International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Deep Learning Modeling for Local Wildflower Recognition

Jannatul Ferdouse*[1], Md. Ashikul Aziz Siddique[2], Md. Saiful Haque[3], Mahady Hasan[4], Md. Tarek Habib[5]

Submitted: 27/12/2023 **Revised**: 04/02/2024 **Accepted**: 11/02/2024

Abstract: Bangladesh is a small country surrounded by greenery. This nation is coated in a variety of lush vegetation, including grasses, flowers, and trees. As time passes, the atmosphere and soil also alter. Because of this, many people are unaware of the true names of many flowers, and some are currently in danger of going extinct. It will be challenging for the new generation to learn about these flowers. Bangladesh is home to a wide variety of regional flora. The Datura Metel, Hill Glory Bower, and Periwinkle plants will be the subjects of our effort. We used four deep neural network models VGG-16, VGG-19, MobileNetV2, and Resnet50 to carry out our research. We gathered a data set of images of three local wildflowers, i.e. Datura Metel, Hill Glory Bower, and Periwinkle flower images, processed them beforehand, and taught the four deep learning models on them separately. We used the holdout method to evaluate each of the four deep-learning models. For each of these models, we tuned different hyperparameters and came up with the best-configured model. Following successful testing, we discovered that the VGG-19 model had performed the best classification performance exhibiting an accuracy of 99.2%.

Keywords: *Wildflower, Transfer Learning, Convolutional Neural Network, VGG-19, Performance Measures, Accuracy.*

1. Introduction

We are very lucky that our country is rich in various natural resources. Flowers symbolize beauty, love, purity, and peace. Bangladesh is a country with a diverse ecosystem. In Bangladesh, there are more than 6,000 plant types, of which 300 are exotic and 8 are endemic [1]. Flowers refresh our minds in a moment. Some flowers are also used as medicine. The most beautiful thing in the universe is a flower. Bangladesh is a country with many waterways and six distinct seasons. Different beauty is used by each season to decorate nature. Fruits, weather, and flora vary according to each of the six seasons and nothing will match with the upcoming season [2]. This country is rich with different kinds of trees and flowers, which are a source of pride for us, but over time, some flowers are on the verge of extinction. One of them Datura Metel (ধুতুরা ফুল), Hill Glory Bower (ঘেটু ফুল) and Periwinkle (নয়নতারা). We, in this paper, proposed an application that easily identifies these flowers only using their images. We chose four CNN (Convolutional Neural Network) models VGG-16, VGG-19, MobileNetV2, and Resnet50 to perform our work. Each of these convolutional neural network models is trained by transfer learning algorithms. We determine the ideal setup for each of these models by tuning the corresponding hyperparameters. For assessing the performance of each of these models, we employ the four indicative measures recall, accuracy, precision, and F_1-score. We expect this research investigation to help build an application that is going to be popular as well as beneficial to the new generation.

*[1] Research Assistant, Fab Lab IUB, Independent University, Bangladesh.
jannatulferdouse019@gmail.com
[2] Research Assistant, Fab Lab IUB, Independent University, Bangladesh.
mdashikulaziz@gmail.com
[3]Assistant Professor, Department of Computer Science and Engineering, Rabindra Maitree University, Kushtia, Bangladesh.
saifulsadat251113@gmail.com
[4]Associate Professor, Department of Computer Science and Engineering, Director, Fab Lab IUB, Independent University, Bangladesh.
mahady@iub.edu.bd
[5]Assistant Professor, Department of Computer Science and Engineering, Faculty Advisor, Fab Lab IUB, Independent University, Bangladesh.
md.tarekhabib@yahoo.com*

2. System Architecture

The formulated expert system, as shown in Figure 1 can readily recognize three wildflowers captured by the camera. To recognize these flowers using a mobile phone or computer, we instruct either install a mobile application or visit the desired website. After that, we need to upload the image to our system. Send the image file to the expert system via the Internet. Then our proposed expert system analyzes the picture with our trained database and gives you feedback on what it is. Finally, the result will appear to the user through the front-end application.

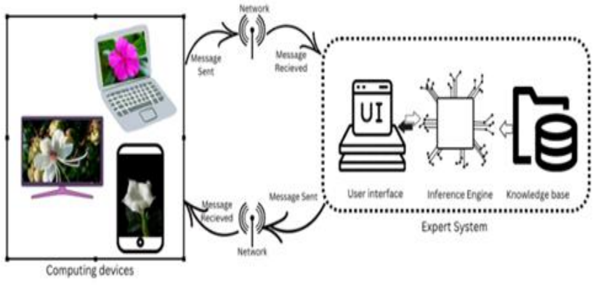


Fig 1. The architecture of the online local wildflower recognition expert system.

3. Related Works

There is a lot of work done about identifying flowers which helped us to complete our research. Das et al. [3] worked on apple flower detection using a DCN (Deep Convolution Network). They try to determine the bloom intensity of apple flowers as it is the most important part. They organized their work into five sections where in section 3 they proposed their approach. In this section, they described in detail by use CNN plus SVM method. Palacios et al. [4] worked on inventing automated grapevine flower detection by using computer vision and deep learning. Typically, the grape is significant to the wine and grape industry's economy. Therefore, they decided to create a non-intrusive technique for counting grapevine flowers. In this work, berry identification in RGB photos taken from a moving automobile with artificial illumination was used to develop a system for assessing vineyard production. Cao and Song et al. [5] employed a deep learning technique driven by visual attention to recognize flowers. They studied deep-learning-based problems of flower recognition and proposed a model to solve them. Moreover, they also perform image augmentation. In their work, they used 17 public flowers and received an accuracy of 85.7%. Patel and Patel et al. [6] employed computer vision and machine learning to recognize and categorize flowers. On a Data set with 25000 images of flowers. They developed a hybrid method for multi-label classification utilizing MKL and SVM. Their work's accuracy was 76.92%. The investigation of the effectiveness of machine learning methods in the detection of flowers is covered in another work by Jain et al. [7]. They used machine-learning methods for the identification of flowers based on their characters and the accuracy rate is 97.3%. Sun et al. [8] discussed four-dimensional deep-learning techniques for rating floral quality with depth information. They gathered photos in RGB and depth of flower buds and converted them into RGBD data. After that, they used RGBD information as inputs of CNN models (VGG-16, Rsenet18, MobileNetV2, and Inception-v3). They gained almost 98% accuracy. The following amazing work done by Patel and Patel et al. [9] uses NAS-FPN and R-CNN to improve a deep-learning model for classifying flowers. They used CNN techniques to evaluate flowers, localization, and classification. They selected 30 common wildflowers in their Data set, and the suggested model had the best accuracy (96.2%). Darwin et al. [10] used deep learning models to identify bloom in crop images. They captured pictures with handheld cameras in various lighting conditions and deep learning algorithms to increase classification accuracy. Mete et al. [11] used deep learning models to identify bloom in crop images. They captured pictures with handheld cameras in various lighting conditions and increased classification accuracy using deep learning techniques. Cengil et al. [12] worked on pre-trained models using transfer learning. They used Alexnet, Googlenet, VGG-16, DenseNet, and ResNet deep learning models among them VGG-16 model provided the highest accuracy. The following is a study regarding floral end-to-end detection using on YOLOv4 model and mobile devices, which was done by Cheng et al. [13]. The author collected flower pictures and passed them through the module with the SPP and PAN of YOLOv3. Sun et al. [14] suggested a semantic segmentation-based automated technique for detecting apples, peaches, and pears in bloom. For the peach, pear, and apple Data sets, their method produces an overall F_1-score of 80.9%, and on the apple Data set, it produces an F_1-score up to 89.7% at the pixel level. Farha et al. [15] used the transfer learning approach to create a detecting system for regional rose breeds. They created 9306 photos for the training Data set and 388 images for the testing Data set using 1939 raw photographs of five distinct breeds. They employed the Inception-v3, ResNet50, Xception, and VGG-16 models, with the latter achieving the maximum accuracy of 99% across the board. Gallmann et al. [16] suggested a way for employing deep learning (Faster R-CNN) object recognition to obtain information on flower abundance in grasslands from drone-based aerial photos. Individual flowers can be recognized and categorized using this study. For multiple flower species, they achieved precision and recall rates of 90% or higher, indicating good results. Albarico et al. [17] were able to predict the optimal greenhouse environment with a work output of almost 98%-100% by using machine learning techniques including random forest, multinational logistic regression (MLR), ANN, and SVM. Narvekar et al [18] used CNN and transfer learning to classify flowers. They used a total of 4323 images, trained them, and tested images were 865. Ariful et al. [19] employed four deep-learning models to identify medicinal plants from leaf images: MobileNet, ResNet50, Xception, and InceptionV3. The MobileNet approach assisted them in achieving the optimum outcome in their study.

4. Research Methodology

In our work, we select three local flowers, namely Datura Metel (ধুতুরা ফুল), Hill Glory Bower (ঘেটু ফুল), and Periwinkle (নয়নতারা) which almost lost by the passing of time. We choose four types of machine learning models VGG-16, VGG-19, MobileNetV2, and Resnet50. We deal with a large portion of data to receive accurate results. We choose 1009 images belonging to 3 classes and 249 images belonging to 3 categories. After that, as we worked with three classes, we added the three output levels. The Adam optimizers in all models have been trained at a rate of 10^{-3}. We substituted the Adam optimizer provided in equation (1) for the stochastic gradient descent method, which iteratively modifies network weights in the training data set. This decreases the error rate and reduces the mistakes. Adam optimizers are crucial. All of the deep learning models used in our study were trained using GPU support. The next step was to gather and pre-process the necessary photos. Then, we used various deep-learning methods and examined the outcomes. Figure 2 shows all steps of our work as follows.

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t + \varepsilon}} \widehat{m_t} \qquad (1)$$

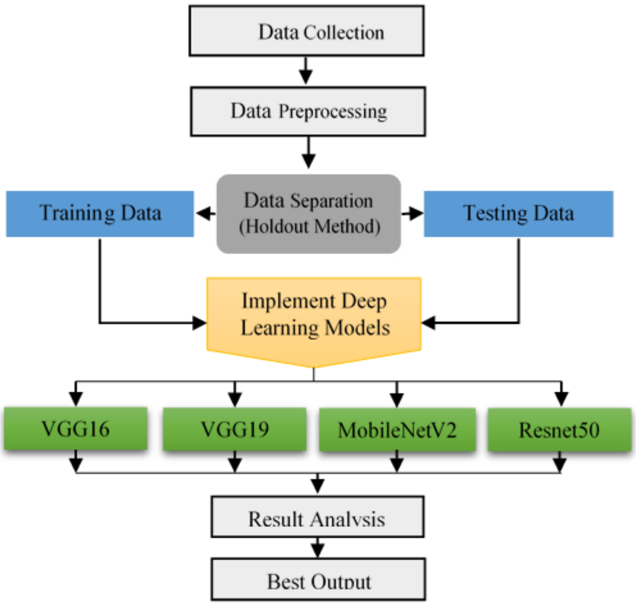


Fig 2. Working procedure diagram for wildflower recognition.

4.1. Description of the Local Wildflowers

In Bangladesh, there are many different kinds of flora. Many wildflowers have powerful medicinal as well as poisonous properties. Research suggests that some are just as effective as modern medicines. Some of these flowers are also poisonous if they are not used properly [20]. Among them, we choose three local wildflowers, namely Datura Metel, Hill Glory Bower, and Periwinkle, as shown in Figure 3.

(a) Datura Metel (b) Hill Glory Bower (c) Periwinkle

Fig 3. Sample image data of wildflowers. (a) Datura Metel (ধুতুরা ফুল); (b) Hill Glory Bower (ঘেটু ফুল); and **(c)** Periwinkle (নয়নতারা).

Datura Metel (ধুতুরা ফুল): Datura Metel (ধুতুরা ফুল, pronounced *dhutura phool*) is a type of blooming plant in the Solanaceae family, also known as Indian Thorn Apple. It is indigenous to South and Southeast Asia, and large portions of Bangladesh, India, Nepal, and other Asian nations are home to it. The flowering plant is perennial or annual with large, trumpet-shaped white or light purple blooms. The shrub can reach a height of two meters and has broad, ovate leaves [21].

Hill Glory Bower (ঘেটু ফুল): The perennial shrub Clerodendrum infortunatum (ঘেটু ফুল, pronounced *ghetu phool*), commonly known as bhat or Hill Glory Bower, is a member of the Lamiaceae family, which is also often referred to as the Verbenaceae [22] grows to a height of 2-4 meters. It is one of the most well-known natural health treatments in Siddha medicine and conventional techniques. In Bangladesh, it is a weed that grows on the vacant ground. Additionally, it can be found throughout the world's tropical and subtropical regions, especially in Bangladesh and India. Flowers on the Hill Glory Bower are white, fragrant, and produced on terminal panicles. petals 5, sepals 5, and petals 5. Red pigment is painted on the lower portions of the petals. Petals are much shorter than stamens. Spring is the time for flowering. The herb is used to treat insect bites, chronic fever, skin conditions, and malaria. It is also used to treat worm and louse infestations [21].

Periwinkle (নয়নতারা): Periwinkle (নয়নতারা, pronounced *noyontara*) is a species of flowering plants in the dogbane family, Apocynaceae, also known as Vinca or Myrtle. Despite being widely cultivated and naturalized throughout the globe, including North America, South America, and Australia, it is native to Europe and Asia and mostly available in Bangladesh. Due to its rapid spread and dense growth pattern, Periwinkle is frequently used as a ground cover plant. Additionally, it is raised as a container plant and as an ornamental shrub for gardens. Periwinkle has been used as a natural bug repellent and a treatment for diabetes in traditional medicine, among other conditions [23].

4.2 Data Set Preparation and Data Preprocessing

In Bangladesh, we collected data from a variety of locations, including gardens and fields. These pictures were all taken with cell phones. Additionally, we gathered some pictures from the Internet. Finally, the data set was comprised of twelve thousand and fifty-eight (1,258) images. Table 1 presents comprehensive statistics of the gathered data set. The gathered pictures come in a variety of sizes and shapes. As a result, we resize the pictures to 224×224 pixels. As shown in Figure 4, we enhance our data by rotating them by 45 degrees, shearing them by 25%, zooming in, out, and resizing them by 25% along the height and width, and flipping them vertically and horizontally by 25%.

Table 1. Summary of the data set used

Class	***Collected Data***	***Data After Augmentation***	***Train Data***	***Test Data***	***Total Train Data***	***Total Test Data***
Datura Metel	190	474	380	94	1009	249
Hill Glory Bower	115	232	347	86		
Periwinkle	141	351	282	69		

(a) Original image (b) Zooming-in (c) Horizontal flip

(d) Vertical flip (e) Shearing

Fig 4. The effects of the data augmentation on a wildflower image. (a) Original image; (b) Zooming-in; (c) Horizontal flip; (d) Vertical flip; (e) Shearing.

4.3 Description of the CNN Models Used

In our research work, we worked with four transfer learning models VGG-16, VGG-19, MobileNetV2, and Resnet50. The one that provides the greatest accuracy is the VGG-19 model. Our data set includes images with RGB channels that are a fixed size (224×224 pixels), so we use the input (244, 244, 3), where 3 denotes the color image. However, every model has a different architecture. Now we are describing all the models as follows:

VGG-16: A 16-layer CNN pre-trained model called VGG-16 is suggested by Simonyan and Zisserman [24]. Our data set comprises pictures with RGB channels that have a constant size of 224×224 pixels, thus we utilize the input (244, 244, 3), where 3 denotes the color image. The output layer of the multiclass classification process uses the softmax function, which is equated in (2) as follows.

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \qquad (2)$$

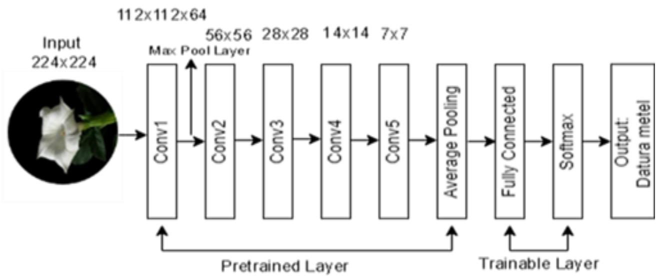


Fig 5. VGG-16 deep learning model architecture.

VGG-19: VGG19 has 19 layers, including 16 convolutional and 3 fully connected layers, and was developed from the VGG architecture [25]. The organization Visual Geometry Group (VGG) founded this network. VGG19 modified with the SVM-RBF classifier provides better results than other classifiers like the SVM-Linear and *k*-NN classifiers [26].

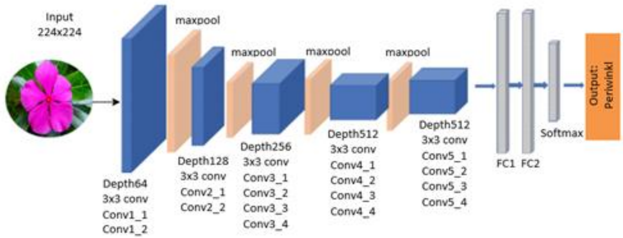


Fig 6. VGG-19 deep learning model architecture.

MobileNetV2: MobileNetV2 is a pre-trained transfer learning model that is lightweight. Additionally, this model is used to identify features, and a softmax classifier is used to categorize features [27]. The model has two different kinds of blocks. A block with a stride of one makes up the first block, while a block with a stride of two makes up the second block [28].

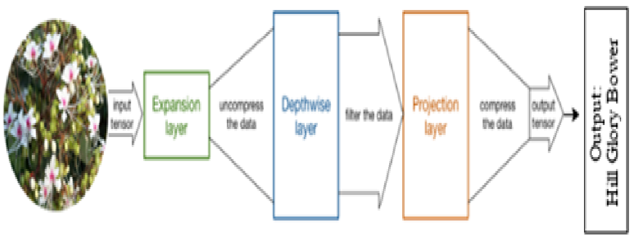


Fig 7. MobileNetV2 deep learning model architecture.

Resnet50: The transfer learning model ResNet stands for residual network. The primary purposes of the ResNet50 model are to solve more challenging problems and enhance classification or recognition accuracy. It has two layers: a dense layer and a pre-trained ResNet layer [29].

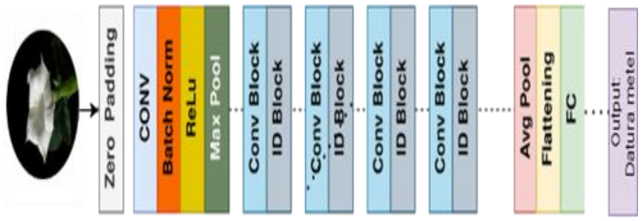


Fig 8. ResNet50 deep learning model architecture.

4.4 Performance Metrics Used

We evaluated many metrics that are frequently used to grade the classification report, for instance, accuracy, recall, precision, and $F1$-score. We employed the equations (3) to (6) to produce the classification report. TP stands for a true positive value and TN for a true negative value. False positives and false negatives are abbreviated as FP and FN, respectively, on the opposite side.

$$Precision = \frac{TP}{TP+FP} \times 100\%. \tag{3}$$

$$Recall = \frac{TP}{TP+FN} \times 100\%. \tag{4}$$

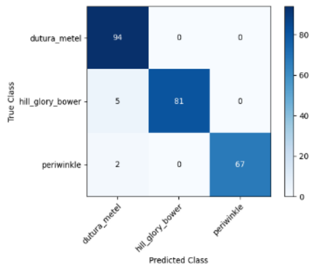
$$F_1 - score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \times 100\%. \tag{5}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100\%. \tag{6}$$

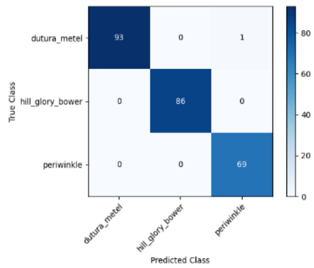
Here is to mention that all of the above metrics are calculated from a 2×2 confusion matrix. Since we have three classes, 3×3 confusion matrices are produced at first. We use the method described and equated in [30] to come up with 2×2 confusion matrices from a 3×3 confusion matric.

5. Experimental Evaluation

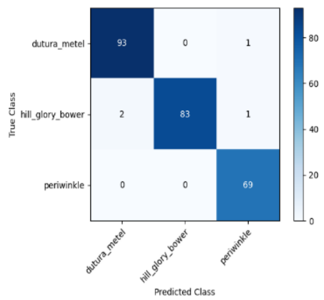
We examined four transfer learning models: VGG-16, VGG-19, MobileNetV2, and ResNet50. We have used 1009 images to learn the model and 249 images to taste it. First of all, the data set was divided into two subsets, which are the train data set and the test data set, by utilizing the holdout approach [31]. In the train data set, we used 80% of the data, and 20% is used for the test data set. In our research study, we have 3 classes. To assess the models' performance, we use 3×3 multiclass confusion matrices as shown in Figure 9. There is a projected class and a genuine class in these multiclass confusion matrices. True class in a confusion matrix refers to the real class in a data set. On the other hand, predicted class refers to the predicted value of the class. Based on this matrix, Figure 9 (b), we can see that the model correctly classified 91 instances of "datura metal" (true positives), but incorrectly classified 1 instance of "datura metal" as "hill glory bower" and 2 instances of "datura metal" as "periwinkle" (false negatives). Similarly, the model correctly classified 86 instances of "hill glory bower" (true positives), but misclassified 0 instances of "hill glory bower" as "datura metal" (false positives) and 0 instances of "hill glory bower" as "periwinkle" (false negatives). Finally, the model correctly classified 69 instances of "periwinkle" (true positives), and misclassified 0 instances of "periwinkle" as "datura metel" (false positives) and 0 instances of "periwinkle" as "hill glory bower" (false negatives). Overall, this confusion matrix provides a detailed breakdown of the model's performance and can be used to calculate various performance metrics, such as accuracy, precision, recall, and F_1-score, to evaluate how well the model is performing for each class.



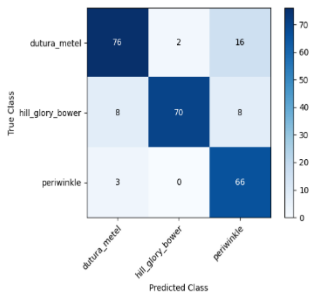
(a) VGG-16



(b) VGG-19



(c) MobileNetV2



(d) Resnet50

Fig 9. Confusion matrix of dimension 3 × 3 for the four CNN models used. (a) VGG-16. (b) VGG-19. (c) MobileNetV2. (d) Resnet50.

Table 2 shows how many hyperparameters were used in our research work. To train the model, we have tried a total of 30 epochs for all the models where the image input size is 224×224 pixels. To minimize the loss function, we used the Adam optimizer, which helps us adjust the weight of a pre-trained model to fit a data set.

Table 2. Different values used for the hyperparameters of classifiers employed.

Classifier	*Input Data Size*	*Batch Size*	*Optimizer*	*Epoch*	*Number of Parameters Used*
VGG-16	224 × 224	16	Adam	30	14,846,787
VGG-19	224 × 224	16	Adam	30	20,156,483
MobileNet V2	224 × 224	16	Adam	30	2,586,691
Resnet50	224 × 224	16	Adam	30	24,113,027

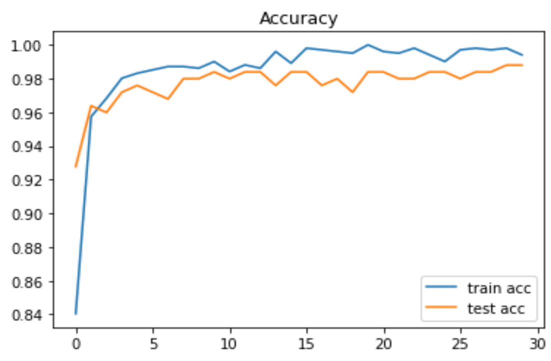
The results of our four CNN models are tabulated in Table 3, showing accuracy, precision, recall, and F_1-score. The goal of this evaluation is to identify the model that properly classified the most photos. The VGG19 model is found to have the highest accuracy, achieving an outstanding score of 99.2%. This implies that the VGG19 model can accurately classify 99.2% of all images that were fed into the model for testing. Additionally, the model's average accuracy, recall, and F_1-score were all very high at 0.97%,

0.98%, and 0.98 respectively. This means that the VGG19 model correctly identified and classified a high proportion of positive instances while minimizing false positives and false negatives. In contrast, the Resnet50 model is found to have the lowest accuracy among the four models, with a score of 90.10%. The precision, recall, and F_1-score for this model are also lower, at 0.86% each. This indicates that the Resnet50 model worked to correctly classify images but had a higher proportion of false negatives and false positives. Altogether, the results of this evaluation suggest that the VGG-19 model is the most accurate and precise model for classifying images among the four models evaluated.

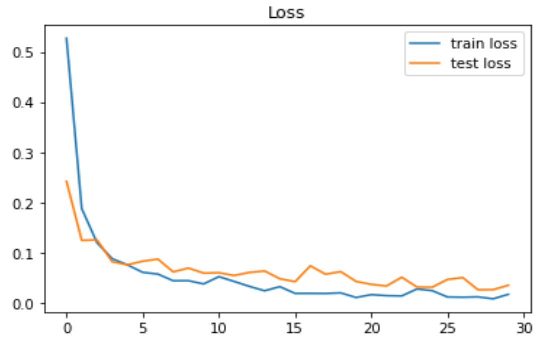
Table 3. Metric-wise results of the performance of the classifiers used.

Classifier	***Accuracy***	***Precision***	***Recall***	***F_1-Score***
VGG-16	98.13%	0.97%	0.98%	0.97%
VGG-19	99.2%	0.99%	0.99%	0.99%
MobilleNet V2	98.93%	0.99%	0.98%	0.98%
Resnet50	90.09%	0.86%	0.86%	0.86%

To monitor a model's performance over time in deep learning, loss curves, training and testing accuracy, and other metrics are commonly utilized. These graphs Figure 10 show the accuracy and loss values of the model across each training epoch which is defined as a complete pass over the entire training dataset.



(a) Accuracy Curve



(b) Loss Curve

Fig 10. The training and test curves for VGG-19. **(a)** Accuracy curve. **(b)** Loss curve.

6. Comparative Analysis of Results

Flowers are one of the ways to make our world beautiful. A lot of research has already been done on flower recognition. So, we need to compare our work with other recently published works. We have researched three common flowers in our country, which sets our work apart from others. We have presented it in Table 4. In article

[19], they collected 20,012 local medicinal plant leaf images and divided the whole data set into two parts: training and test data sets. The recognition rate of medicinal plant leaves is 100%. Deep convolutional networks were used by [3] to recognize apple flowers. They achieved 80% accuracy using CNN and SVM models. The article [5] describes a visual attention-driven deep-learning technique for flower identification. They select five common flowers, and their identification rate is 85.7%. Isha and Patel [6] used the MKL-SVM technique in yet another outstanding piece of work. Additionally, 102 different spices' 25000 flower pictures were used.

Table 4. Comparison of our work with the others.

Work Done	***Domain***	***Locality***	***Problem Dealt with***	***Data Size***	***Classifier***	***Accuracy***
This work	Deep learning	Bangladesh	Wildflower recognition	1009 images	VGG-19	99.2%
Dias [3]	Machine learning (deep + raditional)	US	Apple flower recognition	133,198 images	CNN and SVM models	80%
Cao and Song [5]	Visual-attention-driven deep learning	UK	Flower identification	1360 images	Visual-attention-driven DCNNs, VA-DCNNS	85.7%
Patel and Patel [6]	Computer vision and machine learning	*NM*[1]	Flower identification	25,000 images	MKL-SVM technique	76.92%
Ariful et al. [19]	Deep learning	Bangladesh	Medicinal plant recognition	20,012 images	MobileNet	100%

[1]*NM: Not mentioned*

7. Conclusion and Future Work

Our study focused on creating a computer vision-based method for identifying wildflowers. We correctly identified flowers in the natural environment with 99.2% accuracy using CNN models. The results achieved from our research have significance for multiple domains, including horticulture, botany, and ecological studies. However, it is necessary to acknowledge certain limitations of our research work. Our expert system may not perform well in intense light or with similar flower species. Addressing these challenges and enhancing the system's robustness should be the primary focus of future work.

References

[1] Flora – Banglapedia (available online https://en.banglapedia.org/index.php/Flora) (Last Accessed on January 05, 2023)

[2] Flowers of Bangladesh – Pro Bangladeshi, Available online: https://probangladeshi.com/flowers-of-bangladesh (Last Accessed on January 05, 2023)

[3] Dias, P.A., Tabb, A. and Medeiros, H., 2018. Apple flower detection using deep convolutional networks. Computers in Industry, 99, pp.17-28.

https://www.sciencedirect.com/science/article/abs/pii/S016636151730502X

[4] Palacios, F., Bueno, G., Salido, J., Diago, M.P., Hernández, I. and Tardaguila, J., 2020. Automated grapevine flower detection and quantification method based on computer vision and deep learning from on-the-go imaging using a mobile sensing platform under field conditions. Computers and Electronics in Agriculture, 178, p.105796.

https://www.sciencedirect.com/science/article/abs/pii/S0168169920315428

[5] Cao, S. and Song, B., 2021. Visual attentional-driven deep learning method for flower recognition. Mathematical Biosciences and Engineering, 18(3), pp.1981-1991.

https://www.aimspress.com/aimspress-data/mbe/2021/3/PDF/mbe-18-03-103.pdf
Patel, I. and Patel, S., 2019. Flower identification and classification using computer vision and machine learning techniques. International Journal of Engineering and Advanced Technology (IJEAT), 8(6), pp.277-285.

https://www.researchgate.net/profile/Sanskruti-Patel-2/publication/344249077_Flower_Identification_and_Classification_using_Computer_Vision_and_Machine_Learning_Techniques/links/5f608a13a6fdcc1164133617/Flower-Identification-and-Classification-using-Computer-Vision-and-Machine-Learning-Techniques.pdf

[6] Jain, V. and Yadav, A., 2021, February. Analysis of performance of machine learning algorithms in detection of flowers. In 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV) (pp. 706-709). IEEE.

https://ieeexplore.ieee.org/abstract/document/9388599/

[7] Sun, X., Li, Z., Zhu, T. and Ni, C., 2021. Four-dimension deep learning method for flower quality grading with depth information. Electronics, 10(19),

p.2353.

https://www.mdpi.com/2079-9292/10/19/2353/pdf

[8] Patel, I. and Patel, S., 2020. An optimized deep learning model for flower classification using NAS-FPN and faster R-CNN. International Journal of Scientific & Technology Research, 9(03), pp.5308-5318.

https://www.researchgate.net/publication/344248895_An_optimized_deep_learning_model_for_flower_classification_using_NAS-FPN_and_faster_RCNN

[9] Darwin, B., Dharmaraj, P., Prince, S., Popescu, D.E. and Hemanth, D.J., 2021. Recognition of bloom/yield in crop images using deep learning models for smart agriculture: a review. Agronomy, 11(4), p.646.

https://www.mdpi.com/2073-4395/11/4/646/pdf

[10] Mete, B.R. and Ensari, T., 2019, October. Flower classification with deep cnn and machine learning algorithms. In 2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT) (pp. 1-5). IEEE.

https://ieeexplore.ieee.org/abstract/document/8932908

[11] Cengıl, E. and Çinar, A., 2019, September. Multiple classification of flower images using transfer learning. In 2019 International Artificial Intelligence and Data Processing Symposium (IDAP) (pp. 1-6). IEEE.

https://ieeexplore.ieee.org/abstract/document/8875953

[12] Cheng, Z. and Zhang, F., 2020. Flower end-to-end detection based on YOLOv4 using a mobile device. Wireless Communications and Mobile Computing, 2020, pp.1-9.

https://www.hindawi.com/journals/wcmc/2020/8870649/

[13] Sun, K., Wang, X., Liu, S. and Liu, C., 2021. Apple, peach, and pear flower detection using semantic segmentation network and shape constraint level set. Computers and Electronics in Agriculture, 185, p.106150.

https://www.sciencedirect.com/science/article/abs/pii/S016816992100168X

[14] Farha, A.B., Hakim, M.A. and Khatun, M.E., 2022, October. Local Rose Breeds Detection System Using Transfer Learning Techniques. In 2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-6). IEEE.

https://ieeexplore.ieee.org/abstract/document/9984329

[15] Gallmann, J., Schüpbach, B., Jacot, K., Albrecht, M., Winizki, J., Kirchgessner, N. and Aasen, H., 2022. Flower mapping in grasslands with drones and deep learning. Frontiers in Plant Science, 12, p.3304.

https://www.frontiersin.org/articles/10.3389/fpls.2021.774965/full

[16] Albarico, J.P., La Rosa, G.R.F., Santos, R.A.D., Tesorero, A.J.M., Magboo, M.S.A. and Magboo, V.P.C., 2023. Roses Greenhouse Cultivation Classification Using Machine Learning Techniques. Procedia Computer Science, 218, pp.2163-2171.

https://www.sciencedirect.com/science/article/pii/S1877050923001928

[17] Narvekar, C. and Rao, M., 2020, December. Flower classification using CNN and transfer learning in CNN-Agriculture Perspective. In 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS) (pp. 660-664). IEEE.

https://ieeexplore.ieee.org/abstract/document/9316030

[18] Ariful Hassan, M., Sydul Islam, M., Mehedi Hasan, M., Shorif, S.B., Tarek Habib, M. and Uddin, M.S., 2022. Medicinal plant recognition from leaf images using deep learning. In Computer Vision and Machine Learning in Agriculture, Volume 2 (pp. 137-154). Singapore: Springer Singapore.

https://ieeexplore.ieee.org/abstract/document/9316030

[19] বাংলাদেশ ন্যাশনাল হারবেরিয়াম (available on online http://www.bnh.gov.bd/) (Last Accessed on January 05, 2023)

[20] Loeb, R.E., Walborn, T.N., Leasure, A.J., Manners, J.D., Massimino, R.P. and Mcgraw, O.A., 2022. Spanning the globe for diversity: species selection in early nineteenth century United States botanical gardens. Studies in the History of Gardens & Designed Landscapes, 42(2), pp.67-119.

https://www.tandfonline.com/doi/abs/10.1080/14601176.2022.2097429

[21] Clerodendrum infortunatum (available on online https://en.wikipedia.org/wiki/Clerodendrum_infortunatum) (Last Accessed on January 07, 2023)

[22] Noyontara or Cape Periwinkle, Catharanthus roseus (available on online http://www.floraofbangladesh.com/2020/11/)

[23] Simonyan, K. and Zisserman, A., 2014. Very deep convolutional networks for large-scale image

recognition. arXiv preprint arXiv:1409.1556.

https://arxiv.org/abs/1409.1556

[24] Subetha, T., Khilar, R. and Christo, M.S., 2021. WITHDRAWN: A comparative analysis on plant pathology classification using deep learning architecture–Resnet and VGG-19.

https://www.sciencedirect.com/science/article/pii/S221478532039670X

[25] Dey, N., Zhang, Y.D., Rajinikanth, V., Pugalenthi, R. and Raja, N.S.M., 2021. Customized VGG-19 architecture for pneumonia detection in chest X-rays. Pattern Recognition Letters, 143, pp.67-74.

https://www.sciencedirect.com/science/article/abs/pii/S0167865520304414

[26] Xiang, Q., Wang, X., Li, R., Zhang, G., Lai, J. and Hu, Q., 2019, October. Fruit image classification based on MobileNetV2 with transfer learning technique. In Proceedings of the 3rd international conference on computer science and application engineering (pp. 1-7).

https://dl.acm.org/doi/abs/10.1145/3331453.3361658

[27] Review: MobileNetV2 — Light Weight Model (Image Classification) (available on online https://towardsdatascience.com/review-MobileNetV2-light-weight-model-image-classification-8febb490e61c) (Last Accessed on February 12, 2023)

[28] Reddy, A.S.B. and Juliet, D.S., 2019, April. Transfer learning with ResNet-50 for malaria cell-image classification. In 2019 International Conference on Communication and Signal Processing (ICCSP) (pp. 0945-0949). IEEE.

https://ieeexplore.ieee.org/abstract/document/8697909

[29] Habib, M. T., Majumder, A., Jakaria, A. Z. M., Akter, M., Uddin, M. S., & Ahmed, F. (2020). Machine vision based papaya disease recognition. Journal of King Saud University-Computer and Information Sciences, 32(3), 300-309.

https://www.sciencedirect.com/science/article/pii/S1319157818302404

[30] Han, Jiawei, Jian Pei, and Micheline Kamber. Data mining: concepts and techniques. Elsevier, 2011. Available at: Data mining: concepts and techniques