

Flower Classification Utilisizing Tensor Processing Unit Mechanism

Kanwarpartap Singh Gill
Chitkara University Institute of
Engineering and Technology,
Chitkara University,
Punjab, India
kanwarpartap.gill@chitkara.edu
.in

Avinash Sharma*
Department of Computer
Science and Engineering,
MM Engineering College,
Maharishi Markandeshwar
(Deemed to be University),
Mullana-Ambala, Haryana,
India, 133207
asharma@mmumullana.org

Vatsala Anand
Chitkara University Institute of
Engineering and Technology,
Chitkara University,
Punjab, India
vatsala.anand@chitkara.edu.in

Rupesh Gupta
Chitkara University Institute
of Engineering and
Technology, Chitkara
University,
Punjab, India
rupesh.gupta@chitkara.edu.in

Abstract— The biodiversity of the species and the potential for visual similarity across the many flower class species, categorizing flowers can be quite a difficult undertaking. The process of classifying flowers is fraught with difficulties, such as blurry, noisy, and poor quality photos, as well as those obscured by plant leaves, stems, and occasionally even insects. With the introduction of deep neural networks, machine learning methods were utilized instead of the conventional handmade features for feature extraction. Because of its quick calculation and efficiency, researchers have shifted their attention to using non-handcrafted features for picture classification tasks. We have discovered several varieties of flowering plants in nature. It is challenging to distinguish and classify the species of flower for education purpose. The identification of objects is expanding across several sectors as a result of the recent development of deep learning in computer vision. In order to get over these issues and constraints, our research created an effective and reliable deep learning flower classifier based on transfer learning and the most advanced convolutional neural networks. According to this study's suggested model, the Adam optimizer's accuracy utilising the ResNet50 model is 93 percent.

Keywords— Convolutional Neural Network, Flower Classification, Adam Optimizer, Visualization, ResNet50 Model

I. INTRODUCTION

Deep learning methods are being used in a variety of computer vision applications, including segmentation, classification, and object identification. Because a wide range of flower classes share comparable color, shape, and texture properties, flower categorization and recognition is an attractive study subject. A mixture of visual characteristics collected from floral photographs is used by the majority of the existing flower classification systems, which are then used to classify the images using supervised or unsupervised learning techniques. These methods' classification accuracy is mediocre. Consequently, there is a need for a reliable and precise system to categorize floral photos automatically on a bigger scale. Flower recognition is the most challenging challenge in the field of object detection because to the huge range of flower species with varied colours, forms, and sizes, as well as their surrounds with leaves, bushes, and other things. Human life is getting better and better as a result of the deep learning application sectors' ongoing progress. The identification of flora species benefits greatly from the use of convolutional neural networks. Deep learning techniques let us identify images based on attributes like colour and form.

Regarding characteristics like texture, petal and sepal shapes, each species is unique.

II. LITERATURE

In order to detect floral photos, Gopalakrishnan, T. proposed the CFPA-DLDF model, which was created by combining two DL models. To illustrate the improved performance of the suggested model, a comparison study was carried out. The findings confirmed that the proposed CFPA-DLDF model is superior to current techniques [1]. A suggested floral picture classification approach by M.R. Banwaskar employs pre-trained CNN (Convolutional Neural Network) AlexNet as the feature extractor and is based on deep features and multiclass SVM. It is shown that the suggested transfer learning-based approach performs better in terms of accuracy than the current deep learning-based classification methods [2]. Sharma, V. proposed a comprehensive framework for classifying plants into the best category using machine learning-based techniques. The framework's capacity to encompass all plant breeds with as many species as feasible is its main contribution. The Pearson correlation and Information Gain methods are used to extract features from the model. Support Vector Machine, Multinomial Naive Bayes, Extreme Gradient Boosting, Decision Tree, Random Forest, and K-Nearest Neighbor are the classifiers with the typical performance comparison [3]. Using flower categorization technology and Artificial Intelligence (AI) controlled by drones or robots, Tsai, M.F., presented a novel pollination technique. Drones or robots must be able to identify and categorise flowers that are prepared for pollination in order to pollinate tomato blooms. As a result, they developed an AI picture categorization system employing a convolutional neural network for machine learning [4]. In order to spoof the deep learning systems inside the applications, Cao and H. suggest an efficient "black-box" strategy that involves training alternative models. To conduct black-box adversarial assaults, they tested their methodology using 10 real-world deep learning apps from the Google Play store. Three elements were discovered via the study to have an impact on assault effectiveness. Our method has an average attack success rate of 66.60%, which is pretty high [5]. For the segmentation and classification of skin lesions, Ullah, W., developed the Automated Seeded Growing Segmentation with Optimal EfficientNet (ARGS-OEN) method. The suggested ASRGS-OEN approach entails the creation of an ideal EfficientNet model in which the Flower Pollination

Algorithm is used for the process of hyper-parameter tuning (FPA). Additionally, a classification algorithm based on Multiwheel Attention Memory Network Encoder (MWAMNE) is used to determine the correct class labels for the dermoscopic pictures [6]. In order to improve the status of the roses and promote their best output, Albarico, J.P. set out to categorise the ideal greenhouse environment. Testing was done on four model setups that matched the pre-processing methods. This demonstrates that machine learning algorithms are capable of forecasting remedial steps that will enhance rose conditions. Finding accurate and trustworthy classification algorithms that help farmers estimate the ideal greenhouse microenvironment was a significant contribution of this research [7]. Mu, X. created a method for taking pictures of two apple kinds in an orchard setting. The distribution in the tree canopy and the proportion of the king blooms may be determined using this data. The study's findings are anticipated to provide horticulture expertise and decision-making data for robotic pollination [8]. Furthermore, the CNNAR retrieval architecture developed by D. Nahavandi in this study attained excellent accuracy. In addition, by quickly identifying, categorising, and retrieving priceless architectural images from the database, comparable target images can be found and retrieved in a reasonable and accurate manner. Following that, precise restoration methods for outdated and damaged architectural heritage products can be offered [9]. Anand V. used two optimizers, Adam and Adadelata, to assess the suggested model for the categorization of diseases across 20 epochs and 32 batch sizes. Using the Adadelata optimizer, the model outperformed it with an accuracy rating of 97.96% [10]. This study extracts several deep features from deep learning models and boosts them as input to the Adadelata and SGD optimizer in order to produce an intense perception. The suggested model's remarkable execution power is realised by using the Adadelata optimizer developed by Gill, K.S. [11]. Zhouyi, X created a classification programme for identifying flower species using deep learning and various datasets. When the results are compared, it can be shown that deep learning approaches perform differently in certain models depending on the number of classes in the data set and in most models based on the kind of optimizer [12]. Duman, B. uses image processing and deep learning methods based on game theory and optimization to classify flowers in order to quickly gather a significant quantity of training data. Given the current scarcity of agricultural data sets, the GAN model can produce realistic flower images, demonstrating the viability of an intelligent data gathering strategy for herbaceous flowers [13]. Prema, C.E. suggests a novel method to reduce the likelihood of false alarms by identifying the smoke and analysing its particular textural characteristics. Results of the investigation showed that the proposed smoke identification technique performs better than all other common smoke recognition methods by obtaining improved detection accuracy and processing speed [14]. Sai, A.V. classifies five different types of floral species under the headings of daisy, dandelion, rose, sunflower, and tulip. Convolutional neural networks are the technology used in this case for automatic recognition based on images of plants. They concentrated on a neural network, which suggests a strategy known as skip connections and is adaptable enough to carry out different categorization approaches. By verifying the dataset and focusing on picture categorization, they achieved their goal [15]. S. Singh offers a sequential methodology to create output and build various network layers. After adjusting the

model's essential parameters, the suggested model's maximum accuracy was 90% [16]. Objects are localised in the images through segmentation to extract the Region of Interest, detect the objects, perform feature extraction, and perform supervised classification of flowers into five categories by Rani, R. The images are pre-processed to enhance the key features and suppress the undesirable information [17]. The goal of Prakash, K.B.'s Oxford17 flower dataset was to identify the flowers. For quick and precise detections, they provide a formal contract Yolo object identification model in this study. The suggested model is a brand-new one-step object identification technique for distinguishing between various types of flowers. This technology automatically identifies objects in the picture and localises them [18]. Gu, F. used deep learning to the field of picture identification and utilised the method to solve the problem of flower detection. They created a deep learning multi-classification model based on ResNet and trained it using the PyTorch framework on a data set that included more than 3000 images of five different types of flowers [19]. A. Solanki devised a procedure that consists of two distinct parts. The first step is segmenting the flower photos, and the second is feeding the segmented images into a convolutional neural network to identify the species of the flowers. The PyTorch library was employed in this study to aid with recognition. For reliable real-time flower species predictions, this classifier may be connected with a smartphone application [20].

As a result, the study process is made easier and a lot of valuable research is conducted in this way on a number of aspects of flower categorization.

The primary contributions made by the proposed research are listed in the list below:

- Throughout the entirety of the study, the ResNet50 Model was utilised.
- It has been considered how different key factors, including as optimization techniques, batch sizes, and epoch counts, affect the results.
- This work will assist in addressing issues with finding a solid model for classifying flowers based on the parameters used in this study, a challenge for researchers.

The purpose of the next sections of the study is to illustrate the recommended input dataset in Part 3, describe the architecture of the ResNet50 model in Part 4, present the findings in Part 5, and draw a conclusion in Part 6.

III. INPUT DATASET

Based on the photos, which were taken from five distinct public databases, 104 different varieties of flowers were classified. While some classes include several sub-types of flowers, certain classes are relatively limited, including only one specific sub-type. The dataset has flaws, such as photographs of flowers in unusual locations or as a background to contemporary technology, but that's part of the task. The dataset has three different sets of pictures i.e. 12753 training images, 3712 validation images, and 7382 test images.

Fig. 1 displays an example of these directories being used as dataset pictures for accuracy prediction.

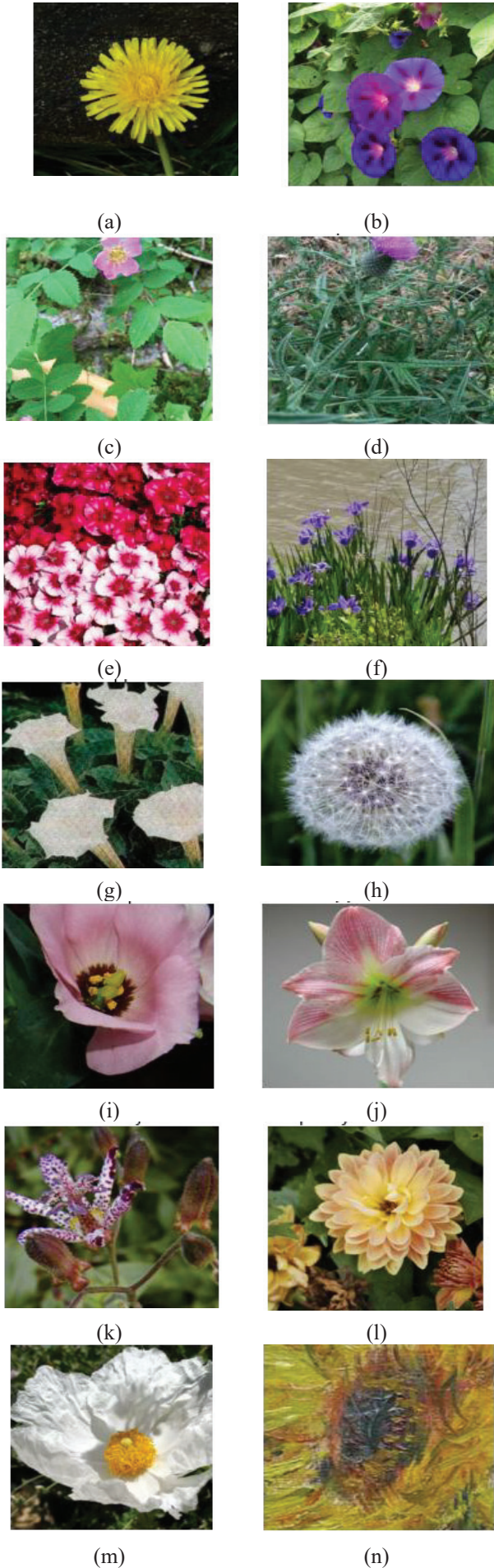


Fig. 1. Sample image of (a) Common Dandelion (b) Morning Glory (c) Wild Rose (d) Spear Thistle (e) Sweet William (f) Iris (g) Thorn Apple (h) Common Dandelion (i) Bolero Deep Blue (j) Hippeastrum (k) Toad Lily (l) Pink Yellow Dahilia (m) Tree Poppy (n) Sunflower (o) Camelia (p) Mangolia

IV. FLOWER CLASSIFICATION USING RESNET 50 MODEL

A 50-layer convolutional neural network is called ResNet-50 (48 convolutional layers, one MaxPool layer, and one average pool layer). Artificial neural networks (ANNs) that use residual blocks to build networks are known as residual neural networks is depicted in Fig 2.

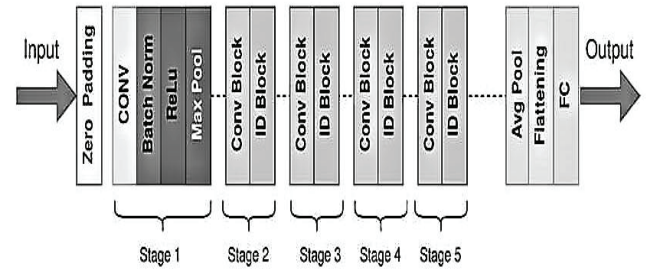


Fig. 2. ResNet50 Model Architecture

V. RESULTS

A. Flower Classification Using ResNet50 Model on Adam Optimizer

The Adam optimizer with an epoch of value 30 is being used by the suggested ResNet50 model to classify flowers.

TABLE I. TRAINING AND VALIDATION LOSS AND ACCURACY ON ADAM OPTIMIZER

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	2.5973	0.4196	8.4902	0.0442
.
5	0.0710	0.9826	4.8513	0.1175
.
10	0.0215	0.9974	0.5499	0.8696
.
15	0.0141	0.9993	0.2823	0.9351
.
20	0.0111	0.9991	0.2813	0.9378
.
.

25	0.0087	0.9993	0.2831	0.9380
.
30	0.0072	0.9995	0.2838	0.9382

Table I shows the accuracy and losses for training and validation using the Adam optimizer for different epochs. The training accuracy shows a value of 0.9826 on a scale of 5 epochs. The validation accuracy for an epoch with a value of 20 is 0.9378. Table I also displays the losses from training and validation. These accuracy and loss numbers are computed after the prediction algorithm uses the dataset.

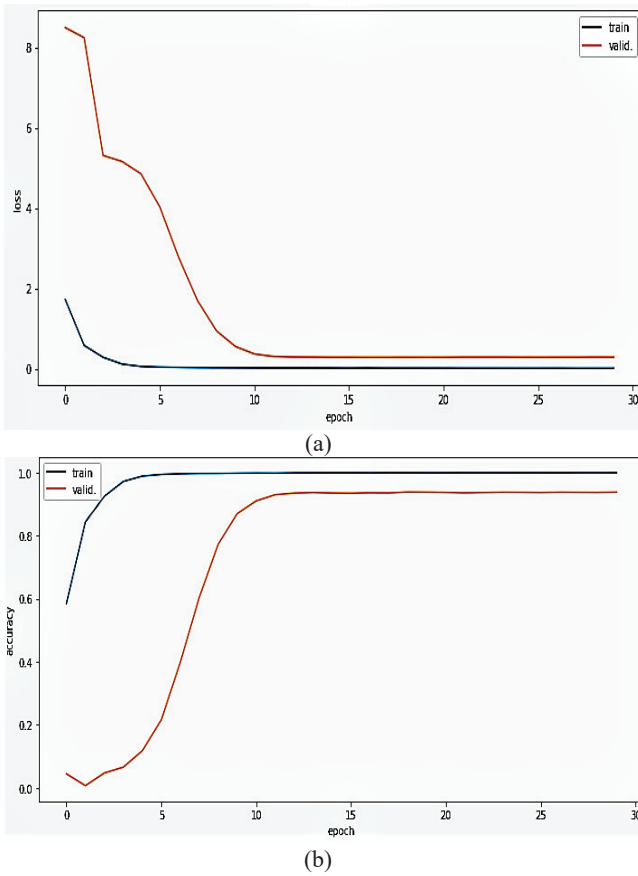
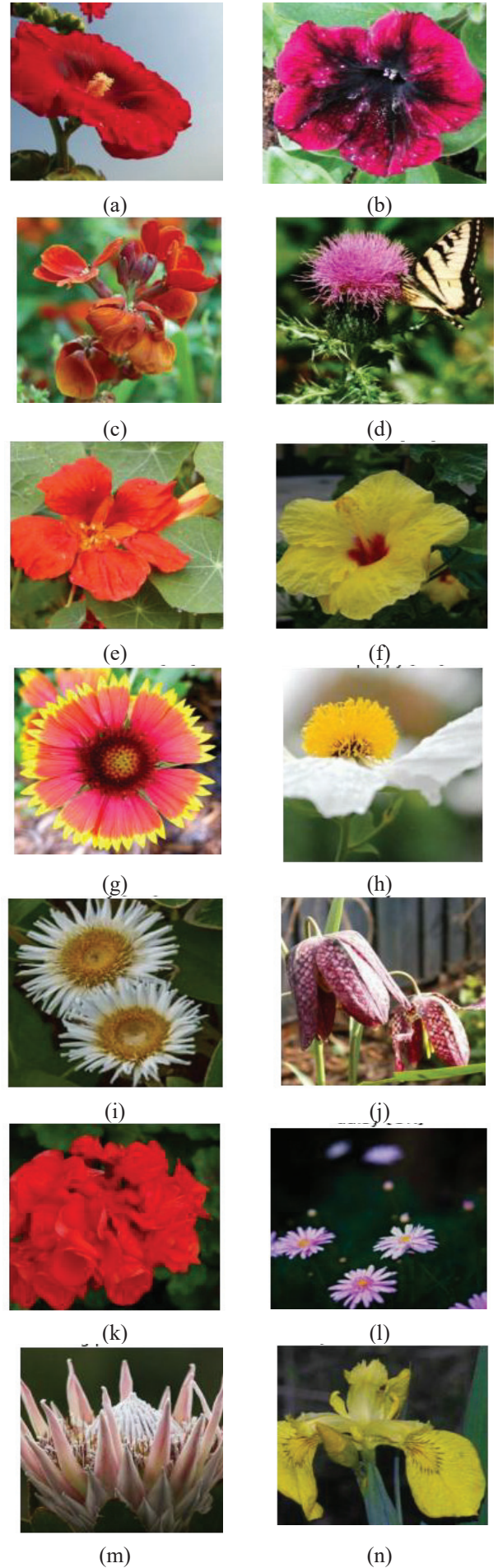


Fig. 3. Training and Validation (a) Accuracy (b) Loss on Adam Optimizer

On the train and validation outputs, epochs and accuracy are compared, and the accuracy and loss of the model are projected in Fig. 3 using the parameters required to represent the desired output.

B. Visual Validation of Flowers after Classification

Checking whether the user finds the visual elements of the application's user interface to be adequate is known as visual validation regression testing or visual testing in software. A different name for it is Visual Validation Testing. Although there are various classes of flowers that are used in the dataset but some of the classes are depicted in Fig 4.





(o)



(p)

Fig. 4. Visual Validation of (a) Common Dandelion (b) Morning Glory (c) Wild Rose (d) Spear Thistle (e) Sweet William (f) Iris (g) Thorn Apple (h) Common Dandelion (i) Bolero Deep Blue (j) Hippeastrum (k) Toad Lily (l) Pink Yellow Dahilia (m) Tree Poppy (n) Sunflower (o) Camelia (p) Mangolia

VI. CONCLUSION

The internet of things, which is heavily utilized and has sensors, data storage, and machine learning built in, is not only used extensively in the manufacturing and computer science sectors but is also moving in the direction of the botanical world as the digital era changes day by day. The most challenging problem in the field of object identification is recognizing flowers since there are so many different kinds with different colors, forms, and sizes, as well as their surrounds with leaves, bushes, and other items. Plants can come in a variety of species that are quite different from one another in terms of their physical characteristics. The accuracy of the suggested model, which makes use of the ResNet50 model and the Adam optimizer, is 93 percent. Botanists have thus long looked for a tool that might aid them in classifying plants into the right species in order to greatly reduce the amount of time they had to spend on the task. The purpose of this study will be to aid botanists in classifying unknown plant species into the right groups.

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