A Mobile App for the Identification of Flowers Using Deep Learning

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***Abstract*—Flowers are admired and used by people all around the world for their fragrance, religious significance, and medicinal capabilities. The accurate taxonomy of these flower species is critical for biodiversity conservation and research. Non-experts typically need to spend a lot of time examining botanical guides in order to accurately identify a flower, which can be challenging and time-consuming. In this study, an innovative mobile application named FloralCam has been developed for the identification of flower species that are commonly found in Mauritius. Our dataset, named FlowerNet, was collected using a smartphone in a natural environment setting and consists of 11660 images, with 110 images for each of the 106 flower species. Seventy percent of the data was used for training, twenty percent for validation and the remaining ten percent for testing. Using the approach of transfer learning, pre-trained convolutional neural networks (CNNs) such as the InceptionV3, MobileNetV2 and ResNet50V2 were fine tuned on the custom dataset created. The best performance was achieved with the fine tuned MobileNetV2 model with accuracy 99.74% and prediction time 0.09 seconds. The best model was then converted to TensorFlow Lite format and integrated in a mobile application which was built using Flutter. Furthermore, the models were also tested on the benchmark Oxford 102 dataset and MobileNetV2 obtained the highest classification accuracy of 95.90%. The mobile application, the dataset and the deep learning models developed can be used to support future research in the field of flower recognition.**

***Keywords*—Flowers; deep learning; mobile application; Mauritius**

I. Introduction

Flowers have long been appreciated as a significant phenomenon in the history of mankind [1]. They are adored and used by humans around the globe to embellish their environment as well as for fragrance, religion, and medicine [2]. Flowering plants, commonly known as angiosperms (Merriam-Webster, 2021), have been the most dominant plant biodiversity in our terrestrial ecosystem for over 60 million years [3]. The dominance of these living organisms over more primitive angiosperms, such as pines and palms, was even described as an "abominable mystery" by Charles Darwin [4]. According to [5], there are about 400,000 species of plants on Earth. Over the last few decades, the world's biomass have undergone a change of more than 10% owing to the various effects of climate change and land use. In addition, the increasing invasion of alien plant species has shown a negative impact on native plants, destroying our natural ecosystem. The accurate identification of invasive non-native plant species can therefore aid in the development of awareness and educational programs contributing to the mitigation of their impacts [5].

According to [6], accurate identification of species is critical for ecological monitoring. Therefore, proper plant and flower identification can help stakeholders with a variety of activities, such as investigating the biodiversity richness of an area and monitoring the population of endangered species while species misidentification can lead to erroneous conservation strategies [7]. As can be deduced, accurate species classification is essential for biodiversity conservation and research. Furthermore, accurate flower classification is a non-tedious task for skilled taxonomists and for people with expertise in anthology and botany [8]. Non-experts and novices typically find it complex and time-consuming to properly identify a flower. They usually must spend a significant amount of time examining botanical guides [9]. Automatic recognition technologies, such as machine learning (ML) and artificial intelligence (AI), can thus be utilised for the automatic identification of flowers, overcoming this taxonomic gap.

Several studies have been conducted on flower detection and recognition systems by employing different flower images and methods. Flower shape and colour, as well as the stamen region, can be used to identify different flowers [10]. Deep learning techniques such as the convolutional neural networks (CNN) are effective in distinguishing between numerous flower species [11]. Also, a mobile application for the automatic recognition of plants from their leaves was developed by [12]. However, no such application for flower recognition has yet been developed in Mauritius. The purpose of this paper is therefore to create such an application to facilitate the identification of flowers among common people with little or no botany knowledge through pictures taken using a smartphone. Moreover, information on the flower, such as its scientific name, common name, and a brief description will be displayed.

Today, it is still challenging to differentiate flowers in image processing systems. This is because many flower species exhibit similar shapes and colours. In addition, there are several difficulties when images are captured in natural outdoor scenes. For example, lighting is largely dependent on the weather conditions and the time of day. Furthermore, due to illumination considerations, specula highlights can affect the appearance of flowers, for example flowers may appear brighter or whiter than usual. Moreover, differences in occlusions, viewpoints, and scales in flower images, as well as uncertainty across different flower species with similar characteristics such as colour and form, contribute to the difficulties of automatic flower recognition. Another challenge is that the flower in the image must be segmented properly and with as few errors as possible [13].

Thus, a mobile application that can automatically identify and categorise flowers found in Mauritius will be developed.

The system will be created using AI and deep learning approaches and will make use of a new dataset of flowers, which are available in th Republic of Mauritius. This paper proceeds as follows. In section II, we provide an overview of all the related works that have been done on the automatic recognition of flowers. The datasets and the deep learning models used are described in section III. Section III discusses the results for each experiment, together with a compariosn with existing works. Section V concludes the paper. A list of all the flowers using in this work are provided in the appendix.

II. Related Works

Artificial intelligence along with machine learning and deep learning, has been used for the development of software involving image recognition. Numerous models, approaches, and methodologies have been adopted in the classification of flower species. This section includes some pertinent research on various flower recognition studies.

One of the first flower recognition studies was conducted by [14] using an approach that indexes flower images based on their colours and spatial domains. Their research focus was mainly based on developing efficient methods for querying a database by colour for identification of flowers. An iterative segmentation algorithm with the aim of reducing unnecessary processing, was used to extract flower regions from their background using the flower's domain knowledge. This allowed for the indexing of flower images based solely on the colours present in the flower rather than the complete image. The database could then be queried by a specific colour or by supplying a sample flower image. This colour-based algorithm, however, makes it difficult to classify flowers primarily based on their colour, without considering their shape and other features.

An approach with the aim of classifying wildflowers based on more than one attribute (shape and colour) was implemented in [15]. Their method involved the use of a three-layered network along with a back propagation learning algorithm. A dataset consisting of 20 sets of images from 16 flower species was used, with each set containing two images of a plant: a leaf and a flower's frontal image captured using a digital camera. The proposed model was trained using 19 sets of images, with the remaining one was used for testing. They obtained an accuracy of 96% by using four features from the leaf and two from the flower. Their study also demonstrated that having too many features from the input images can have an impact on the recognition performance. Images were taken under controlled environments by positioning a black cloth behind the flower and leaf to enable easier segmentation.

Saitoh et al. enhanced their previous work by conducting further research to automatically recognise blooming flowers [16]. The innovation in their research was a new way of extracting the flowers from their background, as opposed to their earlier work, which used K-means clustering. This new method, called "Intelligent Scissors", was proposed by [17]. In this innovative approach, images were taken such that the flowers appeared in the centre of the photo with a defocused background. A total of 600 pictures, comprising 20 images per flower for 30 different species, were taken for this experiment. Of these, 19 images from each flower species were used for training and the rest for testing. They achieved a classification accuracy of 90% by using 10 colour and shape features.

Traditional flower recognition studies usually implicate constraints such as variations in flower positions as well as having multiple flowers in an image, resulting in poor recognition performance. Kim et al. therefore proposed using the Difference Image Entropy (DIE) and contour features retrieved from images comprising of multi-flower objects in their mobile system [18]. Their application works by using two images. Firstly, the user draws a contour line around the flower region on the original congregated flower image to retrieve the first image. Next, contour features such as Zero-Crossing Rate (ZCR), minimum distance, and length of the contour line are extracted from the first image. These features are then used to reduce the number of flower candidates in the entire identification process. Following that, pixel subtraction is used to calculate the difference between the second image (the sub image containing the flower from the original image), and the normalized average of the reduced images obtained from the previous step. Their system used a dataset consisting of 20 images per flower species, for a total of 10 species. Ten images per flower for all species were used in training, and the other 10 images were used for testing the model. The recognition accuracy was 95%.

Automatically extracting flower boundaries from flower images is a key part of the recognition process. Given the difficulties of extracting flowers from its background, Aydin and Ugur presented the IPSOAntK-Means algorithm [19]. Their proposed solution combines the K-means algorithm with particle swarm optimisation and an ant colony algorithm to improve the flower boundary extraction process. Their approach was evaluated by using two different datasets, namely the CAVIAR and Oxford 17 datasets. The first dataset contained 1078 flowers from 113 distinct species, while the second one had flowers from 17 different species. Based on images from the CAVIAR dataset, their investigation revealed that the IPSOAntK-means method performed better than the K-means algorithm, with a segmentation accuracy of 96.4%. However, since only colour was used for the extraction process, the proposed method has decreased extraction performance on flowers with similar colours to that of their background.

Flowers come in a variety of colours and contours, and it is difficult to distinguish between them based only on their contours. In their mobile application, Hong and Choi used both colour and contour aspects, as well as K-means clustering and history matching, to increase the recognition accuracy [20]. A dataset consisting of 500 images was built, with 400 images used for training and the remaining 100 images used for testing their model. Their study demonstrated that they could improve contour detection quality by using colour-based contour detection and edge-based contour detection. They also observed that light and camera angle can lead to recognition failures by wrongly detecting the contours of the flowers. Therefore, they applied image recovery and partial recognition to mitigate this issue. With all these measures, their application obtained an accuracy of 94.8%.

Tiay et al. also attempted to recognise flowers based on their colour and edge properties by using the K-nearest neighbour (KNN) algorithm [21]. Their system displayed the top three similar flowers by using seven edge and forty colour characteristics. Their proposed system consisted of 10 flower species with 50 images per species for testing and 100 images for training. Their study showed that having flowers with overlapping edge and colour properties can impact the classification accuracy. Their method resulted in a classification accuracy of more than 80%.

CNN-based recognition method was used by [22] for apple blossom identification. Dias et al. used a pre-trained CNN model with Support Vector Machines (SVM). Their detection rate was 90%. Another closely related approach was the hybrid method proposed by [23] Their method used CNN models along with feature selection methods. Their dataset had 4242 photos, non-uniformly distributed by species: each flower had a different number of images. Adding to that, their dataset was partitioned into 80% for training and the remaining 20% for testing. For feature extraction, the GoogleNet, AlexNet, ResNet-50, and VGG-16 CNN models were used and trained using the transfer learning method. The features extracted were then combined, and only the efficient ones were finalised using the f-regression and multiple inclusion criterion (MIC) methods yielding two sets of features. The 2-feature sets obtained were then compared and only the intersecting features in both sets (stable features) were extracted and classified using the SVM method. Their research indicated that the stable features obtained by the feature selection methods contributed to their high classification accuracy of 98.91%. However, their study was conducted using only 5 different flower species.

Liao and Zhang also used the feature selection method in their system along with a classification method based on SVM and a DenseNet architecture called DN-F-SVM [24]. DenseNet was utilised to extract several features from the flower images. Furthermore the Fast Correlation-Based Filter (FCBF), was employed to select the most effective features. The proposed model was trained on the Oxford 17 and Oxford 102 datasets. A classification accuracy of 99.12% and 98.90% was obtained, respectively for each dataset.

Researchers have also adopted the CNN ensemble approach to achieve optimum recognition accuracy in real-world applications. Such an approach was proposed by Wang et al. and it consisted of 3 steps [25]. The first phase, known as feature extraction, was achieved by pretraining the MobileNet models on the ILSVRC-2012-CLS image dataset. Following that, the retrieved features were used to train different classifiers. In addition, a re-sampling strategy was used to improve the diversity of the individual models used. Finally, an ensemble model was implemented using the weighted average technique. They tested the effectiveness of their system on two flower datasets consisting of 3670 and 1660 images from 5 flower species. The first dataset consisted of a training set with 3320 images and a test set with 350 images while the second dataset was used entirely for testing. Their findings demonstrated that the ensemble technique outperformed single classifiers. Adding to that, they also noted that the ensemble method can achieve better performance with a larger dataset.

A hybrid approach integrating the Viola-Jones algorithm and multi-template matching for effective and accurate identification of Anthurium flower cultivars was done in [26]. Their system had a computation time of less than 0.5s and a classification accuracy of more than 99%. Their results indicated that the technique had acceptable performance in detecting the spadix region and very good performance in classifying the flower cultivars. Based on the VGG-16 CNN method, Lv et al. designed a flower classification model using the saliency detection algorithm [27]. They also used the stochastic gradient descent algorithm to adjust network weights. The dropout and the transfer learning methods were also used in optimising the model to reduce overfitting. They utilised the Oxford-102 dataset, which included 102 flower species and around 40-258 images per species for a total of 8189 images. The categorisation accuracy was 91.9%.

III. Methodology

This section describes the different steps followed to build the flower recognition system. The datasets and the deep learning models are used are described in detail.

A. Datasets

1) Flowernet: The first and most critical step in implementation of the system is data acquisition. As a result of the non-availability of a large image dataset of flowers found in Mauritius at the beginning of the study, a new dataset had to be created to undertake the research. To achieve the primary objective of building a huge dataset, flower images were captured in various locations, including plant nurseries, neighbourhoods, gardens, and parks from the period of November 2021 to April 2022. For this research, the Huawei Y9 2019 smartphone with a resolution of 13 megapixels was utilised to collect data samples for 106 flower species. The dataset was constructed either by capturing close-up flower pictures continuously or extracting frames from recorded flower videos. The images and recorded videos were captured in a natural environment, such as in sunny and rainy weather conditions with variations in viewpoints, illumination and rotation. This new dataset was named as FlowerNet. It consists of 106 classes of flower species with a total of 11660 images. Each class has 110 different flower images. The dataset can be obtained by contacting the authors.

2) Other datasets: For a fair consideration, we will compare the performance of our implemented models with the Oxford 102 flower dataset. This dataset contains 40 to 258 images for 102 flower species commonly found in the UK with a total of 8189 images. The dataset contains images that vary in terms of scaling, lighting and poses.

Additionally, three different variations of these two datasets were also created:

(i) A merged dataset consisting of flower categories from both the Oxford 102 and the FlowerNet but excluding the overlapping flowers from the Oxford 102 dataset,
(ii) A flower dataset consisting of overlapping flowers from the Oxford 102 dataset only, and
(iii) A flower dataset consisting of overlapping flowers from the FlowerNet dataset only.

3) Overlapping flowernet and oxford 102 datasets: Table I shows the corresponding overlapping flowers in FlowerNet and Oxford 102 datasets. The flowers in the first column are used to create the overlapping flower dataset for the Oxford 102 dataset while the flowers in the second column are used to create the overlapping flower dataset for the FlowerNet dataset.

Also, flowers of different colours were considered as different flower categories in the FlowerNet dataset. However, for the creation of the overlapping flower dataset for the FlowerNet dataset, the different colours were merged as a single flower category as shown in Table II.

TABLE I. OVERLAPPING FLOWERS IN FLOWERNET AND OXFORD 102 DATASETS

#	Oxford 102 Dataset	FlowerNet Dataset
1	anthurium	Flamingo Lily (Pale Pink)
		Flamingo Lily (Dark Red)
2	blackberry lily	Leopard Flower
3	bougainvillea	Paper Flower (Fuchsia)
		Paper Flower (White)
		Paper Flower (Sundown Orange)
4	barbeton daisy	Gerbera (Dark Pink)
		Gerbera Daisy (Dark Orange)
		Gerbera Daisy (Fuchsia)
		Gerbera Daisy (Pale Orange)
		Gerbera Daisy (Pale Pink)
		Gerbera Daisy (Red)
		Gerbera Daisy (White)
		Gerbera Daisy (White_Pink)
		Gerbera Daisy (Yellow)
5	canna lily	Canna Lily
6	desert-rose	Desert Rose (Pink)
		Desert Rose (Dark Red)
7	frangipani	Frangipani (Yellow)
		Frangipani (Pink)
8	geranium	Geranium (Pink)
		Geranium (Red)
9	hibiscus	Hibiscus (Red)
		Hibiscus (Pale Pink)
		Hibiscus (Pale Orange)
10	mexican petunia	Mexican Petunia
11	oxeye daisy	Daisy (White)
12	red ginger	Ostrich Plume
13	rose	Rose (Cream)
		Rose (Pink)
		Rose (Dark Red)

TABLE II. OVERLAPPING FLOWER DATASET FOR FLOWERNET

#	Flower Category	No of Flowers
1	Canna lily	110
2	Daisy (White)	110
3	Desert Rose	220
4	Flamingo Lily	220
5	Frangipani	220
6	Geranium	220
7	Gerbera	990
8	Hibiscus	330
9	Leopard Flower	110
10	Mexican Petunia	110
11	Ostrich Plume	110
12	Paper Flower	330
13	Rose	330

B. Balancing the Imbalanced Datasets

Table III shows the different datasets: Oxford 102, Merged, Overlapping Oxford 102 and Overlapping FlowerNet. A hybrid sampling strategy combining both data augmentation and under sampling is adopted to balance the imbalanced datasets. Data augmentation is the process of artificially generating new data images using available images by utilising a variety of transformation techniques such as rotation, flipping, zooming, image blurring and adjustment of brightness and contrast. Under sampling, on the other hand refers to a technique whereby samples from the majority classes are randomly removed to balance the dataset.

TABLE III. DATASET SUMMARY

Dataset	# Images per Flower Category
Oxford 102	40 - 258
FlowerNet	110
Merged	40 - 258
Overlapping Oxford 102	42 - 171
Overlapping FlowerNet	110 - 990

C. Classification System

Different CNN models were trained on the FlowerNet dataset using the transfer learning approach. Transfer learning, as the term implies, is the application of knowledge gained from one problem to solve other distinct but related problems. In deep learning, the knowledge of a neural network previously trained to tackle one problem can be leveraged as a starting point to address another classification challenge. AlexNet, GoogleNet, MobileNet, ResNet, and VGG19 are a few examples of CNN models trained on the huge ImageNet dataset which encompasses 1.4 million images with 1000 classes. These pre-trained models can be repurposed for another target domain by using the fixed feature extraction and fine-tuning methods. During this study, several models were implemented, and the optimal model is chosen through a series of experiments and converted into TensorFlow Lite for integration into a mobile application. Fig. 1 illustrates the processes in the flower recognition system.

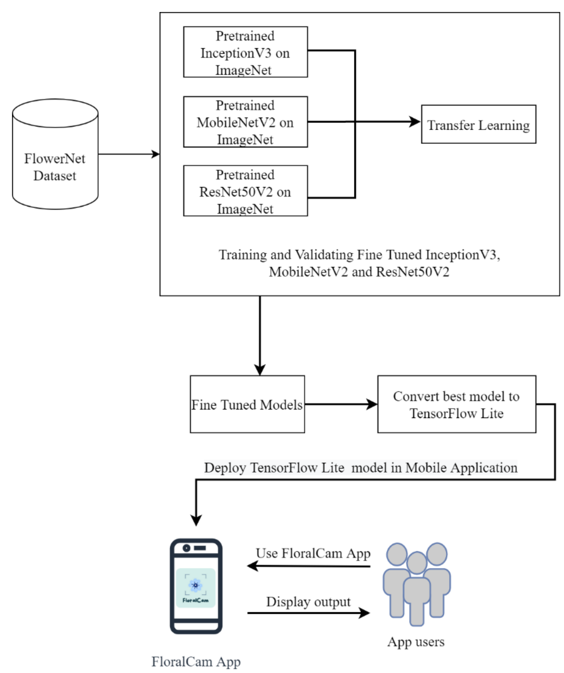


Fig. 1. The flow of processes in the flower recognition system.

D. Fine Tuning Pre-trained CNNs

The InceptionV3, MobileNetV2 and ResNet50V2 models were fine-tuned for the flower classification problem. The fully connected layers of the pretrained networks were removed while the remaining network, consisting of a sequence of convolution and pooling layers, were retained for fixed feature extractor. New classification layers were incorporated to perform classification on the different flower classes. In our study, a global average pooling layer, dropout layer along with two dense layers with ReLu and a dense layer with SoftMax classifier were added as classification layers as shown in Fig. 2.

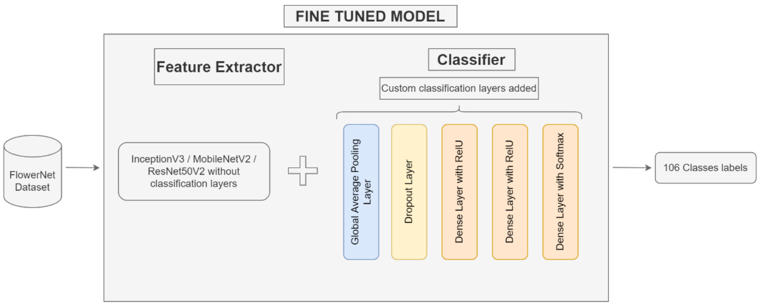


Fig. 2. Proposed architecture of fine-tuned InceptionV3, ResNet50V2 and MobileNetV2.

E. Summary of Models Implemented

Table IV summarises the different models that were implemented in this study.

TABLE IV. SUMMARY OF MODELS

Pre-Trained CNN	Trainable Layer	Classifier
MobileNetV2	True	SoftMax
	False	SoftMax
ResNet50V2	True	SoftMax
	False	SoftMax
InceptionV3	True	SoftMax
	False	SoftMax

F. Summary of Datasets Used

Table V summarises the different datasets that have been used in this study.

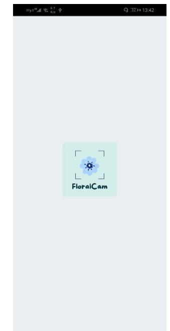
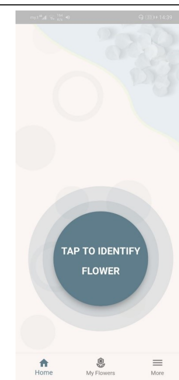
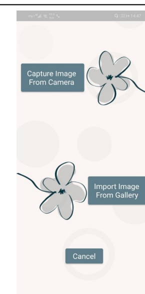
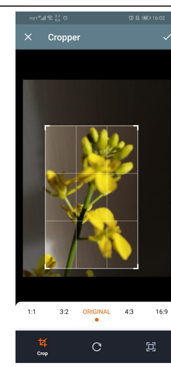
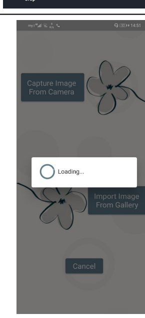
TABLE V. SUMMARY OF DATASETS

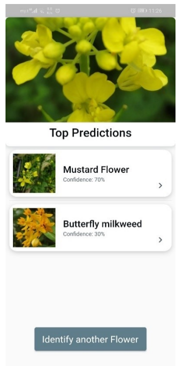
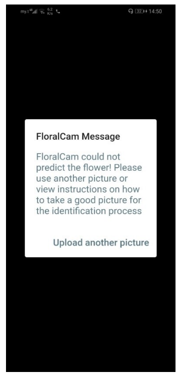
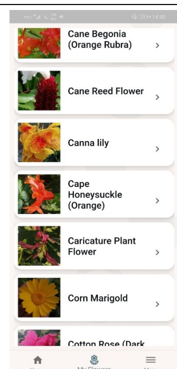
Dataset	Flower Classes	Images per Flower Class	Total Images	Training (70%)	Validation (20%)	Testing (10%)
FlowerNet	106	110	11660	8162	2332	1166
Oxford 102	102	110	11220	7854	2244	1122
Merged	195	110	21450	15015	4290	2145
Overlapping Oxford	13	110	1430	1001	286	143
Overlapping FlowerNet	13	110	1430	1001	286	143

G. Mobile Application

Flutter is chosen as the framework for developing the mobile application since it can be utilised to develop user-friendly interfaces with the help of well-structured documentation. Additionally, Flutter is cross-platform allowing it to run on different mobile operating systems. Table VI shows the different screens developed for the mobile application.

TABLE VI. SCREENS IN MOBILE APPLICATION

Screen	Screen Image
Splash Screen	
Home Page	
Choosing Image Upload Option	
Cropping Screen	
Loading Screen	

<table>
<tr><td>Prediction Screen 1</td><td>
</td></tr>
<tr><td>Prediction Screen 2</td><td>
</td></tr>
<tr><td>My Flowers Screen</td><td>
</td></tr>
<tr><td>Wikipedia WebView Screen</td><td>
</td></tr>
</table>

IV. Results and Discussion

The results obtained by the implemented models on the different datasets are described in this section. The performance of each model is assessed using the classification accuracy and F1 scores. The FlowerNet dataset consists of 11660 images, 106 flowers each having 110 images. The dataset was divided into three sets before training the models: 70% for training, 20% for validation, and remaining 10% for testing.

A. FlowerNet Dataset

Table VII displays the accuracy values achieved after evaluating all the models with the FlowerNet dataset. The MobileNetV2 and InceptionV3 models achieved the highest accuracy scores of 99.74% and 99.31%, respectively. These highest accuracy scores were obtained when the feature extraction layers were set to trainable. When trainable layers are set to true, this implies that all the weights of the neural network are updated during training. When feature extraction layers were not trained, the maximum accuracy score was 98.97%.

TABLE VII. FlowerNet Dataset Results

Model	#	Trainable Layers	Accuracy	F1 Macro	F1 Weighted
MobileNetV2	1	TRUE	99.74%	0.9974	0.9974
	2	FALSE	98.97%	0.9897	0.9897
ResNet50V2	3	TRUE	98.97%	0.9897	0.9897
	4	FALSE	98.97%	0.9897	0.9897
InceptionV3	5	TRUE	99.31%	0.9931	0.9931
	6	FALSE	98.80%	0.9881	0.9881

B. Oxford 102 Dataset

Table VIII displays the accuracy values achieved after evaluating all the models with the Oxford 102 dataset. The MobileNetV2 and InceptionV3 models achieved the highest accuracy scores of 95.90% and 95.28%, respectively. These highest accuracy scores were obtained when the feature extraction layers were set to trainable. When the layers in the InceptionV3 model are set to non-trainable, the accuracy drops to 91%.

TABLE VIII. Oxford 102 Dataset Results

Model	#	Trainable Layers	Accuracy	F1 Macro	F1 Weighted
MobileNetV2	1	TRUE	95.90%	0.9594	0.9594
	2	FALSE	92.87%	0.9278	0.9278
ResNet50V2	3	TRUE	92.25%	0.9217	0.9217
	4	FALSE	91.18%	0.9111	0.9111
InceptionV3	5	TRUE	95.28%	0.9530	0.9530
	6	FALSE	91.00%	0.9089	0.9089

When trainable layers are set to true, the feature extraction layers of the pretrained CNNs are re-trained, and their weights are updated according to the FlowerNet dataset. This explains why the best results are obtained when the trainable layers are set to true. However, when trainable layers are set to false, this implies that the feature extraction layers of the CNNs are using the original weights and features of the ImageNet dataset, and this resulted in poor prediction, as compared to re-training all layers in the pretrained CNNs for the FlowerNet and Oxford 102 dataset. The ImageNet dataset, Oxford 102 and the FlowerNet datasets have distinct characteristics. Therefore, training the feature extraction layers from scratch using the FlowerNet/ Oxford 102 dataset resulted in better accuracies.

C. Merged Dataset

Table IX displays the accuracy values achieved after evaluating all the models with the merged dataset. The InceptionV3 and MobileNetV2 models achieved the highest accuracy scores of 97.30% and 97.11%, respectively. These highest accuracy scores were obtained when the feature extraction layers were set to trainable. When the layers in the InceptionV3 model are set to non-trainable, the accuracy drops to 94.22%.

TABLE IX. MERGED DATASET RESULTS

Model	#	Trainable Layers	Accuracy	F1 Macro	F1 Weighted
MobileNetV2	1	TRUE	97.11%	0.9711	0.9711
	2	FALSE	96.13%	0.9603	0.9603
ResNet50V2	3	TRUE	95.15%	0.9513	0.9513
	4	FALSE	94.87%	0.9474	0.9474
InceptionV3	5	TRUE	97.30%	0.9728	0.9728
	6	FALSE	94.22%	0.9414	0.9414

The models which were trained on the merged dataset have obtained a lower accuracy as compared to the original FlowerNet dataset. As the number of classes in a computer vision task increases, the identification process becomes complex. When the number of classes is increased from 106 (FlowerNet) to 195 (Merged), the complexity of the model increases, which makes the model more prone to errors.

D. Overlapping Flowers Datasets

For the FlowerNet dataset, the images were captured as close-up flower pictures. Oxford 102, on the other hand, consists of a variety of images taken in different positions and orientations. In this study, the effect of training a model with close-up pictures is also analysed with flowers found in both the FlowerNet and the Oxford 102 datasets.

Table X displays the accuracy values achieved after evaluating all the models with the overlapping FlowerNet dataset. A general observation is that all models have obtained an accuracy of above 99%. For the MobileNetV2 and RestNet50V2 models, the accuracies and F1 macro and weighted scores are all 100%. For the InceptionV3 model, the accuracy and F1 macro and weighted scores dropped by 0.7% when trainable layers are set to false.

TABLE X. OVERLAPPING FLOWERNET DATASET RESULTS

Model	#	Trainable Layers	Accuracy	F1 Macro	F1 Weighted
MobileNetV2	1	TRUE	100%	1.0000	1.0000
	2	FALSE	100%	1.0000	1.0000
ResNet50V2	3	TRUE	100%	1.0000	1.0000
	4	FALSE	100%	1.0000	1.0000
InceptionV3	5	TRUE	100%	1.0000	1.0000
	6	FALSE	99.30%	0.9930	0.9930

Table XI displays the accuracy values achieved after evaluating all the models with the overlapping Oxford 102 dataset. When trainable layers are set to true, the InceptionV3 model achieved the best accuracy of 99.30% followed by an accuracy of 96.50% by the MobileNetV2 and ResNet50V2 models. When the layers in the InceptionV3 model are set to non-trainable, the accuracy drops to 97.90%.

TABLE XI. OVERLAPPING OXFORD 102 DATASET RESULTS

Model	#	Trainable Layers	Accuracy	F1 Macro	F1 Weighted
MobileNetV2	1	TRUE	99.30%	0.9930	0.9930
	2	FALSE	97.90%	0.9793	0.9793
ResNet50V2	3	TRUE	96.50%	0.9641	0.9641
	4	FALSE	97.20%	0.9719	0.9719
InceptionV3	5	TRUE	96.50%	0.9646	0.9646
	6	FALSE	95.80%	0.9582	0.9582

Models trained on the overlapping FlowerNet flowers have performed relatively better than models trained on the overlapping Oxford 102 dataset. The overlapping FlowerNet dataset classes consist of mostly close-up images of flowers with minimal background while the overlapping Oxford 102 dataset consists of flower images with a lot of background. This result suggests that the proportion of background in the images has influenced the identification process, hence the difference in accuracy.

E. Model Prediction Time

A good model is not dependent solely on classification accuracy. The prediction time of the model should also be considered. As a result, an experiment is carried out to test the prediction time with models that have trainable layers set to true. To calculate the inference time of the models, the prediction time was recorded for the test images. The experiment was then repeated seven times to obtain an average prediction time for a more realistic inference time. The prediction time per image was then computed and the results are tabulated as shown in Table XII.

From Table XII, it can be deduced that MobileNetV2 has a lower prediction time (0.09 seconds) followed by the ResNet50V2 (0.12 seconds). InceptionV3 has the highest inference time of 0.22 seconds per image. In terms of model size, MobileNetV2 has the smallest size followed by InceptionV3 and ResNet50V2.

MobileNetV2 obtained the least prediction time as compared to ResNet50V2 and InceptionV3. This is because the network size and parameter count affect the inference time and MobileNetV2 (3.1 million) has a lower parameter count as compared to InceptionV3 (23.0 million) and ResNet50V2 (24.8 million). Adding to that, the trained MobileNetV2 model has the lowest size compared to the others. This is another reason influencing the prediction time.

F. Comparison with Existing Works

Wang et al. performed classification on five different flower categories using an initial dataset consisting of a training set to train their model and a test set to evaluate it [25] . Additionally, another dataset set was used to test their models. They used the ensemble method, whereby the predictions of seven MobileNet models were combined. They achieved the best accuracy of 94.63% and 91.14% on their first and second datasets, respectively. Compared to the result in this paper, an accuracy of 99.7% was achieved when the MobileNetV2 model was used. Even with a much more significant number of categories of flowers (106 classes), our models produced better accuracy. The dataset used by [25] was not publicly available to perform additional testing.

Lv et al. used the VGG16 CNN model to perform flower classification [27] . They were able to achieve an accuracy of 91.9% when the model was trained on the Oxford 102 dataset. The Oxford 102 dataset was also used to compare the implemented models with that of [27]. The best accuracy obtained when trained on the Oxford 102 dataset was 95.90% when the MobileNetV2 model was used. Thus, our work outperformed the VGG16 model used in [27].

V. CONCLUSIONS

The classification of flower species is a challenging process. Flower images captured in varying viewpoints, lightings

TABLE XII. MODELS PREDICTION TIME

Model	No of test images	Total Prediction Time for 7 iterations /sec	Average Prediction Time /sec	Prediction time per image /sec	Model Size/ MB
MobileNetV2	1166	730	104	0.09	35.8
ResNet50V2		1010	144	0.12	284.1
InceptionV3		1836	262	0.22	264.4

and occlusion by leaves and other debris make it difficult to classify flower species. Deep learning has recently surfaced as one of the preferred approaches for achieving promising results in such classification problems. A new dataset, named FlowerNet, consisting of 106 flower species was created and deep learning models such as InceptionV3, MobileNetV2, ResNet50V2 were used for the classification. The best performing model, MobileNetV2, achieved an accuracy of 99.74% with the smallest prediction time of 0.09 seconds. Moreover, this model was deployed in a mobile application named FloralCam. In the real environment, FloralCam achieves a good level of accuracy when high-quality close-up flower images are used, but it may result in poor prediction in cases when blurry and low-quality images with a high proportion of background are used. Further experiments may be carried out to fine tune the best model's performance in the real world by utilising a larger and a more diverse dataset.

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APPENDIX

TABLE XIII. FLOWER SPECIES IN FLOWERNET DATASET

#	Common Name	Scientific Name	
1	Purple Allamanda	Allamanda Blanchetii	
2	Yellow Allamanda	Allamanda Cathartica	
3	Angel Wing Begonia (Pink)	Begonia coccinea	
4	Angel Wing Begonia (White)	Begonia coccinea	
5	Billygoat weed	Ageratum conyzoides	
6	Butterfly milkweed	Asclepias tuberosa	

7	Cane Begonia (Orange Rubra)	Begonia coccinea 'Orange'	
8	Cane Reed Flower	Cheilocostus speciosus	
9	Canna lily	Canna 'Yellow King Humbert'	
10	Cape Honeysuckle (Orange)	Tecoma capensis	
11	Caricature Plant Flower	Graptophyllum pictum	
12	Corn Marigold	Glebionis segetum	

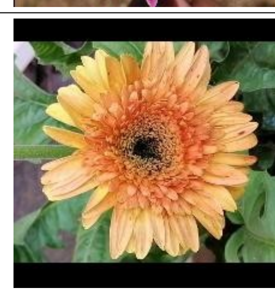
13	Cotton Morning Glory	Ipomoea cordatotriloba	
14	Cotton Rose (Dark Pink)	Hibiscus mutabilis	
15	Cotton Rose (Pale Pink)	Hibiscus mutabilis	
16	Cotton Rose (Red)	Hibiscus mutabilis	
17	Daisy (White)	Bellis perennis	
18	Daylily (Orange)	Hemerocallis fulva	

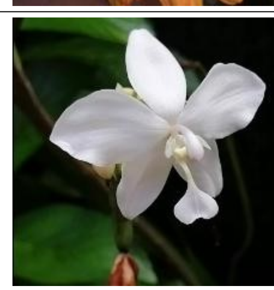
19	Desert Rose (Pink)	Adenium obesum	
20	Dessert Rose (Dark Red)	Adenium obesum	
21	Double Dahlia (Pale Yellow)	Dahlia	
22	Double Dahlia (White)	Dahlia	
23	Dwarf Marigold (Orange)	Tagetes erecta	
24	Dwarf Marigold (Pale Yellow)	Tagetes erecta	

25	Dwarf Marigold (Yellow)	Tagetes erecta	
26	Easter Lily (Red)	Lilium longiflorum	
27	Easter Lily (White)	Lilium longiflorum	
28	Egyptian Starcluster (Pale Purple)	Pentas lanceolata	
29	Egyptian Starcluster (White)	Pentas lanceolata	
30	Madagascar jewel	Euphorbia Leuconeura	

31	Fairy Lily (Pink)	Zephyranthes candida	
32	Fairy Lily (White)	Zephyranthes candida	
33	False sunflower	Heliopsis helianthoides	
34	Firecracker Flower	Crossandra infundibuliformis	
35	Flamevine	Pyrostegia venusta	
36	Flamingo Lily (Pale Pink)	Anthurium andraeanum	

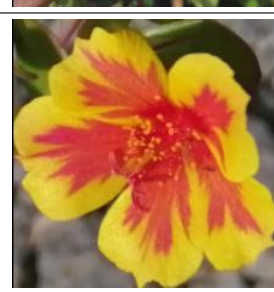
37	Flamingo Lily (Pink)	Anthurium andraeanum	
38	Frangipani (Pink)	Plumeria rubra	
39	Frangipani (White)	Plumeria pudica	
40	Frangipani (Yellow)	Plumeria rubra	
41	French Marigold	Tagetes patula	
42	Garlic Vine	Mansoa alliacea	

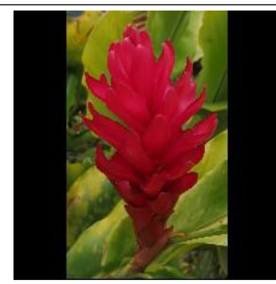
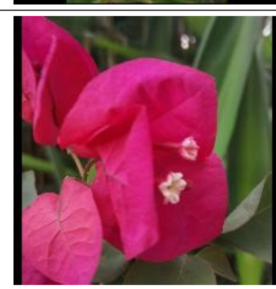
43	Geranium (Pink)	Pelargonium × hortorum	
44	Geranium (Red)	Pelargonium × hortorum	
45	Gerbera (Dark Pink)	Gerbera	
46	Gerbera Daisy (Dark Orange)	Gerbera	
47	Gerbera Daisy (Fuchsia)	Gerbera	
48	Gerbera Daisy (Pale Orange)	Gerbera	

49	Gerbera Daisy (Pale Pink)	Gerbera	
50	Gerbera Daisy (Red)	Gerbera	
51	Gerbera Daisy (White)	Gerbera	
52	Gerbera Daisy (White_Pink)	Gerbera	
53	Gerbera Daisy (Yellow)	Gerbera	
54	Ground Orchid (White)	Spathoglottis plicata	

55	Hibiscus (Light pink)	Hibiscus rosa-sinensis	
56	Hibiscus (Pale Orange)	Hibiscus rosa-sinensis	
57	Hibiscus (Red)	Hibiscus rosa-sinensis	
58	Hummingbird Fuchsia	Fuchsia magellanica	
59	Hydrangea	Hydrangea macrophylla	
60	Pink Orchid Balsam	Impatiens flaccida	

61	Indian chrysanthemum	Chrysanthemum indicum	
62	Ixora (orange)	Ixora coccinea	
63	Japanese Hawkweed	Youngia japonica	
64	Lantana (White)	Lantana camara	
65	Lantana (Yellow)	Lantana camara	
66	Leopard Flower	Iris domestica	

67	Madamfate	Hippobroma	
68	Showy Medinilla	Medinilla magnifica	
69	Mexican Flame Vine	Pseudogynoxys chenopodioide	
70	Mexican Heather	Cuphea hyssopifolia	
71	Mexican Petunia	Ruellia simplex	
72	Moss Flower (Orange_Yellow)	Portulaca grandiflora	

73	Moss Flower (Pale Pink)	Portulaca grandiflora	
74	Mustard Flower	Brassica nigra	
75	Nora Grant (Red)	Ixora coccinea	
76	Ostrich Plume	Alpinia purpurata	
77	Paper Flower (Fuchsia)	Bougainvillea glabra	
78	Paper Flower (Sundown Orange)	Bougainvillea glabra	

79	Paper Flower (White)	Bougainvillea glabra	
80	Parakeet Flower (Red_Orange)	Heliconia psittacorum	
81	Parakeet Flower (Yellow)	Heliconia psittacorum	
82	Peregrina	Jatropha integerrima	
83	Periwinkle (Pink)	Catharanthus roseus	
84	Periwinkle (Red)	Catharanthus roseus	

85	Periwinkle (White with Pink centre)	Catharanthus roseus	
86	Periwinkle (White)	Catharanthus roseus	
87	Princess Flower	Pleroma urvilleanum	
88	Rose (Cream)	Rosa	
89	Rose (Dark Red)	Rosa	
90	Rose (Pink)	Rosa	

91	Rose Balsam (Lavender)	Impatiens balsamina	
92	Rose Balsam (Red)	Impatiens balsamina	
93	Rose Balsam (White_Pink)	Impatiens balsamina	
94	Rose Balsam(Fuchsia)	Impatiens balsamina	
95	Shower Orchid	Congea tomentosa	
96	Silver Cockscomb (Fuchsia)	Celosia argentea	

97	Single Dahlia (Yellow)	Dahlia	
98	Singapore daisy	Sphagneticola trilobata	
99	Spiny sowthistle	Sonchus asper	
100	Stargazer Lily	Lilium Stargazer	
101	Tagar Flower	Tabernaemontana divaricata	
102	Thai Eggplant Flower	Solanum melongena	

103	Thornless Crown of Thorns	Euphorbia geroldii	
104	Turmeric Flower	Curcuma longa	
105	Wax Begonia	Begonia cucullata	
106	Yesterday Today and Tomorrow	Brunfelsia latifolia