Fine-Grained Flower Classification

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1. Introduction

Recently models for fine-grained flower-based classification tasks, in particular models that use features from pre-trained convolutional neural network as an image representation, show outstanding results, with more than 95% mean class accuracy on the Oxford Flower Database [4][6][7]. It would seem that these emerging tools may be able to address the more realistic and challenging problems posed by the varying appearance of flowers in the wild, including 'super-fine-grained' classification tasks. In accordance, we collected a new and even more fine-grained database of Israeli wild flowers with varying levels of similarity between categories. We then followed the classification paradigm described in Razavian et al [1] to classify both the Oxford 102 flower database and the new one. Using the most recent representations based on deep learning networks, the results on the Oxford dataset are excellent, with 94.9% mean class accuracy. When training the same classifier with our database it achieved only 79.3%, an evidence for the higher challenge the Israel Flower Database poses. The Israel Flower Database is also unique in being hierarchical (genus and species), while being labeled with accurate scientific botanical names.

2. Databases

Oxford Flowers 102 (OF 102) database [3]

Oxford Flowers 102 consists of 8,189 images from 102 categories. Each category contains 40-258 images of common wild flowers in the UK. Most of the categories are genera rather than species and they are labeled using their common English name. The flowers appear at different scales, pose and lighting conditions.

Israel Flower Database[1]:

In this project we introduce a hierarchical database consisting of 3,439 images from 39 genera and about 115 species of common wild flowers in Israel, photographed in their natural environment. Figure 1 in the appendix shows one example from each species. Most of the images were collected from donor photographers or from the web. A few hundred images were acquired by taking the pictures ourselves. The database is still not completed, as for many of the species we do not have enough images.

For the purpose of this project we defined 2 recognition tasks – Israel 43 (IF 43) and Israel 64 (IF 64), consisting of 43 and 64 categories respectively (see Table 1 in the appendix for more details). A category may correspond to genus, sub-genus or one species, depending on intra-species similarity and the number of images per species. IF 43 was constructed to be more genus-specific with categories that can be readily discriminated by human observers. The

[1] Israel Flower Database is available online here: www.cs.huji.ac.il/~daphna/IsraeliFlowers/flower_classification.html

categories in IF 64 are more species-specific, and its classification is therefore challenging even for human observers. IF 64 has 64 categories rather than 115 (the number of different species in our database), because we merged into a single category some species that are almost impossible to differentiate based on the flower alone (as judged by an expert botanist).

In IF 43 the categories are quite different from each other, similarly to OF 102. Here, the difference between the appearance of flowers in different categories is quite significant. On the other hand, since Israel 64 is essentially species-specific, it is much more complicated. This is because while different species within the same genera can sometimes be easily discriminated (e.g. *Cistus* and *Nympahaea*), in many genera it is almost impossible to distinguish between the flowers of different species (e.g. *Iris*, *Orchis* and *Ophtys*). Moreover, some species from different genera are very similar (e.g. *Crocus canacellatus*, *Colchicum hierosolymitanum* and *Romulea nivalis*). As a result, Israel Flowers database sets a new level of difficulty for fine-grained flower-based classification task.

3. Method

Random augmentation:

For different experiments we used an increasing level of augmentation. Image augmentation X2 was done by taking the image and its mirror. Augmentation of X4 or more was done by adding random cropping of the images to the original images and their mirrors. Our method for random cropping takes the original image or its mirror, chooses a random corner, and then cuts from each dimension a random number of pixels distributed uniformly between 0 to 1/3 of the length of this dimension. The parameter of maximal cropping (1/3) was varied in subsequent experiments. At test time, when we had multiple representations for each test image, we measured the average of the feature vectors

Fixed augmentation:

In some experiments we used (almost) the same augmentation method of Razavian et al. For each image and its mirror we added 5 cropped versions of the original image and its mirror (12 in total). The cropping was done by taking 4/9 of the image area from each corner and from the center. We did not apply rotation, since many flowers have a natural composition angle.

Features:

In all experiments, we used the one before last, fully connected layer (pool_3) of the pre-trained network Inception-3 [2] as a 2048 dimension feature vector representation of the images. Inception-3 was trained on ILSVRC and was not fine-tuned for our task. In some of the experiments, the feature vector was further L2 normalized to unit length.

Classification:
20 images from each class in OF 102 and 10 images in IF 43/64 were used to train a Linear-SVM, and the rest were used for testing. In all experiments, unless stated otherwise, we report the mean class accuracy.

4. Results

Table 1 shows the mean class accuracy on OF 102. Our model outperforms off-the-shelf classifiers by 8%. After testing our model with different settings, we concluded that this impressive improvement can be explained by the superiority of the pre-trained network that we used to generate the feature vectors. We used Inception 3, while Razavian et al used Overfeat. The features from Inception 3 have lower dimension (2048 vs 4096), so it is less likely to overfit since smaller hypothesis space provides better generalization bound for the same number of training samples.. Generally speaking, Inception 3 seems to represent images better, as can be seen from the top-5 error of Inception 3 on ILSVRC which is significantly lower than the error of Overfeat (3.6% vs. 17% [2][5]). Normalizing the feature vectors to unit length gave insignificant improvement to the results, but the training time of the SVM classifier was shortened. Fixed augmentation increased the accuracy by more than 1%, which we think resulted mostly from the contribution of the center cropping of the images.

model	**Top-1**
Off-the-shelf	74.7
Ours	86
Off-the-shelf + fixed aug	86.8
Ours + random aug	93.5
Ours + random aug w/o norm	93.8
Ours + fixed aug	94.9±0.2
Ours + fixed aug w/o norm	**94.9±0.04**

Table 1

Top-1 mean class test accuracy (%) for different models and settings. We show average result using 3 random partitions of Oxford 102 to train and test sets.

To assess the importance of augmentation we tested our model with increasing amount of augmentation of the training images (Figure 1) and separately for the test set (Figure 2). In addition we tested how the maximal percentage of random cropping affected the results (Figure 3). In each one of those three experiments, we show the average result using three random partitions of Oxford 102 to train and test sets.

Table 2 summarizes the best results of our model (with random augmentation) on the databases Oxford 102, Israel 43 and Israel 64. Qualitative similarity between the results of Israel 43 and Oxford 102 suggest that the challenge of recognizing the two databases is comparable. This is not surprising as the 'within classes similarity' and 'between classes variability' of the two datasets are rather similar. While the

	Top-1	**Top-2**	**Top-3**	**Top-5**
Oxford 102	93.8	96.7	97.7	98.5
Israel 43	92.6	95.8	96.9	98.3
Israel 64	79.3	88.1	92	95.3

Table 2

Top-1 mean class test accuracy (%) of the same model (random aug w/o norm) on different tasks.

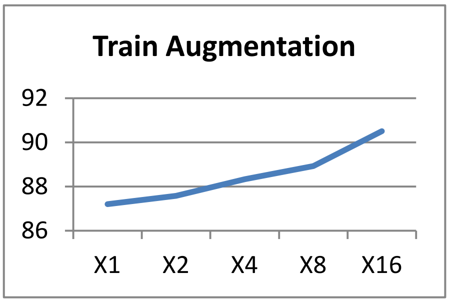

Figure 1

Test accuracy (%) when applying different amounts of random augmentation to the training set. w/o test aug and w/o normalization.

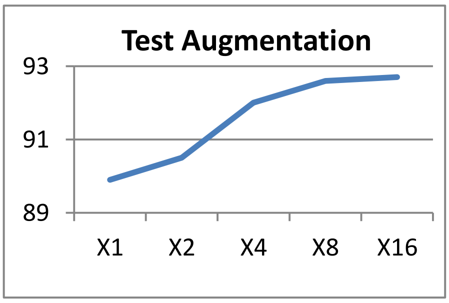

Figure 2

Test accuracy (%) when applying different amount of random augmentation to the test set. Augmentation of the training set is X4, w/o normalization.

number of classes in OF 102 is twice the number in IF 43, it also provides twice as many training images per class (10 for IF 43 vs 20 for OF 102). IF 64, however, is clearly more difficulty. The gap between the top-1 accuracy of IF 64 and IF 43 is quite significant, decreasing in top-2 and top-3 to almost unnoticeable in top-5. This is consistent with the fact that in IF 64, species from the same genus are similar but species from different genera are different (in most cases).

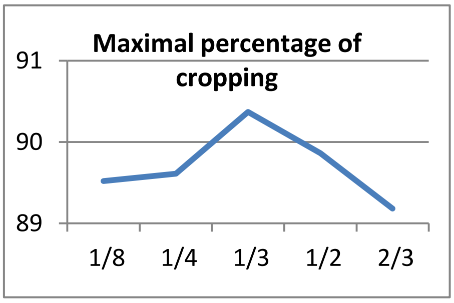

Figure 3
Test accuracy (%) after setting the maximal cropping parameter to different values and applying random augmentation of X8 w/o norm to the training set.

Label	Error rate	Most confused with
Crocus damascenus 	62	Crocus cancellatus 
Crocus cancellatus 	60	Crocus damascenus 
Allium other 	60	Allium meronense 
Iris atrofusca 	60	Iris atropurpurea 
Colchicum ritchii 	51	Colchicum tuviae 
Crocus hermoneus 	47	Crocus damascenus 
Colchicum tunicatum 	46	Colchicum stevenii 
Pancratium 	45	Colchicum tauri 
Crocus aleppicus 	40	Crocus pallasii 
Ornithogalum 	40	Gagea 

Table 4
Categories in IF 64 with the worst error rate.

Finally, Table 1 presents 10 categories in IF 64 with the worst error rate and for each one, the category with which the model was most confused. We noticed that the model has approximately the same difficulties as human, which suggests that the model captures the images in a similar way to the human eye. One noticeable and disappointing exception is the confusion between Ornithogalum, which is always white, and Gagea which is always yellow. To confirm our hypothesis that the model is mostly confused with species within the same genus, we calculated for each genus its mean class error rate within the genus and outside of the genus, as shown in Figure 4. Indeed, for most of the genera the model is mostly confused with species within the same genus and on average the error rate within genus is twice bigger.

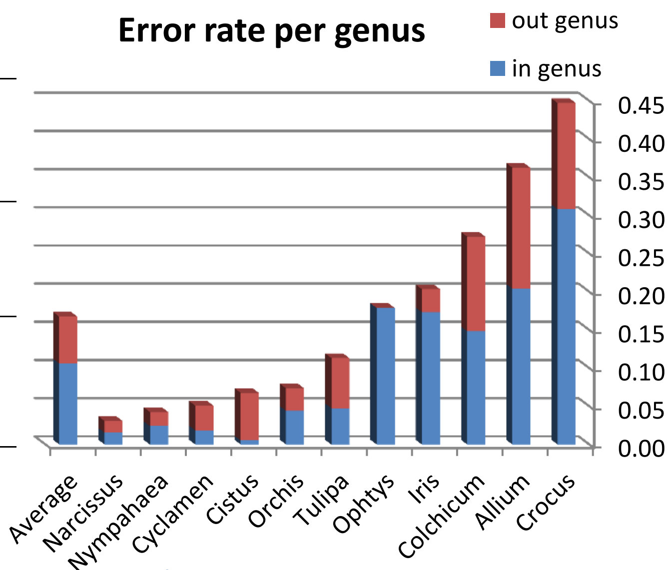

Figure 4
Mean class error rate within and outside of the genus.

5. Bibliography

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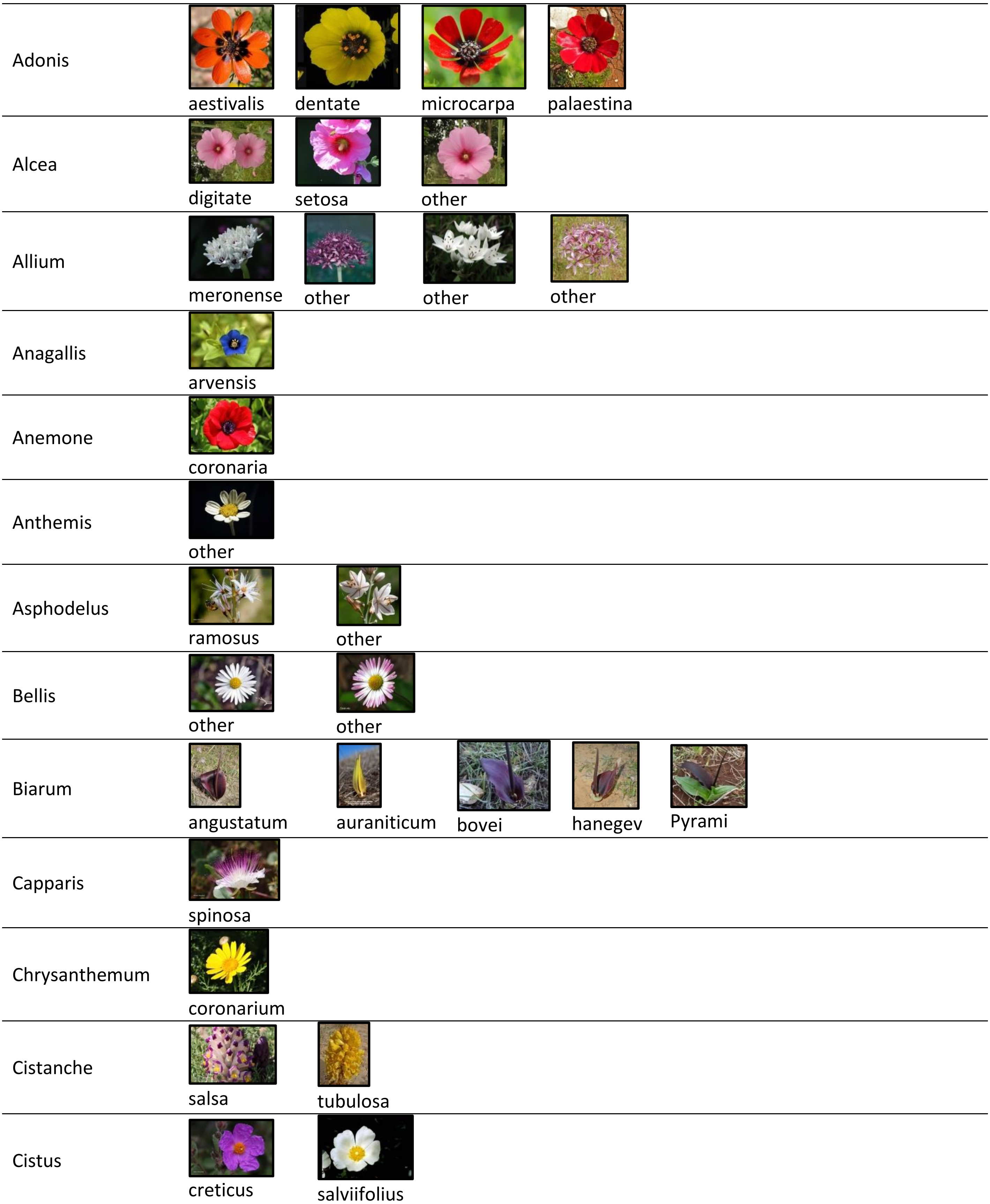
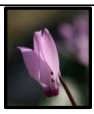
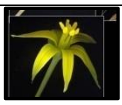
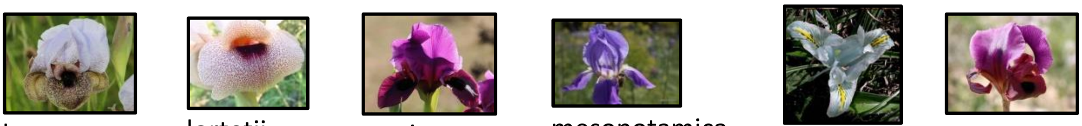
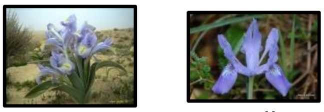
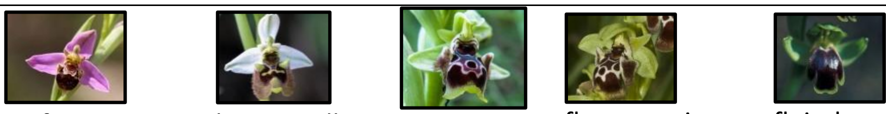
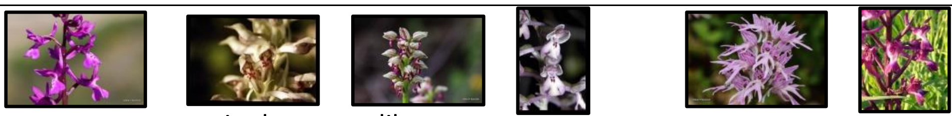
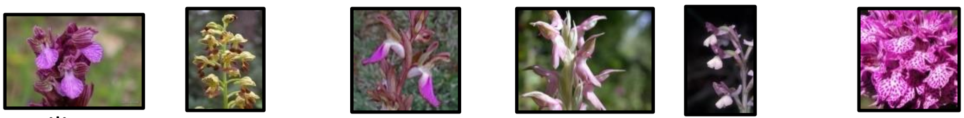
6. Appendix

Figure 1: Israel Flower Database. Each image is an instance of a species, the genus name is on the left.



Colchicum	 feinbruniae  hierosolymitanum  ritchii  stevenii  tauri  troodi  tunicatum  tuviae
Convolvulus	 other  other  other
Crocus	 aleppicus  cancellatus  damascenus  hermoneus  hyemalis  ochroleucus  pallasii
Cyclamen	 coum  persicum
Gagea	 other
Glaucium	 other  other  other
Gynandriris	 monophylla  sisyrinchium
Iris	 atrofusca atropurpurea bazra bismarckiana grant-duffii haynei  hermona lortetii mariae mesopotamica palaestina petrana  regis-uzziae vartanii
Linum	 pubescens
Lupinus	 luteus  pilosus  other

Narcissus	 serotinus	 tazetta				
Nympahaea	 alba	 caerulea				
Oenothera	 drummondii	 rosea				
Ophtys	 apifera	bornmuelleri	carmeli	flavomarginata	fleischmannii	
	 fuciflora	iricolor	lutea	transhyrcana		
Orchis	 anatolica	coriophora	galilaea	israelitica	italica	laxiflora
	 papilionacea	punctulata	saccata	sancta	syriaca	tridentata
Ornithogalum	 narbonense	 other	 other			
Paeonia	 mascula					
Pancratium	 maritimum	 parviflorum	 sickenbergeri	 other		
Papaver	 other	 other	 other			
Picris	 other	 other				
Ranunculus	 asiaticus					
Romulea	 nivalis	 other	 other	 other		

Senecio	 vernalis			
Sternbergia	 clusiana	 colchiciflora		
Tulipa	 agenensis	 lownei	 polychroma	 systola
Urginea	 maritima			

Table 1: detailed list of the species and their labels in Israel 43 and Israel 64.

Genus	Species	Label (43)	Label (64)	Hebrew genus	Hebrew species	Common names	#images
Adonis	aestivalis	1	1	דמומית	עבת-שיבולת		9
Adonis	dentata	1	1	דמומית	משוננת	Toothed pheasant's eye	4
Adonis	microcarpa	1	1	דמומית	קטנת-פרי	Small Pheasant's Eye	13
Adonis	palaestina	1	1	דמומית	ארץ-ישראלית	Aleppo Adonis	5
Alcea	digitata	2	2	חטמית	מאובצעת		16
Alcea	other	2	2	חטמית	אחר		12
Alcea	setosa	2	2	חטמית	זיפנית	Bristly Hollyhock	5
Allium	meronense	3	3	שום	הגליל		26
Allium	other	4	4	שום	אחר		70
Anagallis	arvensis			מרגנית	השדה	Scarlet Pimpernel	17
Anemone	coronaria	5	5	כלנית	מצויה	Crown Anemone	209
Anthemis	other	6	6	קחוון	אחר		29
Asphodelus	other	7	7	עירית	אחר		6
Asphodelus	ramosus	7	7	עירית	גדולה	Common Asphodel	14
Bellis	silvestris	8	8	חיננית	הבתה	Southern Daisy	25
Biarum	angustatum	9	9	אחילוף	צר-עלים		5
Biarum	auraniticum	9	9	אחילוף	החורן		14
Biarum	bovei	9	9	אחילוף	קטן		8
Biarum	hanegev	9	9	אחילוף	הנגב		26
Biarum	Pyrami	9	9	אחילוף	הגליל		39
Capparis	spinosa	10	10	צלף	קוצני	Common Caper	56
Chrysanthemum	coronarium			חרצית	עטורה	Crown Daisy	10
Cistanche	salsa	11	11	יחנוק	המלחות	Broomrape	25
Cistanche	tubulosa	11	11	יחנוק	המדבר	Desert Broomrape	10
Cistus	creticus	12	12	לוטם	שעיר	Soft-Hairy Rockrose	101
Cistus	salviifolius	13	13	לוטם	מרווני	Sage-Leaved Rock Rose	53
Colchicum	feinbruniae	14	14	סתוונית	התשבץ		32
Colchicum	hierosolymitanum	15	15	סתוונית	ירושלים	Jerusalem Autumn-crocus	84
Colchicum	ritchii	14	16	סתוונית	הנגב		41
Colchicum	stevenii	16	17	סתוונית	היורה	Steven's Meadow-saffron	179

Colchicum	tauri	14	18	סתוונית	החרמון		23
Colchicum	troodi	14		סתוונית	בבירה		12
Colchicum	tunicatum	14	19	סתוונית	הקליפות		21
Colchicum	tuviae	14	20	סתוונית	טוביה		25
Colchicum	unknown			סתוונית	לא-ידוע		84
Convolvulus	other	17	21	חבלבל	אחר	bindweed;morning glory	47
Crocus	aleppicus	18	22	כרכום	גיירדו		18
Crocus	cancellatus	19	23	כרכום	השבכה		20
Crocus	damascenus	19	24	כרכום	דמשקאי		31
Crocus	hermoneus	18	25	כרכום	חרמוני	Crocus hermoneus palaestinus	25
Crocus	hyemalis	20	26	כרכום	חורפי	Crocus	64
Crocus	ochroleucus	18		כרכום	צהבהב		6
Crocus	pallasii	18	27	כרכום	נאה		24
Cyclamen	coum	21	28	רקפת	יוונית	Round-Leaved Cyclamen	18
Cyclamen	persicum	22	29	רקפת	מצויה	Persian Cyclamen	118
Gagea	other	23	30	זהבית	אחר	yellow star of Bethlehem	30
Glaucium	other	24	31	פרגה	אחר		28
Gynandriris	monophylla	25	32	צהרון	קטן		6
Gynandriris	sisyrinchium	25	32	צהרון	מצוי	Barbary Nut	24
Iris	atrofusca	26	33	איריס	שחום	Judean Iris	25
Iris	atropurpurea	26	34	איריס	הארגמן	Coastal Iris;Dark-purple Iris	48
Iris	bazra	26		איריס	בצרה		15
Iris	bismarckiana	26		איריס	נצרתי	Nazareth Iris	18
Iris	grant-duffii	27		איריס	הביצות	Grant-Duff's Iris	7
Iris	haynei	26		איריס	הגלבוע	Gilboa Iris	12
Iris	hermona	26	35	איריס	החרמון	Mt. Hermon Iris	43
Iris	lortetii	26	36	איריס	הדור	Lortet's Iris	25
Iris	mariae	26	37	איריס	הנגב	Negev Iris	28
Iris	mesopotamica	26	38	איריס	ארם-נהריים	Mesopotamian Iris	21
Iris	palaestina	27	39	איריס	ארץ-ישראלי	Palestine Iris	34
Iris	petrana	26	40	איריס	ירוחם	Sand Iris;Petra Iris	29
Iris	regis-uzziae	27		איריס	טוביה	King Uzziae Iris	15
Iris	vartanii	27	41	איריס	הסרגל	Vartan's Iris	31
Linum	pubescens			פשתה	שעירה		13
Lupinus	luteus	28	42	תורמוס	צהוב	Yellow Lupin	7
Lupinus	other	28	42	תורמוס	אחר		9
Lupinus	pilosus	28	42	תורמוס	ההרים	Blue Lupine	35
Narcissus	serotinus	29	43	נרקיס	סתווי	Late-flowering Narcissus	19
Narcissus	tazetta	29	44	נרקיס	מצוי	Common Narcissus	75
Nympahaea	alba	30	45	נימפאה	לבנה	White Water-Lily	187
Nympahaea	caerulea	31	46	נימפאה	תכולה	Blue Water-Lily	59
Oenothera	drummondii			נר-הלילה	החופי	Evening-primrose	6
Oenothera	rosea			נר-הלילה	הורוד	Pink Evning Primose	7
Ophtys	apifera	32		דבורנית	הדבורה	Bee Orchid	9
Ophtys	bornmuelleri	32	47	דבורנית	נאה	Bornmuller’s ophrys	28
Ophtys	carmeli	32	48	דבורנית	דינסמור	Carmel Bee-Orchid	27
Ophtys	flavomarginata	32		דבורנית	צהובת-שוליים		11

Ophtys	fleischmannii	32		דבורנית	שחומה		5
Ophtys	fuciflora	32	49	דבורנית	גדולה	Drone Bee-Orchid	20
Ophtys	iricolor	32		דבורנית	כחלחלה		4
Ophtys	lutea	32		דבורנית	צהובה	Yellow Bee Orchid	4
Ophtys	transhyrcana	32		דבורנית	הקטיפה	Early Spider Orchid	11
Orchis	anatolica	33	50	סחלב	אנטולי	Anatolian Orchid	21
Orchis	coriophora	33		סחלב	ריחני		3
Orchis	galilaea	33	51	סחלב	הגליל		27
Orchis	israelitica	33		סחלב	מצויר		9
Orchis	italica	33		סחלב	איטלקי		11
Orchis	laxiflora	33		סחלב	הביצות		6
Orchis	papilionacea	33	52	סחלב	פרפרני	Pink Butterfly Orchid	20
Orchis	punctulata	33		סחלב	נקוד	Punctate orchid	3
Orchis	saccata	33		סחלב	השקיק		4
Orchis	sancta	33		סחלב	קדוש	Holy Orchid	3
Orchis	syriaca	33		סחלב	סורי		4
Orchis	tridentata	33	53	סחלב	שלוש-השיניים	Toothed Orchid	27
Ornithogalum	narbonense	34	54	נץ-חלב	צרפתי		2
Ornithogalum	other	34	54	נץ-חלב	אחר	Star of Bethlehem	53
Paeonia	mascula	35	55	אדמונית	החורש		34
Pancratium	maritimum	36	56	חבצלת	החוף	Sea daffodil	11
Pancratium	other	36	56	חבצלת	אחר		4
Pancratium	parviflorum	36	56	חבצלת	קטנת-פרחים	Small-Flowered Pancratium	3
Pancratium	sickenbergeri	36	56	חבצלת	הנגב	Desert Pancratium	12
Papaver	other	37	57	פרג	אחר		26
Picris	other	38	58	מררית	אחר	Reichardia	21
Ranunculus	asiaticus	39	59	נורית	אסיה	Turban Buttercup	24
Romulea	nivalis	40	60	רומוליאת	השלג	Snow romulea	10
Romulea	other	40	60	רומוליאה	אחר		18
Senecio	vernalis			סביון	אביבי	Spring Groundsel	9
Sternbergia	clusiana	41	61	חלמונית	גדולה	Large Sternbergia	268
Sternbergia	colchiciflora			חלמונית	זעירה		17
Tulipa	agenensis	42	62	צבעוני	ההרים	Sun's-eye Tulip	62
Tulipa	lownei	43	63	צבעוני	החרמון		23
Tulipa	polychroma	43	64	צבעוני	ססגוני	Two-Flowered Tulip	24
Tulipa	systola	42		צבעוני	המדבר		11
Urginea	maritima			חצב	מצוי	Sea Squill;Medicinal squill	15