and U. R. Acharya, "Automated classification of remote sensing images using multileveled MobileNetV2 and DWT techniques," Expert Syst. Appl., vol. 185, p. 115659, 2021.

[48] P. N. Huu, N. N. Thi, and T. P. Ngoc, "Proposing Posture Recognition System Combining MobilenetV2 and LSTM for Medical Surveillance," IEEE Access, vol. 10, pp. 1839–1849, 2021.