Petals to the Metal - Flower Classification on TPU

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***Abstract*—The main purpose of this project is to understand and find an appropriate algorithm for flower image classification. This process is vital in the classification because of its significance in the real life in different ways. One such is understanding the likeness of the components in several species, understanding the complexity of the image, etc. The classification algorithm with the most accuracy is important as there are numerous classification techniques are being developed. Here in our project, we use the datasets of 104 types of images of flowers with their own subtypes.**

I. INTRODUCTION

The classification of flowers is a mandatory requirement in many applications ranging from medicine to GIS. There are 250,000 classified flowering plants however, there are even more which are not even classified. In addition, many types of flowers have similar names and shapes but differ in color. Many approaches have been used in the past to classify images of flowers. Previously, in 1999, Das et al proposed an approach that focuses solely on color. Since then, many approaches have been developed that take into account different flower characteristics such as texture, shape, etc., and introduce new classification methods and algorithms.

Image classification is the task of inserting classes of information from multiband raster imagery. During classification, there are two types: supervised and unsupervised. Supervised classification uses spectral signatures obtained from training samples to classify images while unsupervised classification detects spectral classes in multiband images without analyst intervention. In this project, we focus on the image classification of flowers.

II. RELATED WORKS

The reviewed relevant publications on flower image classification and summarized the methods and sorted by year of publication is presented as Diah Harnoni et.al, in 2013 developed a system to recognize the orchid species using images of flower via Maximal Similarity based on Region Merging (MSRM). The result showed that the proposed method improved the accuracy by 85.33percent in the training phase whereas 79.33percent in the testing phase. Later on, Shubra Aich et al, 2015 proposed to substitute the lower number of original training images with a large number of counterparts, artificially generated by manifold mapping resulting in all the images with 64-64 resolution giving 43percent of accuracy. In 2016 Yuanyuan Liu et al proposed a framework based on Convolutional Neural Networks (CNN) and achieves a classification accuracy equal to 84.025 percent on the oxford 102 flower dataset. A year later, S Krishnaveni et.al, proposed an automatic quality detection of jasmine flowers based on color, shape, and texture to identify the flower quality using Support Vector Machine (SVM) and Random Forest Tree (RFT). The used database contains 500 images consisting of 350 good quality and 150 defects. The resulting accuracy of this approach produced 83 percent with SVM and 57 percent by RFT. In the same year, Xiaolng Xia et.al, used transfer learning technology to retain the flower dataset based on the Inception V3 model of TensorFlow on two datasets which is Oxford 17 and Oxford 12, and got better accuracy of flower classification equaling 95 percent and 94 percent respectively.

III. PROBLEM STATEMENT

- Building a machine learning model that can recognize the different types of flowers in a dataset of images is a difficult task. We are categorizing 104 distinct varieties of flowers in this research using their photos that were taken from five separate public sources. Pink primroses are an example of a highly limited class that only has one specific subtype of flower, whereas other classes include many different subtypes (e.g. wild roses).
- Identify the method that is most suited for the dataset by examining and contrasting previously constructed pre-trained models. Think about extending the neural network with layers and analyzing the results.

IV. IDENTIFYING CUSTOMERS

The customer will be the person who buys a product or service. The first person in consideration would be nurseries, gardeners, and bouquet manufacturers such as all the people who work with flowers and the people who are interested in the flowers (anthophile). So the main role of the customer would be to provide a proper classification of a particular flower. All companies and organizations that include flowers and classifications of them are the customers for this project.

V. IDENTIFYING END-USERS

The individual who purchases a goods is the customer. Nurseries, gardeners, and bouquet producers—all those who deal with flowers and those who are interested in them—would be the first persons to be taken into account (anthophile). Therefore, the primary responsibility of the consumer would be to properly classify a specific bloom. Customers for this initiative include all businesses and organizations that deal with flowers and different types of them.

VI. Customer-imposed constraints that might include

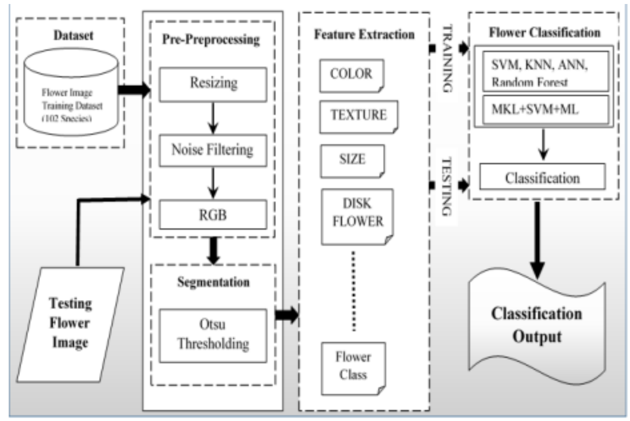
As we are working on a flower classification project, information such as the texture, color, and type of the flower is needed to give accurate results. The inputs given by the customers should be matched from the dataset to give the result. Due to this, the main constraint is that the dataset we are using for the training of the machine would include all types and sub-types of flowers.

VII. Assumptions and Risks

The assumption of the project includes keywords like the type of flower, the texture of the flower, the type of the petal, the color of the petal, etc. The main challenge is to build a machine learning module that identifies the type of flower in a dataset of images. So in this, we are classifying particular subtypes of flowers based on the provided dataset, and the challenge here is whether will the image provided by the customer would match the classification data. In such a case what do we need to do in such cases where we have new images outside of the dataset? What if there are more sub-types of the flower than we already have? Stakeholder risks would be insufficient information about flower color petals, shape, and texture our main constraints. If the information provided lacks the types of classifications it would be different to classify the particular flower into a particular family. Here stakeholders play a significant role in providing the information.

VIII. Literature Review

Flowers are one of the most beautiful creations God has ever made and there are many different types and shades to choose from. Identifying each requires a botanist with extensive knowledge and skill. Is it difficult to classify flowers because there are so many flowers that have similar environmental factors such as shape, appearance, and the shape of leaves and grass? Flower detection is an important problem that can be solved manually by experts, but it is time consuming and consequently inefficient. Therefore, automatic recognition of plants is an important research topic. In this technologically advanced age, we use artificial intelligence to solve real-world problems and make us think of the seemingly impossible. It is challenging to create a machine learning model that can distinguish between the various kinds of flowers in a dataset of photos. In this study, 104 different flower species were categorized using images that were collected from five different public databases. Pink primroses are an illustration of a very restricted class that only has one particular subtype of flower, as opposed to other classes that contain a wide variety of subtypes (e.g. wild roses). contain a wide variety of subtypes (e.g. wild roses).



IX. Model for the classification

A. Image Pre-processing

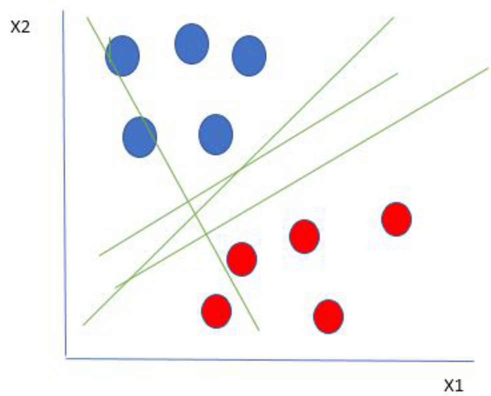
Before processing the images, the work performs some pre-processing operations, such as resizing and gray scaling. The larger the picture, the slower the algorithm will be. Also, to avoid insufficient use of high-resolution images, images are resized. This is done in order to save time. Because the texture and color features extracted from an image depend on a probability distribution, the image size shouldn't affect the results of a comparison. It is essential to make sure the image is not cropped too closely so that important features of the image are not missed. The flower image is first converted to a gray scale image and then a median filter is applied to remove any noise.

B. Previous Methodologies

1) Maximal Similarity Mechanism
2) Support Vector Machine
3) Random Forest
4) Inception V3

1) Maximal Similarity Mechanism: The scientific method is a way to figure out if a hypothesis is true. It involves using evidence to see if what you are thinking is true. The scientific method is a process that is used to figure out how something works. The scientific method is a way to test hypotheses and determine whether they are true. It is a process that involves using evidence to try to understand how something works. Classification of flowers can be a difficult task, especially when the flowers are in a natural setting. There are a number of methods that can be used to improve accuracy, but it is important to select the method that is most appropriate for the data being studied. The flower region can be divided based on the color features that are present in its images. The green area and the flower area are two distinct parts of the region. The green area around the flower represents the leaves surrounding it. The flower region, which is characterized by its color, is located within the green area. To create a color segmented image, you need to find the difference or distance between two colors. In this work, the images are transformed to Lab space using the specified color transformations. The user then selects a frame that includes the flower.

2) Support Vector Machine: A support vector machine is a model that constructs a hyperplane or set of hyper planes in high-dimensional space. This method aims to find a near-optimal function without knowing the statistical distribution and allows prediction. It relies only on training data by finding the separating hyperplane between two classes as shown in figure below.



3) Random Forest: Random forest is a conditional weighted method that uses only the features that are important for classification. An input dataset D consisting of N samples of d dimensions is first considered the root of the classification tree. Loop to find the best fit. The Gini Impurity is chosen as the metric for splitting the routes to measure the potential of the data. In this dataset, obtaining a floral image to use as the system's input. Recognizing the image using the techniques that have been developed using training and test data and prior data. using the textural attributes of the image to create a histogram. Using Matplotlib to plot the histogram. Using a collection of photos of flowers from each species, the random forest tree was trained. Using a different set of pictures of each species' blooms, we test the random forest tree. The end result is a technology that accurately and precisely recognizes each blossom. Based on the type of flower species, information on the species of flowers, such as its name, species, family, and genus, is generated.

4) Inception V3: The Inception V3 is a deep learning model based on Convolutional Neural Networks, which is used for image classification. It is a superior version of the basic model Inception V1 which was introduced as GoogLeNet in 2014. When multiple deep layers of convolutions were used in a model it resulted in the overfitting of the data. To avoid this from happening the inception V1 model use multiple filters of different sizes on the same level. This model used several techniques for optimizing the network for better model adaptation. It has higher efficiency. It has a deeper network compared to the Inception V1 and V2 models, but its speed isn't compromised.It is computationally less expensive. Figure 1 [2] is the model graph for the inception v3

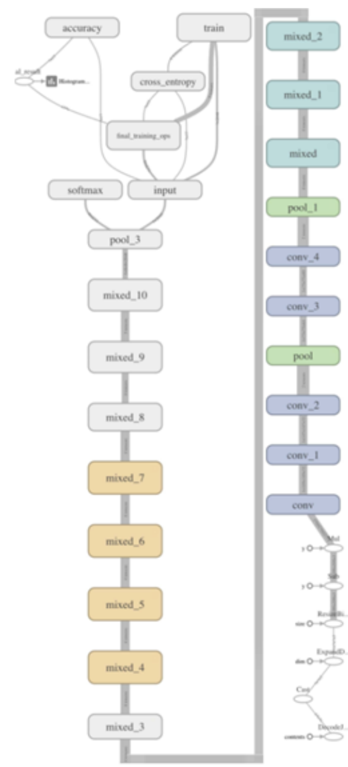


Fig. 1. shows the model graph for Inception v3

The Inception-v3 network model is a deep neural network. Training directly on a low-configuration computer is very difficult and takes at least several days. Tensorflow provides a tutorial where you can retrain his Inception's final layer for a new category using transfer learning. It adopts the transfer learning method to keep. Remove the previous level parameters, remove the last level of the Inception-v3 model, and then retrain the last level. The number of output nodes in the last level corresponds to the number of categories in the dataset.

X. Implementation

To improve the classification accuracy of the model on the test dataset, the following are explored:

1) Input image size
2) Pretrained model and number of trainable parameters of the final model
3) Data augmentation
4) Regularization techniques
5) Use of learning rate schedule

A. Input image size

The available image sizes in the dataset is: 192x192, 224x224, 331x331, 512X512 total is equal 5.15 GB.

Dataset Images are provided in TFRecord format, a container format frequently used in Tensorflow to group data files for optimal training performace.
Each file contains the id, label and image.
12753 training images.
3712 validation images.
7382 unlabeled test images

B. Pretrained model and number of trainable parameters of the final model

For training the model we have used a deep learning technique called Transfer learning with fine tuning means that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem. A stored network that has previously undergone training on a sizable dataset, generally for a sizable image-classification task, is referred to as a pre-trained model. Either apply transfer learning to adapt the pretrained model to a specific task, or use the model as is.

The idea behind transfer learning for image classification is that if a model is trained on a sizable enough dataset with adequate generality, it will be able to represent the visual world as a whole. By training a big model on a big dataset, you can then use these learnt feature maps to your benefit instead of having to start from scratch. Fine-tuning is the final, optional step. It entails unfreezing the entire model you received earlier (or a portion of it) and retraining it using the new data at a very slow learning rate. By gradually adjusting the pretrained features to the fresh data, this has the potential to provide significant improvements

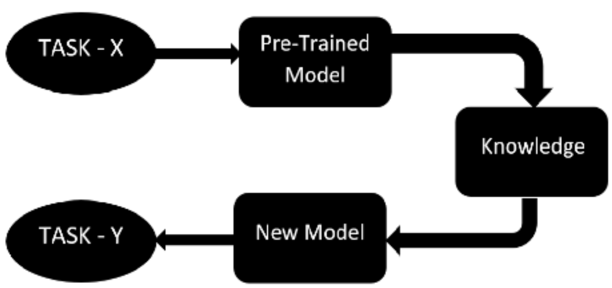


Fig. 2. shows the block diagram for transfer learning.

C. Data augmentation

Increasing the variability of your training set through the use of arbitrary (but realistic) modifications like image rotation is known as data augmentation.

TensorFlow Addons is a collection of contributions that follow well-known API patterns but add additional features that are not included in the core TensorFlow library. Large numbers of operators, layers, metrics, losses, and optimizers are natively supported by TensorFlow. With more data available, deep learning neural networks frequently perform better. Image data augmentation is a method for artificially increasing the size of a training dataset by producing altered versions of the dataset's images.

D. Regularization techniques

TPUs are powerful hardware accelerators with deep learning ability. Google applications including Translate, Photos, Search, Assistant, and Gmail are all powered by Cloud TPU, a machine learning ASIC that was created specifically for Google. To process huge image databases, Google built and employed them first. The chip has been specifically created for Google's TensorFlow framework, which is a symbolic math library used in machine learning programs like neural networks.

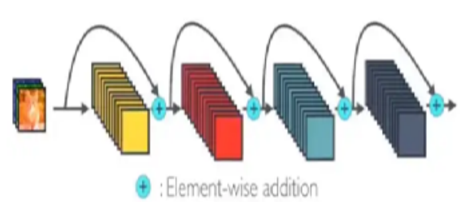
In this project, first we provide a brief overview of the dataset,then we go into depth about the experiment's methodology. We will have the overview of the results with which we conduct a comparison experiment to confirm the method's efficiency.

1) Dataset: Images are provided in TFRecord format, a container format frequently used in Tensorflow to group data files for optimal training performance. Each file contains the id, label and image.

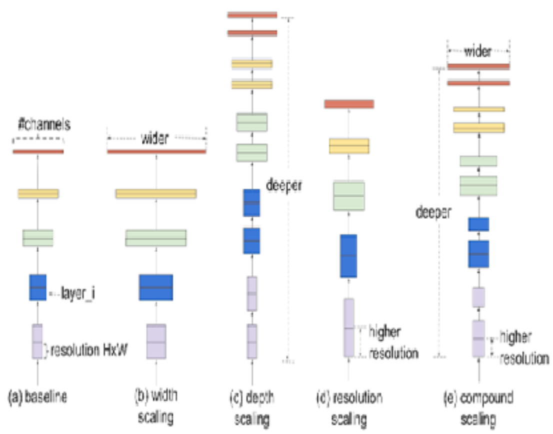
- 12753 training images
- 3712 validation images
- 7382 unlabeled test images

2) Methods to use: Transfer learning for machine learning is when elements of a pre-trained model are reused in a new machine learning model. If the two models are developed to perform similar tasks, then generalised knowledge can be shared between them. This approach to machine learning development reduces the resources and amount of labelled data required to train new models. It is becoming an important part of the evolution of machine learning and is increasingly used as a technique within the development process

1) Dense Net
   Convolutional networks that have shorter connections between their input and output layers can be trained to be significantly deeper, more accurate, and more efficient. The Dense Convolutional Network (DenseNet) connects each layer to every other layer in a feed-forward manner.



2) Efficient Net The EfficientNet-B7 outperforms the best known ConvNets by being 8.4 times smaller and 6.1 times faster at inference while achieving state-of-the-art 84.3 percent top-1 accuracy on ImageNet. On the CIFAR-100 (91.7 percent), Flowers (98.8 percent) and 3 other transfer learning datasets, our EfficientNets likewise transfer learning. Our EfficientNets were compared to other CNNs that were already running on ImageNet. In general, the EfficientNet models outperform previous CNNs in terms of accuracy and efficiency, reducing parameter size and FLOPS by a factor of two. For instance, our EfficientNet-B7, which is 8.4 times smaller and 6.1 times quicker on CPU inference than the prior Gpipe, achieves state-of-the-art 84.4 percent top-1 / 97.1 percent top-5 accuracy on ImageNet in the high-accuracy regime. Our EfficientNet-B4 uses comparable FLOPS to the widely used ResNet-50 while increasing top-1 accuracy from 76.3percent of ResNet-50 to 82.6percent (+6.3percent). The below figure shows the flow of EfficientNet



3) VGG16 VGG-16 is a convolutional neural network that is 16 layers deep. You can load a pretrained version of the network trained on more than a million images. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

E. Use of learning rate schedule

By lowering the learning rate in accordance with a predetermined schedule, learning rate schedules aim to modify the learning rate during training. Step decay, exponential decay, and time-based decay are three common learning rate schedules. In order to compare the performances, I build a convolutional neural network trained on CIFAR-10 using the stochastic gradient descent (SGD) optimization algorithm and various learning rate schedules.

Adapting the learning rate for SGD optimization procedure can increase performance and reduce training time. this is called as Learning rate schedule or adaptive learning rates. The simplest and perhaps most used adaptation of learning rate during training are techniques that reduce the learning rate over time. These have the benefit of making large changes at the beginning of the training procedure when larger learning rate values are used, and decreasing the learning rate such that a smaller rate and therefore smaller training updates are made to weights later in the training procedure. This has the effect of quickly learning good weights early and fine tuning them later. Two popular and easy to use learning rate schedules are as follows:

- Decrease the learning rate gradually based on the epoch.
- Decrease the learning rate using punctuated large drops at specific epochs

XI. Ensemble Learning

The high variance of neural networks can be overcome by training several models and combining their predictions.

The goal is to aggregate the results of several reliable, yet distinct models.

A good model has skill, which means that its forecasts are more accurate than those made by chance. The models must be accurate in various ways and, more importantly, they must have distinct types of prediction mistakes. The variance of a single trained neural network model is balanced out by the bias added by combining the predictions from other neural networks. The outcomes are forecasts that are less dependent on the particulars of the training data, the training scheme selected, and the luck of a single training run.

The ensemble can produce better forecasts than any single best model, in addition to lowering the variation in the prediction.

XII. Conclusion

This essay discusses the identification and classification of floral photographs according to their species. A dataset with 12000 flower photos from 104 classifications has been compiled. With the use of picture pre-processing and image segmentation algorithms, basic and morphological elements of floral photographs are recovered. Using a prediction model that incorporates the supervised machine learning method known as neural networks and multi-labeling, non-botanists can quickly and simply classify various flower species, assisting them in their further research and study. It was found that the suggested strategy, using the greatest number of retrieved features, could reasonably achieve a good classification accuracy.

References

[1] S. Kishotha and B. Mayurathan, ”Machine Learning Approach to Improve Flower Classification Using Multiple Feature Set,” 2019 14th Conference on Industrial and Information Systems (ICIIS), 2019, pp. 141-145, doi: 10.1109/ICIIS47346.2019.9063349.

[2] Xiaoling Xia, Cui Xu and Bing Nan, ”Inception-v3 for flower classification,” 2017 2nd International Conference on Image, Vision and Computing (ICIVC), 2017, pp. 783-787, doi: 10.1109/ICIVC.2017.7984661.
[3] J. E. Vera Vera, S. Mora Martinez, A. T. Pérez and J. Avendano, ”Classification of Gerbera Type Flowers Based in Decision Tree Rules,” 2019 XXII Symposium on Image, Signal Processing and Artificial Vision (STSIVA), 2019, pp. 1-4, doi: 10.1109/STSIVA.2019.8730221.
[4] R. Lv, Z. Li, J. Zuo and J. Liu, ”Flower Classification and Recognition Based on Significance Test and Transfer Learning,” 2021 IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE), 2021, pp. 649-652, doi: 10.1109/ICCECE51280.2021.9342468.
[5] N. Alipour, O. Tarkhaneh, M. Awrangjeb and H. Tian, ”Flower Image Classification Using Deep Convolutional Neural Network,” 2021 7th International Conference on Web Research (ICWR), 2021, pp. 1-4, doi: 10.1109/ICWR51868.2021.9443129.
[6] R. Lv, Z. Li, J. Zuo and J. Liu, ”Flower Classification and Recognition Based on Significance Test and Transfer Learning,” 2021 IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE), 2021, pp. 649-652, doi: 10.1109/ICCECE51280.2021.9342468.
[7] F. Hu, F. Yao and C. Pu, ”Learning Salient Features for Flower Classification Using Convolutional Neural Network,” 2020 IEEE International Conference on Artificial Intelligence and Information Systems (ICAIIS), 2020, pp. 476-479, doi: 10.1109/ICAIIS49377.2020.9194931.
[8] T. Tiay, P. Benyaphaichit and P. Riyamongkol, ”Flower recognition system based on image processing,” 2014 Third ICT International Student Project Conference (ICT-ISPC), 2014, pp. 99-102, doi: 10.1109/ICT-ISPC.2014.6923227.
[9] H. M. Zawbaa, M. Abbass, S. H. Basha, M. Hazman and A. E. Hassenian, ”An automatic flower classification approach using machine learning algorithms,” 2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI), 2014, pp. 895-901, doi: 10.1109/ICACCI.2014.6968612.
[10] https://www.javatpoint.com/transfer-learning-in-machine-learning
[11] S. Giraddi, S. Seeri, P. S. Hiremath and J. G.N, ”Flower Classification using Deep Learning models,” 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE), 2020, pp. 130-133, doi: 10.1109/ICSTCEE49637.2020.9277041.
[12] C. Narvekar and M. Rao, ”Flower classification using CNN and transfer learning in CNN- Agriculture Perspective,” 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS), 2020, pp. 660-664, doi: 10.1109/ICISS49785.2020.9316030.
[13] https://blog.roboflow.com/how-to-train-efficientnet/
[14] https://towardsdatascience.com/review-densenet-image-classification-b6631a8ef803