

Towards Generic Image Classification with Tree-Based Learning: an Extensive Empirical Study: Supplementary data

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I. INTRODUCTION

This document includes some supplementary data (results, explanations, tables, figures, and images) which we could not include in the main paper due to space constraints.

Topics covered in this supplement are:

- Listing and short description of all 80 datasets and their evaluation protocols: Table I, Figures 1 to 4
- Computational requirements and implementation details of the methods
- Results for both method variants and their parameters
 - ET-DIC subwindow size intervals: Table II
 - ET-DIC subwindow descriptors: Table III
 - ET-DIC number of random tests: Table IV
 - ET-DIC number of trees: Table V
 - ET-DIC minimum node sample size: Table VI
 - ET-FL subwindow size intervals: Table VII
 - ET-FL minimum node sample size: Tables VIII and IX
 - ET-FL number of random tests: Table X
 - ET-FL encoding scheme: Table XI
 - ET-FL number of trees: Table XII
- Results with simple optimizations, Table XIII
- Comparison with other methods
 - Comparison with extremely randomized trees without random subwindows: Table XIV
 - Comparison with baselines: Table XV
 - Comparison with various other approaches

II. DATASETS

A. Description of all datasets and evaluation protocols

Datasets	Images	Img sizes	Protocols	Classes	Short description	Ref.
ACROSOMES	1851	$\pm 100 \times 100$	10 RS \times 1296/555	2	intact/damaged acrosomes of boar spermatozoa	[1]
AGEMAP-FAGING	850	1388 \times 1040	10 RS 423 \times 106	4	mouse liver tissues at different development stages	[2]
ALL-IDB2	260	256 \times 256	10 RS \times 208/52	2	normal and lymphoblast cells	[3]
ALOI	72000	192 \times 144	I 1000/71000	1000	uniform background, viewpoint changes	[4]
ALOT	25000	384 \times 286	10 RS \times 10000/15000	250	textures with varying illuminations	[5]
APOPTOSIS	700	67 \times 67	10 RS \times 630/70	2	DIC images of (non-)apoptotic cells	[6]
BINUCLEATE	40	640 \times 512	10 RS \times 20/20	2	DAPI images of binucleate and regular cells	[2]
BIRDS	600	various	10 RS \times 300/300	6	background, illumination, orientation	[7]
BREAST-CANCER	361	760 \times 570	10 RS \times 289/72	3	biopsies of breast cancer (H&E staining)	[8]
BUILDINGSAB	249	$\pm 800 \times 534$	10 RS \times 68/181	68	grayscale buildings	[9]
BUTTERFLIES	619	various	10 RS \times 182/437	7	www butterfly pictures	[10]
BUTTERFLIES-CLEAN	619	various	10 RS \times 182/437	7	same but butterflies are cropped	[10]
CALTECH-101	9145	various	10 RS \times 3030/5168	101	objects and clutter	[11]
CALTECH-256	29780	various	10 RS \times 7680/6400	256	objects and clutter	[12]
C.ELEGANS	237	1600 \times 1200	10 RS \times 120/117	4	C.elegans muscles at different ages	[2]
C.ELEGANS-LIVEDEAD	97	$\pm 400 \times 400$	10 RS \times 78/19	2	C.elegans live/dead assays	[13]
CHARS74KEIMG	7705	$\pm 50 \times 50$	10 RS \times 930/930	62	characters in natural images	[14]
CHO	327	512 \times 382	10 RS \times 100/65	5	subcellular localizations	[15]
CIFAR-10	60000	32 \times 32	I 50000/10000	10	tiny object/scene images	[16]
COIL-100	7200	128 \times 128	I 100/7100	100	uniform background, viewpoint changes	[17]
CONVEX	58000	28 \times 28	I 8000/50000	2	single white convex regions on black background	[18]
ETH-80	3280	256 \times 256	20 RS 2952/328	8	man-made objects	[19]
EVENTS	1579	various	10 RS \times 560/480	8	sport scenes	[20]
FAMOUSLAND	1000	$\pm 300 \times 200$	10 RS \times 800/200	100	www pictures of famous places	[21]
FLOWERS17	1700	various	10 RS \times 1360/340	17	flowers, pose, light variations	[22]
FLOWERS102	8189	$> 500 \times 500$	10 RS \times 2040/6149	102	larger set of flowers	[23]
GALAXYZOO	75746	200 \times 200	10 RS \times 49991/25755	4	galaxies from imaging sky survey	[24]
GTSRBCROP	51839	$\pm 75 \times 75$	I 39209/12630	43	traffic signs	[25]
HCC	363	$\pm 3096 \times 4140$	20 RS \times 266/14	14	Human carcinoma cell lines	[26]
HEP2	721	$\pm 100 \times 100$	10 RS 361/360	6	cells in indirect immunofluorescence	[27]
HPA	1057	$\pm 64 \times 64$	10 RS \times 952/105	4	Immunostaining patterns	[28]
INDOOR	15620	$> 200 \times 200$	10 RS \times 5360/1340	67	indoor scenes	[29]
IRMA 2005	10000	$< 512 \times 512$	I 9000/1000	57	human body radiographs	[30]
IRMA 2006	11000	$< 512 \times 512$	I 10000/1000	116	human body radiographs (fine-grained)	[30]
KTH-TIPS	810	200 \times 200	10 RS \times 400/410	10	scale, illumination, pose changes	[31]
KTH-TIPS2	4752	200 \times 200	20 RS 3564/1188	11	texture categorization	[32]
LANDUSE	2100	256 \times 256	10 RS 1680/420	21	land use from overhead imagery	[33]
LYMPHOMA	374	1388 \times 1040	10 RS \times 337/37	3	biopsies of lymphoma (H&E staining)	[2]
MMODALITY	5010	$\pm 1200 \times 1200$	I 2390/2620	8	biomedical imaging modalities	[34]
MNIST	70000	28 \times 28	I 60000/10000	10	handwritten digits centered on uniform background	[35]
MNIST-12000	62000	28 \times 28	I 1000/50000	10	subset of MNIST	[18]
MNIST-ROTATION	62000	28 \times 28	I 12000/50000	10	digits with random rotation	[18]
MNIST-BIMG	62000	28 \times 28	I 12000/50000	10	digits with background image	[18]
MNIST-BRAND	62000	28 \times 28	I 12000/50000	10	digits with random background noise	[18]
MNIST-BIMG-ROT	62000	28 \times 28	I 12000/50000	10	digits with random background noise and rotation	[18]
MSTAR-S1	3617	128 \times 128	I 1860/1757	3	synthetic aperture radar images	[36]
NATURALSCEENES	4485	$\pm 300 \times 200$	10 RS \times 1500/2985	15	graylevel natural scenes (OLIVA superset)	[37]
NORB-UNIFORM	58600	96 \times 96	I 24300/24300	5	normalized object sizes and uniform background	[38]
NORB-JITCLUTT	349920	108 \times 108	I 291600/58320	6	jittered objects and cluttered background	[38]
OLIVA	2688	256 \times 256	10 RS \times 1200/1488	8	color images of natural scenes	[39]
ORL	400	92 \times 112	10 RS \times 200/200	40	graylevel, centered, faces	[40]
OUTEX	864	128 \times 128	10 RS \times 432/432	54	color textures	[41]
PFID	1098	$\pm 250 \times 250$	10 RS \times 732/366	61	segmented fast food items	[42]
POLLEN	6039	25 \times 25	10 RS \times 5490/549	7	pollen grains	[2]
PPMI24	4800	258 \times 258	I 2400/2400	24	people holding or playing instruments	[43]
PUBFIG83	13838	100 \times 100	10 RS 7470/830	83	unconstrained faces of celebrities	[44]
RBC	5062	128 \times 128	10 RS \times 1500/1125	3	red-blood cells	[45]
RECT-BASIC	51200	28 \times 28	I 1200/50000	2	tall or wide rectangles at variable position	[18]
RECT-BIMG	62000	28 \times 28	I 12000/50000	2	same with backgrounds	[18]
RNAI	200	1024 \times 1024	10 RS \times 160/40	10	cells following RNA interference	[2]
SEROUS	3652	$\pm 25 \times 25$	10 RS \times 3286/366	11	serous cells	[46]
SHAPE1	724	500 \times 500	10 RS \times 200/100	10	geometric object classes	[47]
SMEAR	917	$< 500 \times 500$	10 RS \times 825/92	2	Cells from PAP smears	[48]
SOCCER	280	$\pm 300 \times 300$	10 RS \times 175/105	7	soccer teams	[49]
SPORTS	2449	$\pm 500 \times 375$	10 RS \times 1837/612	5	www pictures of sports	[50]
SOIL-24	264	$\pm 360 \times 288$	I 24/240	24	man-made objects, uniform background	[51]
SOIL-47	987	$\pm 360 \times 288$	I 47/940	47	man-made objects, uniform background	[51]
STOIC-101	3847	$\pm 320 \times 240$	I 3187/660	101	color buildings in Singapore	[52]
STOMATA	114	$\pm 320 \times 320$	10 RS \times 103/11	2	opened/closed stomata in <i>Arabidopsis thaliana</i>	[6]
STONEFLY9	3845	$> 1000 \times 1000$	I 2697/1148	9	stonefly species	[53]
SUBCELLULAR	948	$\pm 512 \times 382$	10 RS \times 862/86	10	subcellular localizations	[54]
SUN397	108754	$> 200 \times 200$	10 RS \times 19850/19850	397	scenes from abbey to zoo	[55]
SWELEAF	1875	$> 1500 \times 1500$	10 RS \times 1125/750	15	swedish leaves, uniform background	[56]
TERMINALBULB	970	300 \times 300	10 RS \times 280/690	7	DIC of pharynx terminal bulb	[2]
TINYGRAZ03	1148	32 \times 32	10 RS \times 1033/115	20	tiny object/scene images	[57]
TSG-60	180	320 \times 240	10 RS \times 120/60	60	color buildings	[58]
UIUCTEX	1000	640 \times 480	10 RS \times 500/500	25	grayscale textures	[59]
WANG	1000	384 \times 480	10 RS \times 500/500	10	from Corel collection	[60]
XEROX-6	1082	various	10 RS \times 984/98	6	users' pictures of objects	[61]
ZEBRATOXIC	1249	696 \times 520	I 1153/96	3	developmental status of zebrafish embryos	[62]
ZUBUD	1120	640 \times 480	I 1005/115	201	color buildings in Zurich	[63]
TOTAL	1517317	-	-	3854	-	

TABLE I

SUMMARY OF DATASET CHARACTERISTICS AND EVALUATION PROTOCOLS (I MEANS ONE RUN WITH INDEPENDANT LEARNING AND TEST SETS OF GIVEN SIZES, X RS MEANS X RUNS WITH RANDOM SAMPLING OF INDEPENDANT LEARNING AND TEST SETS OF GIVEN SIZES).

B. Illustration of biomedical datasets

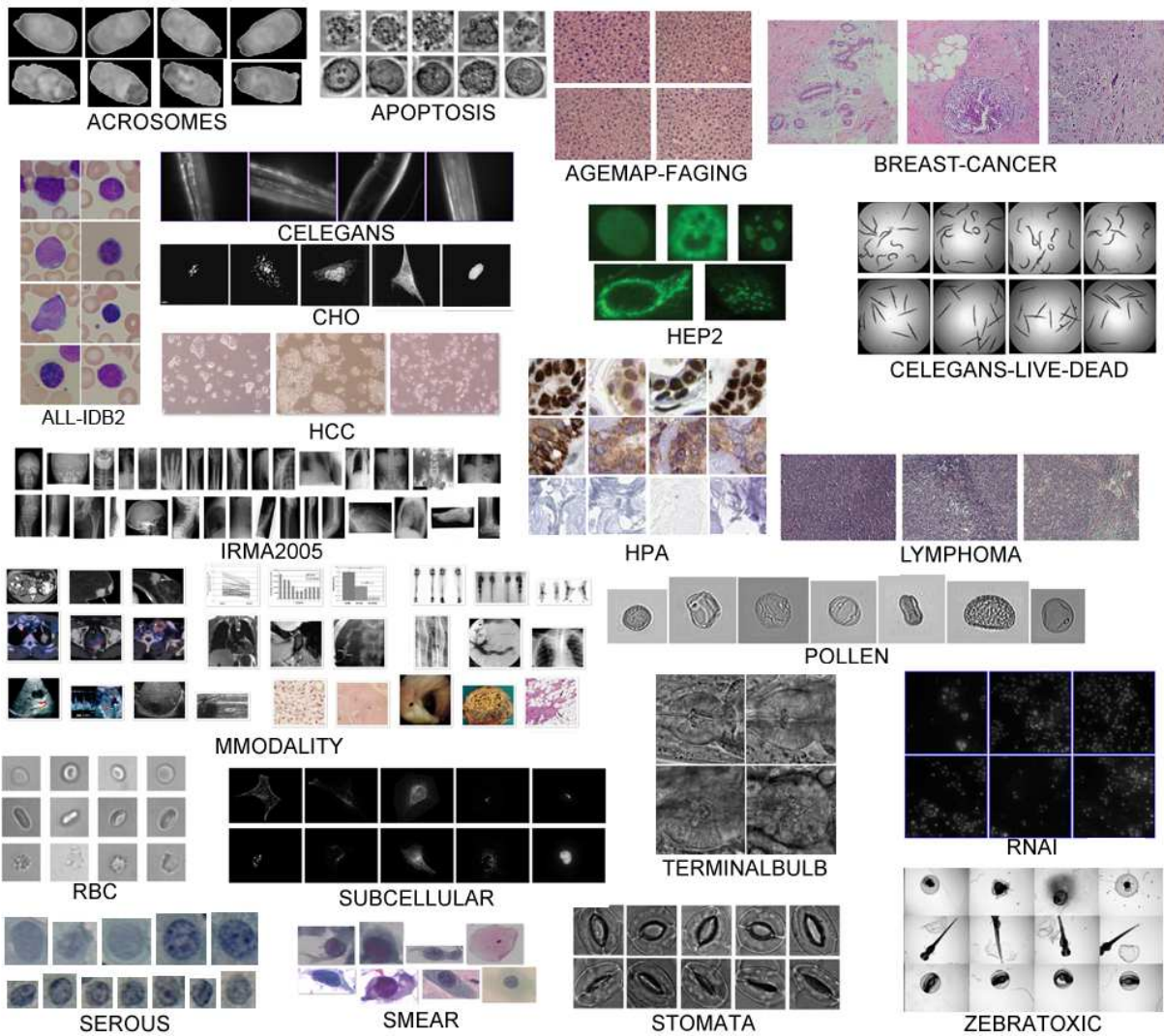


Fig. 1. Illustration of bioimaging classification datasets tackled in our experiments, including various cells, tissues, embryos, preparation protocols and imaging modalities.

C. Illustration of other datasets

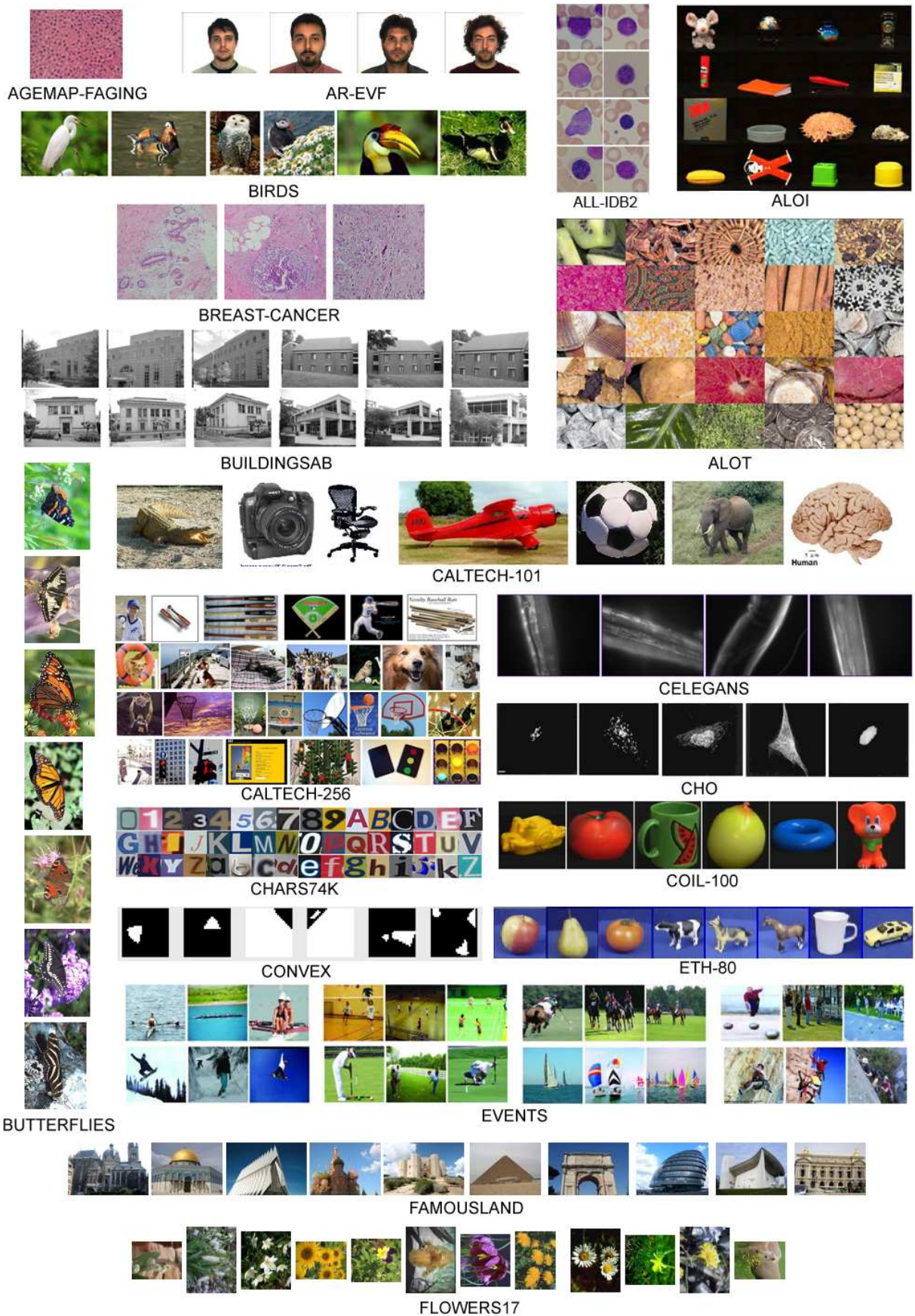


Fig. 2. An overview of several image classes used in our experimental setup. Images taken from publications or websites of the datasets from AGEMAP-FAGING to FLOWERS17 (see Table I for a summary of dataset characteristics).

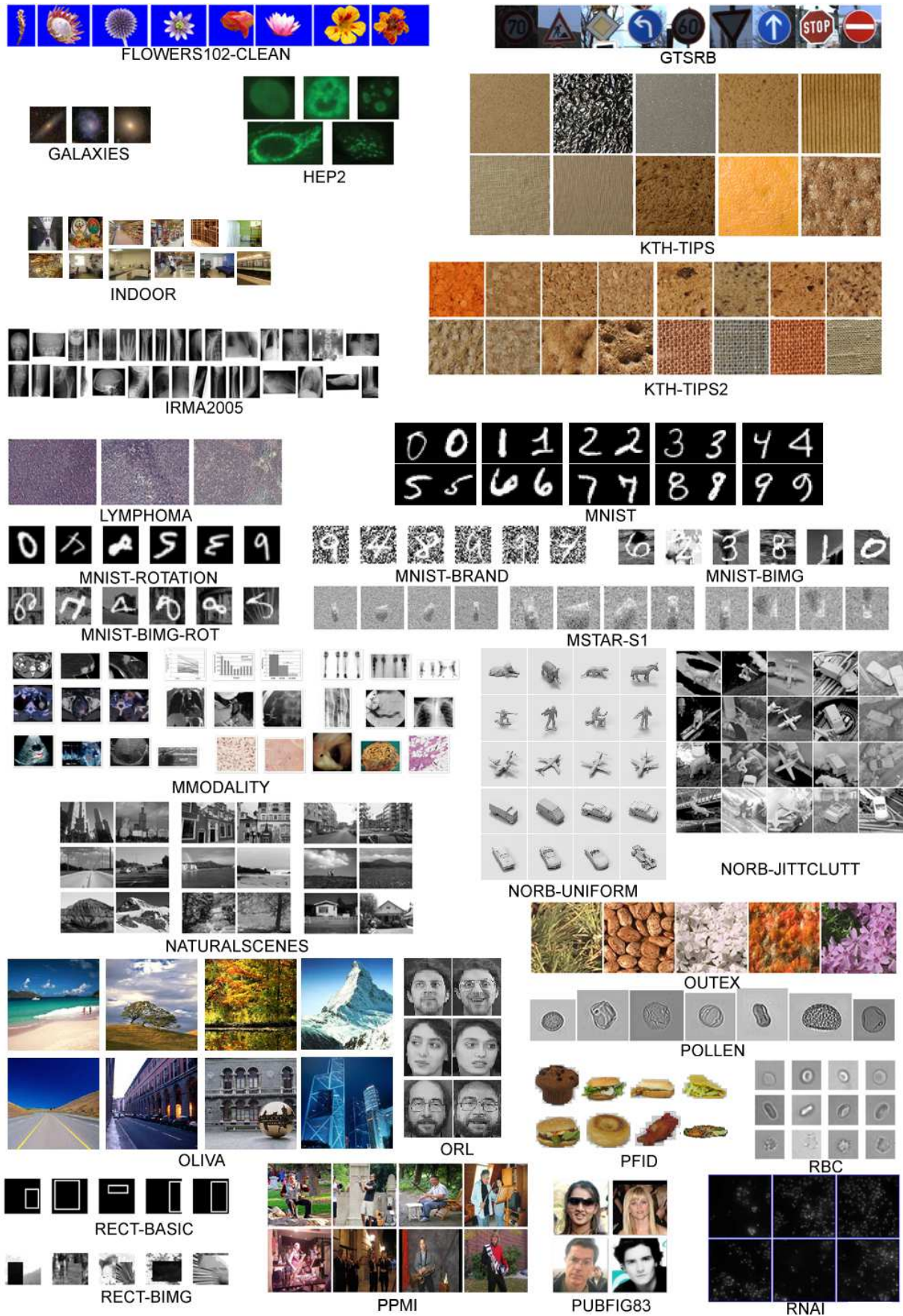


Fig. 3. An overview of several image classes used in our experimental setup. Images taken from publications or websites of the datasets from FLOWERS102-CLEAN to RNAI (see Table I for a summary of dataset characteristics).

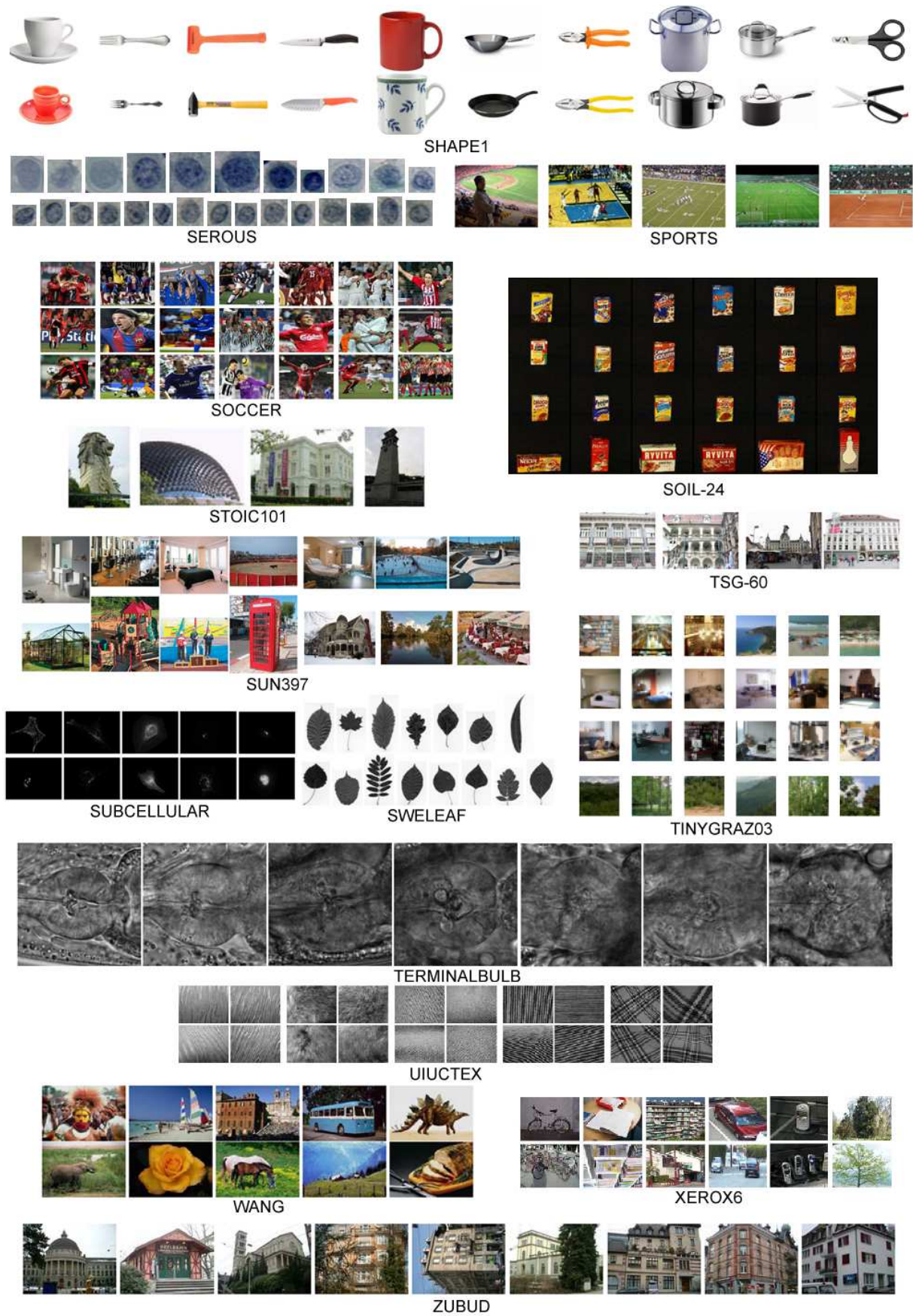


Fig. 4. An overview of several image classes used in our experimental setup. Images taken from publications or websites of the datasets from SEROUS to ZUBUD (see Table I for a summary of dataset characteristics).

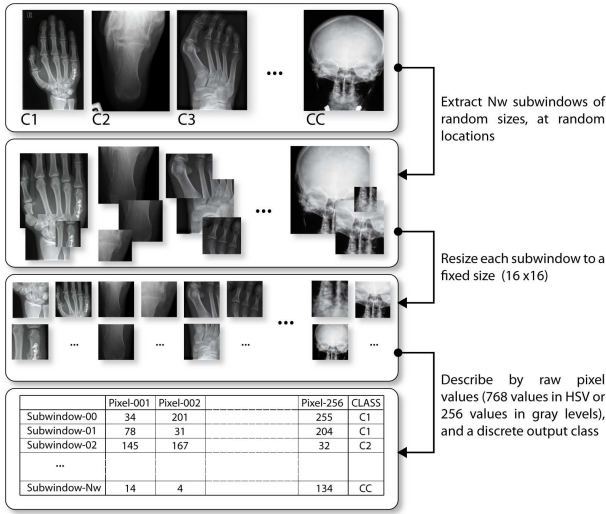


Fig. 5. Random subwindows extraction and description by raw pixel values.

III. METHODS

A. Computational requirements

The computational requirements could be subdivided in the method steps.

1) *Random Subwindows*: As location and size of random subwindow are chosen randomly, the detection process is very fast compared to common interest point detection methods that involve several image operations (normalization, convolution, resampling, ...). Then, resizing subwindows to a fixed-size essentially depends on the image size (number of pixels) in original subwindows, which could be time-consuming when large subwindows are extracted from large images. In practice, we observed nearest neighbor interpolation yields comparable recognition results (although on a few datasets recognition results were lower) while being much faster than bilinear or bicubic interpolation.

2) *Extra-Trees*: The time complexity of the Extra-Trees training algorithm is on the order of $kTN_{ts} \log N_{ts}$. The size of the Extra-Trees may grow substantially with very large training sets of subwindows, but the propagation step is on the order of $N_{test}Td$, where N_{test} denotes the number of subwindows extracted from an image, and d the average tree depth (which is on the order of $\log N_{ts}$ as we observed in our experiments). Thus, the approach scales very well and, moreover, it is highly parallelizable.

Regarding space complexity, during learning, each tree of the ensemble is learned individually and could be saved after its construction. Thus the minimum memory requirement is the memory space necessary for one tree, and the memory to store the training set of subwindows. A binary decision tree has a theoretical maximum number of nodes equals to $2N_{ts} - 1$ nodes when fully developed, but this number is generally smaller in practice. In internal nodes, an attribute index and a real-valued threshold are stored, in addition to two pointers to successor nodes. In each terminal node, for ET-DIC we store a vector of probability

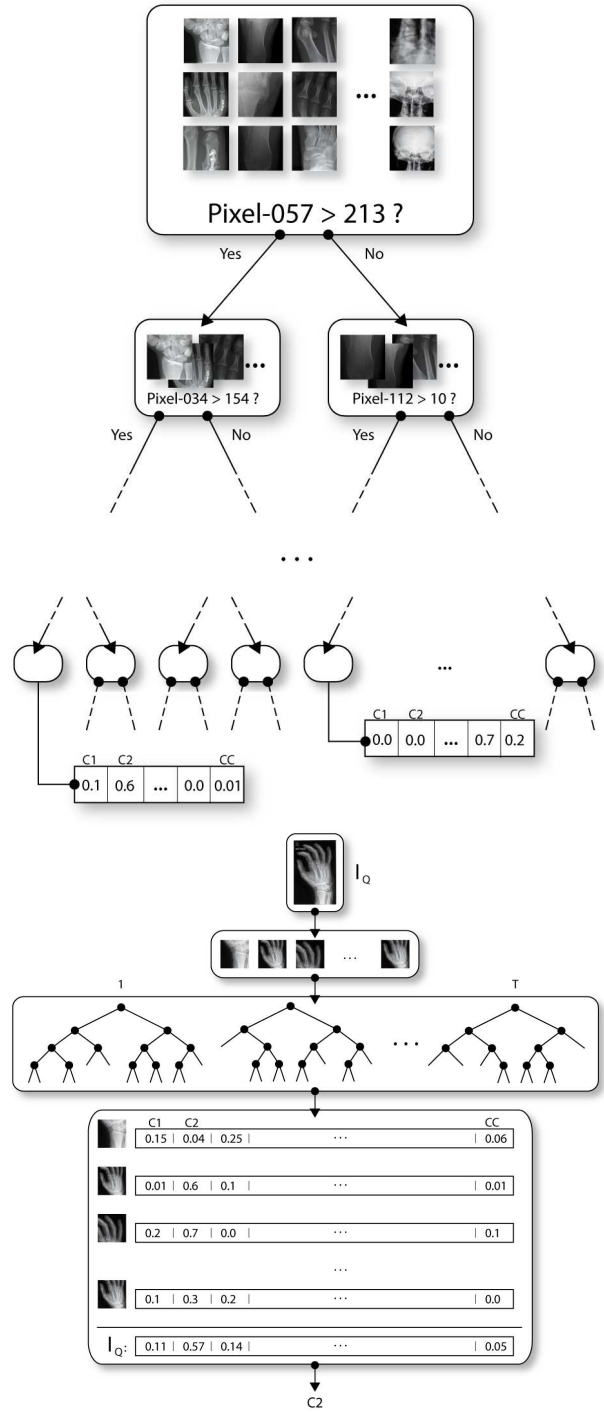


Fig. 6. ET-DIC. Training one tree (left), prediction with an ensemble of trees (right).

estimates which dimension equals to the number of classes. This could be highly memory demanding when there are a lot of classes and when we use a large number of training subwindows and trees are deeply constructed. For ET-FL, there is no information stored at terminal nodes, global image representation being calculated on-the-fly, so the tree ensemble model is significantly lighter.

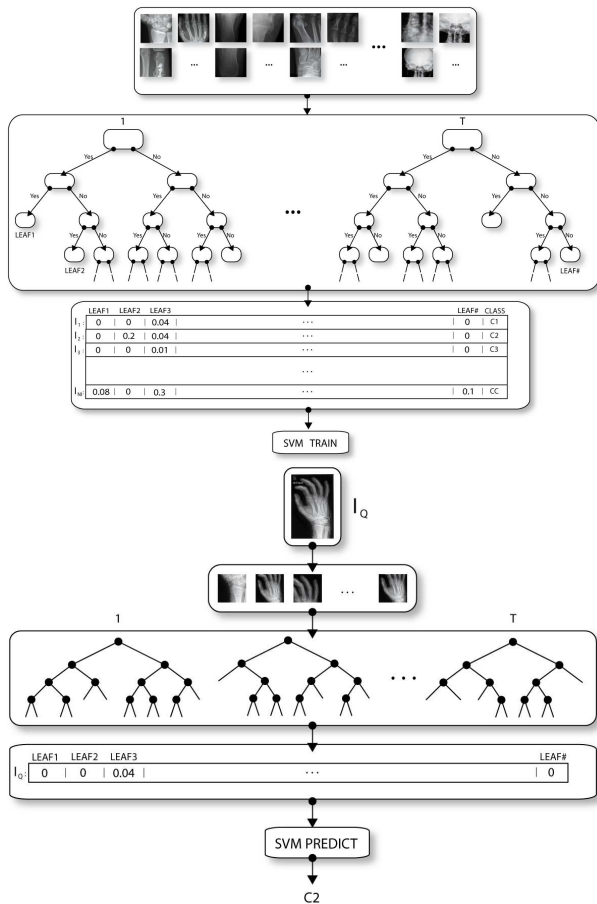


Fig. 7. ET-FL: training an ensemble of trees from random subwindows, building global feature vectors and training SVM (left); propagation of random subwindows of a test image in the ensemble of trees, building of its global feature vector, prediction of its class with SVM classifier (right).

3) *Final classifier in ET-FL:* For the ET-FL variant, the final classifier has to be built which space and time complexity depend on the specific implementation. With Libsvm, time complexity depends on the number of iterations which may be higher than linear to the number of training images [64]. With Liblinear implementation, time complexity scales linearly with the number of training images.

4) *Implementation details:* All our experiments were done using our Java implementation of random subwindow extraction and Extra-Trees. For ET-FL, we integrated the Java implementation of the SVM linear classifier of LIB-SVM v2.85 [64] that uses a “one-against-one” approach for multi-class problems, with default parameters (C-SVC with cost $C = 1$, $\epsilon = 0.1$). For larger problems (e.g. where the number of instances or classes was very large, and for $n_{min} < 1000$ and $T > 10$) we used the faster LIBLINEAR [65] tool v1.34 also using default parameter values (L2-loss SVM (dual) solver, $C = 1$, $\epsilon = 0.1$). As suggested by authors of these packages, each attribute was normalized using the svm-scale tool before training the SVM model and the normalization parameters obtained on the training set are used to scale each test instance.

The present study was made possible due to the availability of a computer cluster of roughly 450 cores (with up to 512GB of main memory per server) which reduced roughly 40 years of single processor computing times down to several months. The amount of intermediate data generated was also substantial, on the order of several tens of terabytes.

5) *Availability:* To ease future research and comparison, we offer our single-threaded, command-line, Java implementation of the method on request. We are also integrating in a rich internet application [66] multi-threaded versions of these algorithms in Python based on the scikit-learn toolbox [67]. See <http://www.montefiore.ulg.ac.be/~maree/> for updates.

IV. RESULTS

A. Tables of method variants and influences of parameter values

In the main paper we only presented summary of our results for ET-FL variant averaged over the 80 datasets. Below, we first present summary graphs also for ET-DIC, in Figure 8 together with ET-FL graphs (already in main paper) to ease comparison.

In the following pages, we report detailed results for each parameter studied individually for both variants ET-DIC and ET-FL. Otherwise stated, our experiments are run using a fixed number of subwindows for training (a total of approximately 1 million training subwindows), those are resized to 16×16 pixels encoded by raw pixel values in greylevels or in the *HSV* colorspace if images are colorized, $T = 10$ trees are built with the filtering parameter equals to the rounded square value of the number of attributes (ie. 16 for greylevel images and 28 for color images), $n_{min} = 2$ corresponding to fully developed trees in ET-DIC and $n_{min} = 5000$ for ET-FL, terminal node frequency encoding for ET-FL, and a fixed number of test subwindows. In order to study the influence of each parameter individually, in each following table we vary a single parameter while the others remain constant. We first find the best subwindow size intervals for each method (ET-DIC in Table II and ET-FL in Table VII), then other parameter influences are evaluated based on the best size interval for each dataset and each method (ET-DIC in Tables III to VI, and ET-FL in Tables VIII to XII).

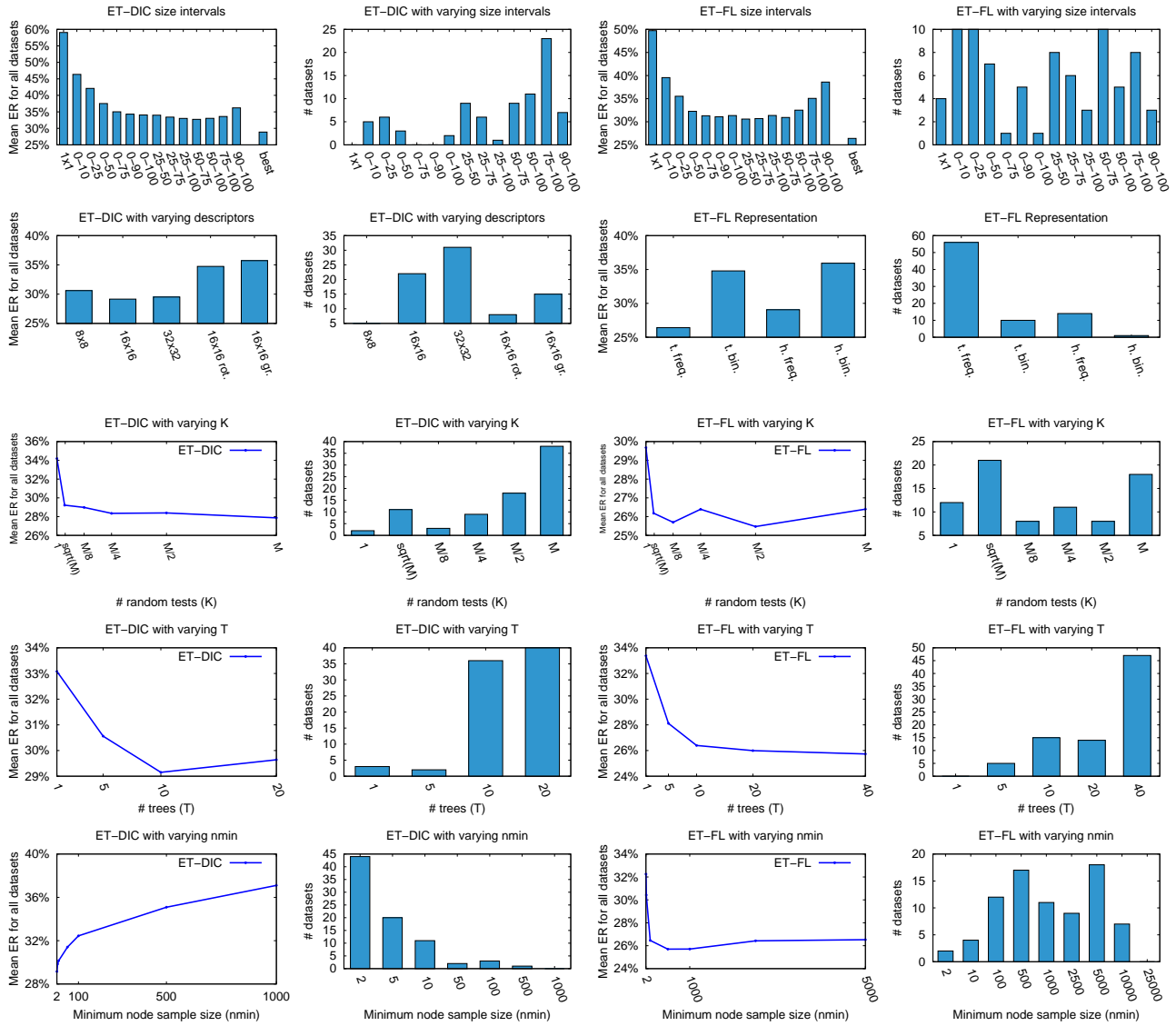


Fig. 8. Results averaged over all 80 datasets. ET-DIC (two first columns): Left: average of error rates for all datasets with subwindow size intervals (1st row), pixel descriptors (2nd), number of random tests (3rd), number of trees (4th), minimum node sample sizes (5th). Second column: Number of datasets for which the parameter values yield the best error rates. ET-FL (two last columns): Third column: Average of error rates for all datasets with subwindow size intervals (1st row), image representation (2nd), number of random tests (3rd), number of trees (4th), minimum node sample sizes (5th). Right: Number of datasets for which the parameter values yield the best error rates. See Supplementary Tables II to XII for detailed results.

Datasets	1 × 1	0 - 10%	0 - 25%	0 - 50%	0 - 75%	0 - 90%	0 - 100%	25 - 50%	25 - 75%	25 - 100%	50 - 75%	50 - 100%	75 - 100%	90 - 100%
ACROSOMES	37.87 ± 1.00	19.48 ± 3.12	9.75 ± 1.22	6.27 ± 1.27	5.26 ± 1.13	6.88 ± 1.46	6.29 ± 1.06	4.02 ± 0.31	4.99 ± 0.86	5.86 ± 0.94	5.60 ± 0.83	5.96 ± 0.91	5.59 ± 0.69	5.78 ± 0.97
AGEMAP-FAGING	54.48±3.01	55.99±1.94	55.43±4.08	56.10±5.19	53.62±3.19	54.10±2.98	53.71±3.74	51.90±4.92	51.71±3.90	49.62±4.41	49.14±2.56	50.29±3.27	47.90±4.78	47.23±3.02
ALL-IDB2	8.85±3.57	5.96±2.50	3.08±2.88	1.73±2.35	1.92±1.72	2.31±1.15	1.92±1.49	1.73±1.60	0.96±1.29	1.35±1.23	1.92±1.92	2.12±1.60	1.15±1.28	2.50±2.28
ALOI	65.59	50.22	41.81	30.47	22.63	30.47	22.63	23.03	22.57	22.63	22.87	23.33	25.00	25.76
ALOT	66.12±0.20	44.70±0.38	43.19±0.48	42.74±0.30	42.11±0.37	41.40±0.38	40.76±0.38	38.8±0.37	39.08±0.36	38.47±0.29	37.48±0.32	36.67±0.40	34.08±0.40	31.64±0.36
APOPTOSIS	42.86±0.0	31.71 ± 1.40	19.71 ± 2.91	12.29 ± 3.90	12.43 ± 3.56	14.57 ± 1.40	12.43 ± 3.89	13.14 ± 2.98	11.86 ± 3.94	12.43 ± 3.84	12.14 ± 2.87	11.71 ± 2.84	8.14 ± 2.86	11.29 ± 3.03
BINUCLEATE	48.72±0.00	4.36±5.26	4.36±5.85	7.44±4.36	6.15±6.51	8.97±3.33	4.62±3.59	6.41±6.20	9.74±5.94	6.92±7.07	12.56±6.12	7.95±6.33	11.54±7.80	12.56±5.67
BIRDS	66.07±1.93	62.8±2.69	58.5±1.29	56.77±1.65	51.87±2.26	51.30±2.15	50.07±2.50	50.67±1.53	47.60±2.37	48.60±2.05	44.97±3.43	46.53±2.29	46.60±3.34	49.10±2.62
BREAST-CANCER	20.69±2.59	15.00±5.23	14.72±3.06	18.06±5.38	14.44±3.41	16.11±2.93	17.78±3.15	17.78±3.15	13.33±4.49	14.72±4.13	14.58±1.89	13.39±3.99	14.58±1.89	17.78±3.72
BUILDINGSAB	82.82±2.15	44.42±3.04	42.82±2.07	44.59±1.75	44.59±3.42	45.91±2.10	47.29±3.54	45.03±2.23	47.29±2.17	48.01±2.15	48.39±2.71	50.77±2.22	58.67±2.02	66.29±2.45
BUTTERFLIES	69.31±2.54	62.88±1.68	58.44±2.51	53.34±1.47	51.10±2.11	51.92±2.72	52.81±3.06	50.64±2.09	50.85±2.08	51.60±3.89	50.43±3.03	49.86±2.39	54.30±2.37	56.84±2.35
BUTTERFLIES-CLEAN	42.8±2.46	29.4±2.36	24.22±3.39	21.78±2.49	20.58±1.61	21.22±2.25	18.69±1.96	17.80±1.41	18.69±1.43	18.56±1.49	20.29±1.42	22.49±1.26	24.64±1.78	30.02±1.55
CALTECH-101	88.24	85.85	82.38	79.8	76.89	76.11	74.66	77.11	74.80	72.92	73.43	71.82	70.61	73.21
CALTECH-256	96.47±0.21	94.92±0.08	93.82±0.33	92.24±0.29	91.01±0.22	90.12±0.37	89.84±0.37	90.57±0.34	89.64±0.26	88.83±0.36	88.82±0.40	88.30±0.24	88.26±0.26	89.39±0.19
C.ELEGANS	46.75±3.11	41.54±4.68	38.63±4.97	44.53±6.12	46.75±4.56	47.52±3.16	48.46±3.27	40.68±3.67	46.07±3.41	50.17±3.22	46.32±4.29	48.55±3.95	48.46±3.20	50.34±2.40
C.ELEGANS-LIVE-DEAD	47.89±1.58	10.53 ± 4.08	7.37 ± 6.32	4.74 ± 2.83	3.16 ± 3.49	5.79 ± 3.68	5.26 ± 4.08	6.84 ± 5.79	7.37 ± 4.82	3.16 ± 2.58	3.68 ± 3.37	7.89 ± 6.34	4.74 ± 4.37	6.84 ± 5.29
CHARS74K	97.29±0.36	93.55±0.88	91.58±0.84	87.86±0.99	83.31±1.00	81.86±1.03	79.83±1.06	86.67±1.00	81.87±1.43	77.78±1.57	77.69±1.37	74.20±0.94	71.16±1.66	73.99±1.67
CHO	27.38±3.63	2.92±1.75	3.38±2.15	2.62±1.83	4.00±2.19	3.54±2.49	5.54±3.45	3.85±2.94	5.23±1.71	5.85±2.73	8.46±3.10	8.77±3.23	14.77±4.25	21.38±4.98
CIFAR-10	77.70	69.07	61.16	58.71	57.45	58.71	57.45	59.91	57.25	54.02	52.89	50.84	49.61	49.61
COIL-100 mv1	27.75	15.11	12.66	12.15	12.73	13.11	13.72	14.20	14.79	16.21	19.70	19.87	25.25	31.96
CONVEX	50.60	35.72	22.86	15.87	12.58	10.07	8.80	14.36	11.86	8.49	10.83	8.04	9.34	13.00
ETH-80	41.04±0.35	34.67±8.17	28.72±6.35	28.51±8.22	19.15±8.00	21.31±7.48	22.13±6.26	22.26±9.92	22.07±5.65	21.43±21.80	21.80±5.83	17.74±7.39	16.83±5.17	17.44±6.05
EVENTS	49.92±2.04	43.71±2.20	43.25±1.98	42.29±1.89	37.48±1.63	37.33±2.18	37.38±2.47	38.71±2.47	37.19±2.16	36.04±1.64	37.23±1.73	36.04±1.28	36.04±1.28	38.13±2.41
FAMOUSLAND	88.25±2.03	84.45±2.37	81.75±2.37	77.7±2.75	74.85±1.98	73.75±1.86	74.3±2.93	73.55±2.62	71.9±1.95	70.25±1.74	66.85±3.55	70.45±1.52	72.05±1.39	74.15±1.96
FLOWERS17	52.53±1.69	43.82±2.75	41.35±2.53	35.94±0.93	37.32±2.15	35.59±1.93	33.97±2.00	35.06±1.74	33.50±2.51	33.71±1.98	33.88±3.18	33.24±1.16	34.79±2.43	38.44±1.83
FLOWERS102-CLEAN	78.23	70.97	60.41	59.04	58.47	59.04	58.47	57.76	59.04	57.76	58.08	57.19	57.38	64.99
GALAXYZOO	29.93±0.12	26.39±0.14	21.19±0.19	14.76±0.14	12.69±0.23	11.88±0.21	11.36±0.20	11.42±0.15	10.94±0.15	10.09±0.15	9.68±0.27	8.78±0.20	6.43±0.16	4.22±0.17
GTSRBCROP	83.09	77.48	73.65	64.38	51.61	48.04	48.04	52.53	48.96	43.34	37.80	37.45	31.55	29.01
HCC	45.71 ± 13.05	38.21 ± 8.23	37.50 ± 10.80	39.64 ± 10.22	38.57 ± 10.93	40.00 ± 10.20	38.93 ± 12.67	42.14 ± 9.01	36.43 ± 11.93	37.50 ± 12.55	42.86 ± 11.74	40.00 ± 9.15	33.21 ± 14.86	37.14 ± 10.50
HEP2-ICPR2012	66.89	66.21	63.62	64.17	64.03	64.17	64.44	63.90	62.67	63.90	64.17	64.85	64.85	65.12
HPA	17.43±1.91	14.67 ± 1.96	10.95 ± 2.60	8.38 ± 3.12	9.71 ± 2.33	8.76 ± 2.16	8.86 ± 1.95	6.19 ± 1.30	9.52 ± 2.79	7.52 ± 1.73	7.71 ± 2.46	9.24 ± 2.09	12.19 ± 2.20	14.57 ± 2.04
INDOOR	91.68±0.45	87.84±0.84	87.68±0.82	87.60±0.89	86.96±0.64	86.66±0.94	86.70±1.16	86.63±1.03	86.46±0.53	85.68±1.11	86.53±0.72	85.09±0.90	85.24±0.88	86.61±0.99
IRMA2005-BALANCED	93.20	45.90	32.40	23.90	18.70	16.90	16.5	20.60	17.40	15.70	15.70	14.90	15.10	16.80
IRMA2005	70.3	69.8	63.5	52.2	40.8	36.2	33.60	36.70	30.80	26.80	22.5	19.90	16.90	18.30
IRMA2006-BALANCED	95.60	64.60	47.5	33.5	31.30	29.90	34.00	31.80	30.80	28.80	30.5	28.00	26.40	27.50
KTH-TIPS	63.27±1.63	22.61±1.03	23.85±2.44	27.44±1.08	27.56±0.89	28.37±1.19	28.71±1.54	25.17±1.93	26.49±1.59	27.39±1.10	26.85±1.65	26.61±2.36	26.80±2.48	31.78±1.81
KTH-TIPS2	60.24±5.87	49.81±9.07	48.81±7.02	48.32±8.66	48.56±9.18	50.72±7.81	50.50±11.20	42.77±8.41	46.94±9.90	51.33±7.15	46.25±10.74	47.42±9.32	46.97±7.32	46.97±7.32
LANDUSE	40.17±2.58	30.71±1.15	30.26±1.65	29.57±2.11	30.81±1.22	30.19±3.11	30.50±1.53	29.21±2.57	31.00±1.67	30.67±1.64	30.24±1.68	30.19±1.61	33.24±2.68	43.14±1.86
LYPHOMA	35.41±4.90	23.51±6.95	26.22±5.55	25.41±6.64	28.11±4.55	24.86±7.91	27.03±6.51	21.55±7.20	23.51±5.68	20.81±8.64	22.43±4.84	23.51±4.53	20.54±6.86	21.55±6.73
MMDALITY	46.22	26.11	26.34	28.47	28.78	29.20	29.16	29.81	29.50	30.08	31.68	30.73	32.18	33.44
MNIST	87.59	75.86	48.42	4.88	2.97	2.62	2.43	3.76	2.69	2.28	2.36	2.11	1.84	1.82
MNIST-12000	87.13	78.03	59.17	3.84	3.15	2.82	3.15	5.15	3.30	2.71	2.87	2.55	2.35	2.57
MNIST-ROTATION	87.73	83.38	79.17	45.46	18.36	14.13	12.20	30.39	15.10	11.33	12.58	10.59	9.78	10.06
MNIST-BIMG	88.46	87.44	83.97	65.23	49.94	44.29	39.00	45.49	38.55	33.72	31.21	29.99	27.35	28.02
MNIST-BRAND	88.40	87.01	81.08	59.97	44.86	35.35	28.93	40.38	33.62	24.30	23.50	19.13	14.86	15.41
MNIST-BIMG-ROT	88.67	89.14	88.04	83.59	79.24	76.90	74.85	76.96	74.45	70.47	67.70	65.81	61.60	63.46
MSTAR-S1	63.23	51.85	45.48	42.80	41.43	41.15	40.07	39.16	40.24	38.99	38.59	36.71	32.04	41.61
NATURALSCENES	83.52±0.70	54.19±0.48	51.40±0.62	52.09±1.17	54.32±0.80	55.16±0.98	56.42±0.84	54.32±0.80	55.62±1.38	57.63±0.89	59.75±0.85	60.53±1.04	64.62±0.53	69.64±0.93
NORB-UNIFORM	73.89	54.77	29.64	19.03	16.12	13.06	10.86	14.51	14.03	9.50	10.86	8.07	5.24	5.27
NORB-JITTLUFT	80.28	80.33	74.94	65.90	56.26	54.39	58.08	55.16	51.72	49.54	47.60	43.57	43.77	43.77
OLIVA	55.38±0.96	45.61±1.82	40.70±0.73	36.32±0.62	34.42±1.01	34.13±1.19	33.88±1.17	34.50±1.38	33.93±1.36	33.95±0.77	34.77±0.85	35.38±1.21	38.26±1.68	41.53±0.96
ORL	53.05±2.38	3.35±1.18	2.2±1.36	1.1±1.24	1.75±1.05	1.65±1.27	2.05±1.68	1.25±1.55	2.4±1.59	1.75±0.87	2.05±1.94	2.7±1.45	1.95±1.25	3.2±1.73
OUTEX	5.23±1.00	2.01±0.72	4.35±1.37	6.27±0.72	8.03±1.16	8.56±1.63	9.05±1.02	8.50±1.52	10.16±0.95	11.39±2.11	12.25±1.84	13.15±1.58	18.52±0.92	30.72±1.31
PFID	82.95±2.42	75.55±2.78	74.95±2.77	76.78±2.80	75.71±3.01	75.14±2.28	74.40±2.80	75.11±2.01	74.89±3.25	77.13±3.00	77.27±2.98	76.48±1.63	76.31±2.20	76.42±2.27
PPMI24	94.17	93.42	91.79	90.83	88.79	88.79	88.79	88.62	90.17	88.62	87.54	86.71	86.71	88.58
POLLEN	57.96±0.70	53.70±1.12	47.67±1.77	36.72±1.28	30.69±1.08	27.85±1.47	26.79±1.35	26.09±0.68	23.42±1.14	22.31±0.70	19.40±1.07	19.03±0.92	15.30±1.24	13.13±0.77
PUBFIG83	96.34±0.64	95.33 ± 0.57	93.16 ± 0.57	89.95 ± 1.53	87.11 ± 0.66	85.99 ± 0.58	85.10 ± 0.57	86.07 ± 1.11	84.23 ± 0.91	82.88 ± 0.68	82.06 ± 1.07	81.99 ± 1.48	82.01 ± 1.39	86.40 ± 1.41
RBC	60.36±1.22	51.44±1.79	40.85±2.29	36.22±1.59	35.70±2.20	35.25±1.53	35.38±1.28	31.98±1.38	33.93±1.63	34.38±1.76	31.27±1.12	33.61±1.07	34.32±0.75	37.71±1.25
RECT-BASIC	50.03	18.72	6.13	0.26	0.01	0.01	0.01	0.06	0.01	0.01	0.01	0.03	0.03	0.60
RECT-BIMG	49.86	44.94	38.09	21.50	17.59	17.56	17.48	16.25	15.78	16.58	16.00	17.07	18.47	21.19
RNAI	76.5±3.57	42.75±6.17	45.25±6.17	51.25±5.27	58.0±4.58	61.75±6.71	62.25±6.93	57.0±8.05	58.25±4.04	62.25±6.07	68.5±7.68	71.0±4.5	76.5±5.39	76.5±5.27
SEROUS	51.86±0.92	36.64±1.54	36.64±1.54	36.28±1.47	35.63±2.47	35.08±2.22	34.48±2.53	32.84±2.23	34.07±2.91	34.07±2.24				

Datasets	HSV-8 × 8	HSV-16 × 16	HSV-32 × 32	HSV-ROTATE360-16 × 16	GRAY-16 × 16
ACROSOMES	4.49±0.75	4.02 ± 0.31	4.81 ± 1.21	6.65 ± 1.14	4.02 ± 0.31
AGEMAP-FAGING	43.71±4.39	47.23±3.02	49.52 ± 5.15	51.05±4.51	55.62±2.73
ALL-IDB2	1.15±1.76	0.96±1.29	1.73±1.35	1.54±1.68	5.77±2.72
ALOI	22.26	22.57	21.41	39.48	39.56
ALOT	31.70±0.30	31.64±0.36	31.29±0.32	41.41±0.23	58.43±0.50
APOPTOSIS	9.14 ± 2.94	8.14 ± 2.86	9.71 ± 2.37	10.29 ± 3.25	8.14 ± 2.86
BINUCLEATE	12.25±4.10	4.36±5.26	6.25 ± 3.75	11.50 ± 8.15	4.36±5.26
BIRDS	48.23±1.83	44.97±3.43	47.03±1.85	48.8±1.15	45.4±2.07
BREAST-CANCER	15.42±5.18	13.33±4.49	15.69±3.29	15.42±3.48	34.03±6.37
BUILDINGSAB	42.98±2.79	42.82±2.07	43.70±2.51	51.16±2.27	42.82±2.07
BUTTERFLIES	51.53±2.60	49.86±2.39	50.05±2.54	46.00±3.46	45.42±2.77
BUTTERFLIES-CLEAN	17.76±1.56	17.80±1.41	16.07±1.43	20.53±1.77	16.56±1.51
CALTECH-101	71.48	70.61	71.07	77.56	72.09
CALTECH-256	88.34±0.29	88.26±0.26	88.25±0.21	90.44±0.21	89.79±0.37
C.ELEGANS	39.40±4.91	38.63±4.97	37.95±4.67	39.03±5.92	38.63±4.97
C.ELEGANS-LIVE-DEAD	4.74±2.83	3.16 ± 3.49	4.74±5.49	11.05±7.61	3.16 ± 3.49
CHARS74K	71.58±1.61	71.16±1.66	71.28±1.23	79.59±1.64	71.16±1.66
CHO	3.99±2.77	2.62±1.83	3.23±1.88	2.46±2.09	2.62±1.83
CIFAR-10	50.08	48.91	49.05	55.31	55.24
COIL-100 nv1	12.15	12.15	12.20	13.89	35.75
CONVEX	9.36	8.04	8.00	9.87	8.04
ETH-80	17.35±4.73	16.83±5.17	19.70±7.35	21.19±8.50	18.96±6.33
EVENTS	35.17±2.10	36.04±1.28	35.31±1.36	46.98±2.71	49.42±1.81
FAMOUSLAND	67.45±2.13	66.85±3.55	69.65±2.06	76.65±3.02	72.95±2.11
FLOWERS17	34.41±2.22	33.24±1.16	34.47±1.95	36.12±2.82	57.74±1.54
FLOWERS102-CLEAN	56.68	57.19	56.76	62.39	73.24
GALAXYZOO	5.85±0.18	4.22±0.17	3.45±0.09	5.79±0.18	5.25±0.15
GTSRBCROP	36.52	29.01	28.31	46.37	21.01
HCC	35.00±9.81	33.21 ± 14.86	40.36±12.01	43.57±10.81	69.29±9.61
HEP2-ICPR2012	63.49	62.67	62.13	63.76	62.67
HPA	7.24 ± 1.55	6.19 ± 1.30	5.90 ± 2.29	9.90±1.91	11.52±1.78
INDOOR	85.81±0.66	85.09±0.90	85.38±0.70	88.23±0.65	88.98±0.68
IRMA2005-BALANCED	15.0	14.9	14.40	31.40	14.9
IRMA2006-BALANCED	27.7	26.40	26.10	43.60	26.40
KTH-TIPS	23.88±2.52	22.61±1.03	21.34±1.80	26.27±1.61	22.61±1.03
KTH-TIPS2	45.78±10.50	42.77±8.41	50.39±6.84	47.16±8.61	54.99±4.60
LANDUSE	27.21±1.08	29.21±2.57	28.07±1.91	40.55 ± 1.81	41.67±1.55
LYMPHOMA	23.07±4.38	20.54±6.86	22.13±5.73	24.0±5.40	42.40±5.19
MMODALITY	27.48	26.11	26.64	29.05	35.99
MINST	2.39	1.82	1.69	4.53	1.82
MINST-12000	2.66	2.35	2.30	6.64	2.35
MINST-ROTATION	10.43	9.78	9.48	8.15	9.78
MINST-BIMG	32.84	27.35	23.95	46.54	27.35
MINST-BRAND	20.38	14.86	12.70	30.06	14.86
MINST-BIMG-ROT	66.29	61.60	58.29	56.29	61.60
MSAR-S1	34.66	32.04	29.99	38.70	32.04
NATURALSCENES	50.60±0.97	51.40±0.62	50.68±0.86	65.83±0.93	51.40±0.62
NORB-UNIFORM	5.65	5.24	5.64	13.31	5.24
NORB-JITICLUIT	48.80	43.57	40.61	51.72	43.57
OLIVA	34.13±1.03	33.88±1.17	33.60±0.56	44.64±0.91	39.09±1.58
ORL	1.2±1.27	1.1±1.24	1.4±1.04	5.6±1.71	1.1±1.24
OUTEX	2.80±0.70	2.01±0.72	2.08±0.39	3.94±0.65	20.39±0.82
PFID	75.41±3.73	74.40±2.80	75.00±2.60	80.74±3.54	80.36±2.14
POLLEN	15.99±1.07	13.13±0.77	11.75±0.84	14.43±1.16	13.13±0.77
PPMI24	86.38	86.71	86.25	90.38	91.33
PUBFIG83	82.67±0.48	81.99 ± 1.48	81.93±1.32	91.59±1.02	84.82±0.98
RBC	33.31±1.48	31.27±1.12	29.93±1.83	31.66±1.30	31.27±1.12
RECT-BASIC	0.01	0.01	0.01	6.55	0.01
RECT-BIMG	15.74	15.78	15.64	38.60	15.78
RNAI	47.5±4.33	42.75±6.17	45.75±7.99	47.25±7.02	42.75±6.17
SEROUS	35.38±1.49	31.78±2.63	32.54±2.14	30.85±1.96	41.53±1.98
SHAPE1	17.2±3.31	15.7±4.56	16.7±4.20	25.8±4.28	10.7±2.79
SMEAR	13.41±3.64	9.67 ± 2.24	9.67 ± 2.07	9.45±3.58	14.18±2.8
SOCCER	19.24±3.04	18.48±3.69	18.76±3.13	23.14±3.07	51.05±4.82
SOIL-24	0.83	0.0	0.0	7.5	43.33
SOIL-47	18.94	18.51	17.23	29.26	61.06
SPORTS	15.44±1.57	15.06±1.35	14.90±1.61	19.30±1.17	35.18±1.56
STOIC101	45.61	44.70	44.70	53.79	59.55
STOMATA	25.45 ± 12.06	16.36 ± 12.06	25.45 ± 9.79	12.73 ± 10.91	16.36 ± 12.06
STONEFLY9	22.13	19.51	19.08	28.66	25.09
SUBCELLULAR	20.58±2.90	19.07±3.53	20.35±5.36	17.09±2.50	19.07±3.53
SUN397	94.37±0.16	94.22±0.12	94.20±0.17	95.90±0.13	n/a
SWELEAF	7.03±0.43	6.37±0.80	7.24±0.69	12.36±1.31	6.37±0.80
TERMINALBULB	65.87±2.33	63.56±2.99	63.37±1.46	66.09±2.79	63.56±2.99
TINYGRAZ03	51.06±4.90	47.61±2.65	47.96±3.99	52.74±3.74	66.46±4.03
TSG-60	2.58±0.45	2.25±0.53	2.33±0.73	3.49±1.22	13.00±1.50
UIUCTEX	26.34±2.43	24.92±1.89	25.02±1.42	29.50±1.15	24.92±1.89
WANG	15.36±1.21	14.52±1.44	15.22±1.44	17.10±1.05	24.12±2.08
XEROX-6	16.12±2.77	13.98±2.96	14.80±2.97	20.81±3.42	28.16±4.64
ZEBRATOXIC	5.21	4.17	4.17	4.17	6.25
ZUBUD	4.35	3.48	4.35	11.30	11.30

TABLE III
 EVALUATION OF THE SUBWINDOW DESCRIPTORS WITH ET-DIC.
 OTHER PARAMETERS ARE CONSTANT: $n_{min} = 1, T = 10,$
 $k = \text{sqr}(M), N_{l_s} = 1$ MILLION WITH BEST SIZE INTERVALS.

Datasets	1	\sqrt{M}	$M/8$	$M/4$	$M/2$	M
ACROSOMES	6.23 ± 1.13	4.02 ± 0.31	4.29 ± 1.27	4.18 ± 1.05	4.40 ± 0.55	4.50 ± 0.99
AGEMAP-FAGING	58.10±3.74	47.23±3.02	45.52±3.76	42.10±3.85	42.29±5.01	44.00±3.48
ALL-IDB2	2.31±2.24	0.96±1.29	1.73±1.60	1.35±1.93	1.92±1.72	2.12±1.35
ALOI	25.58	22.57	20.03	18.86	17.54	16.16
ALOT	32.85±0.46	31.64±0.36	29.96±0.36	29.41±0.24	28.42±0.28	28.81±0.35
APOPTOSIS	9.86 ± 3.41	8.14 ± 2.86	8.86 ± 3.25	8.71 ± 2.51	9.71 ± 2.91	7.86 ± 3.51
BINUCLEATE	12.50±8.80	10.00±9.55	4.36±5.26	4.75 ± 6.93	8.50 ± 6.82	7.50 ± 5.24
BIRDS	51.33±2.29	44.97±3.43	45.30±2.77	43.1±1.95	42.73±3.11	42.37±1.86
BREAST-CANCER	18.88±3.47	13.33±4.49	15.0±4.02	14.58±3.47	15.14±4.71	14.86±5.34
BUILDINGSAB	42.54±2.15	42.82±2.07	43.37±2.31	42.65±1.76	40.88±1.95	43.20±2.32
BUTTERFLIES	60.02±2.03	49.86±2.39	45.56±1.65	44.49±3.24	41.28±3.14	39.91±3.18
BUTTERFLIES-CLEAN	24.93±2.61	17.80±1.41	16.31±2.12	15.89±1.40	17.02±1.83	16.58±2.29
CALTECH-101	72.07	70.61	70.82	70.77	71.07	71.73
CALTECH-256	88.32±0.29	88.26±0.26	88.18±0.43	88.07±0.29	88.34±0.28	88.12±0.37
C.ELEGANS	44.27±5.55	38.63±4.97	39.66±5.55	38.29±4.32	38.12±4.36	38.72±4.73
C.ELEGANS-LIVE-DEAD	2.11 ± 3.49	3.16 ± 3.49	5.79 ± 4.97	6.84 ± 5.29	5.79 ± 4.37	5.26 ± 5.26
CHARS74K	73.01±1.22	71.16±1.66	71.17±1.26	71.65±1.02	71.51±1.30	71.40±1.25
CHO	4.92±2.26	2.62±1.83	3.08±1.82	3.54±1.55	3.23±2.22	3.38±2.04
CIFAR-10	53.50	48.91	47.84	47.24	47.00	46.33
COIL-100 nv1	13.13	12.15	12.37	12.25	12.20	12.75
CONVEX	11.35	8.04	7.92	7.89	7.79	7.87
ETH-80	19.42±5.16	16.83±5.17	14.94±6.35	14.97±6.20	19.86±9.47	16.20±5.93
EVENTS	37.69±1.95	36.04±1.28	34.42±1.56	33.02±1.71	34.96±1.70	35.06±1.89
FAMOUSLAND	64.6±3.35	66.85±3.55	70.05±2.35	70.65±3.32	72.65±1.61	73.4±4.27
FLOWERS17	40.24±1.97	33.24±1.16	33.44±1.75	31.82±1.93	32.12±2.11	30.91±1.97
FLOWERS102-CLEAN	59.16	57.19	56.20	55.81	55.36	55.65
GALAXYZOO	15.87±0.55	4.22±0.17	3.20±0.11	2.94±0.13	2.73±0.07	2.64±0.13
GTSRBCROP	47.30	29.01	23.59	21.15	19.50	18.73
HCC	48.93 ± 15.20	33.21 ± 14.86	35.71 ± 10.83	30.71 ± 15.17	50.00±11.52	41.56±8.78
HEP2-ICPR2012	64.71	62.67	62.53	61.85	62.40	61.85
HPA	11.71 ± 2.00	6.19 ± 1.30	5.24 ± 0.88	6.29±2.45	5.90±1.75	5.03±2.14
INDOOR	85.49±1.29	85.09±0.90	85.19±0.51	84.78±0.57	84.54±0.91	84.94±0.69
IRMA2005-BALANCED	17.00	14.90	13.90	14.20	14.40	14.20
IRMA2006-BALANCED	29.60	26.40	26.60	25.40	25.30	25.80
KTH-TIPS	26.80±1.94	22.61±1.03	23.46±1.96	20.41±1.66	20.95±1.78	21.37±2.02
KTH-TIPS2	48.89±10.96	42.77±8.41	47.77±7.28	47.86±8.27	48.83±8.99	45.52±8.39
LANDUSE	32.43 ± 1.57	29.21±2.57	27.07 ± 2.67	26.10 ± 1.96	25.21±1.67	25.33 ± 2.42
LYMPHOMA	32.53±3.78	20.54±6.86	21.47±3.40	22.67±3.48	16.53±3.22	17.99±5.54
MMODALITY	28.70	26.11	31.68	26.64	25.88	25.50
MINST	2.95	1.82	1.65	1.54	1.52	1.63
MINST-12000	3.81	2.35	2.26	2.26	2.20	2.25
MINST-ROTATION	12.72	9.78	9.53	9.20	9.08	8.94
MINST-BIMG	54.90	27.35	23.92	21.27	19.79	18.61
MINST-BRAND	39.39	14.86	12.64	11.33	10.59	10.05
MINST-BIMG-ROT	78.66	61.60	58.65	55.45	52.55	50.66
MSTAR-S1	37.28	32.04	29.77	26.98	23.96	21.63
NATURALSCENES	53.77±1.23	51.40±0.62	50.69±0.86	49.49±0.88	48.99±0.74	49.00±0.75
NORB-UNIFORM	8.87	5.24	5.46	6.33	6.65	7.08
NORB-JITCLUTT	61.28	43.57	40.54	38.68	37.22	36.14
OLIVA	37.67±1.36	33.88±1.17	33.64±0.67	33.56±0.89	32.50±1.48	31.93±1.21
ORL	1.25±0.90	1.1±1.24	1.05±1.23	0.95±0.79	1.75±0.78	1.2±0.81
OUTEX	2.85±0.88	2.01±0.72	2.31±0.85	1.90±0.85	1.67±0.63	1.74±0.78
PFID	76.53±3.35	74.40±2.80	75.22±3.29	74.10±3.37	76.31±2.54	75.60±3.97
POLLEN	20.47±1.46	13.13±0.77	11.75±1.10	10.47±0.79	9.54±0.77	9.51±0.80
PPM124	88.79	86.71	85.46	85.83	85.38	85.04
PUBFIG83	84.86±1.26	81.99 ± 1.48	80.86±1.35	80.63±0.96	80.49±1.25	79.58±1.56
RBC	34.74±1.37	31.27±1.12	29.96±1.61	30.20±1.63	34.47±1.01	29.86±1.66
RECT-BASIC	0.01	0.01	0.01	0.01	0.01	0.01
RECT-BIMG	17.80	15.78	15.67	15.55	15.48	15.47
RNAI	45.0±6.61	42.75±6.17	43.5±4.89	40.75±3.54	44.0±6.82	40.25±7.37
SEROUS	37.32±2.69	31.78±2.63	31.42±2.21	32.92±1.32	31.20±1.67	31.23±2.45
SHAPE1	18.3±4.15	15.7±4.56	17.7±5.16	13.9±2.74	14.6±2.97	15.9±4.18
SMEAR	14.62 ± 3.37	9.67 ± 2.24	11.87 ± 3.10	9.23 ± 3.12	10.00 ± 1.59	8.48±2.01
SOCCER	24.95	18.48±3.69	17.33±2.20	17.33±2.17	16.76±2.93	18.48±3.08
SOIL-24	6.67	0.0	0.0	0.0	0.42	0.0
SOIL-47	28.72	18.51	17.13	16.38	16.60	15.85
SPORTS	24.75±1.19	15.06±1.35	14.02±1.62	14.80±0.74	12.79±1.29	13.07±1.24
STOIC101	49.39	44.70	42.73	42.12	41.36	39.39
STOMATA	40.00 ± 8.33	16.36 ± 12.06	20.00 ± 7.93	26.36 ± 10.33	21.82 ± 13.61	20.00 ± 6.80
STONEFLY9	31.10	19.51	18.55	18.03	18.38	16.99
SUBCELLULAR	20.93±3.08	19.07±3.53	19.42±2.33	19.53±3.28	16.63±4.19	18.14±3.61
SUN397	94.76±0.15	94.22±0.12	94.11±0.15	94.09±0.09	93.86±0.14	93.78±0.20
SWELEAF	6.69±0.96	6.37±0.80	7.08±0.64	6.95±1.20	6.28±0.96	6.71±0.94
TERMINALBULB	64.99±1.48	63.56±2.99	64.25±1.90	63.85±2.84	62.49±2.62	61.82±1.56
TINYGRAZ03	52.12±3.44	47.61±2.65	48.05±3.43	47.08±3.03	46.99±3.10	46.37±5.67
TSG-60	2.42±0.45	2.25±0.53	2.58±0.69	2.50±0.91	2.67±0.73	2.08±0.77
UIUCTEX	27.5±2.05	24.92±1.89	25.04±1.03	24.62±2.09	24.80±0.95	23.04±1.99
WANG	15.82±0.77	14.52±1.44	15.06±1.87	14.58±1.36	14.60±1.34	14.58±0.99
XEROX-6	16.53±3.76	13.98±2.96	15.20±3.14	13.88±3.17	13.78±3.14	13.57±2.66
ZEBRATOXIC	5.21	4.17	4.17	4.17	4.17	3.12
ZUBUD	4.35	3.48	3.48	3.48	3.48	3.48

TABLE IV

EVALUATION OF THE NUMBER OF RANDOM TESTS IN A TREE NODE (K) WHERE M IS THE TOTAL NUMBER OF ATTRIBUTES ($M = 256$ IN GRAYSCALE IMAGES, 768 IN COLOR IMAGES WITH ET-DIC). OTHER PARAMETERS ARE CONSTANT: $n_{min} = 1$, $T = 10$, $N_{I_s} = 1$ MILLION WITH BEST SIZE INTERVALS AND 16×16 DESCRIPTORS.

Datasets	1	5	10	20
ACROSOMES	5.14 ± 0.85	4.23 ± 0.65	4.02 ± 0.31	4.40 ± 1.16
AGEMAP-FAGING	47.05 ± 3.49	46.10 ± 3.39	47.23 ± 3.02	49.52 ± 3.13
ALL-IDB2	1.73 ± 1.35	2.12 ± 1.60	0.96 ± 1.29	1.15 ± 1.76
ALOI	36.89	24.41	22.57	21.09
ALOT	40.58 ± 0.29	32.98 ± 0.41	31.64 ± 0.36	30.98 ± 0.44
APOPTOSIS	12.14 ± 4.48	9.71 ± 2.91	8.14 ± 2.86	7.43 ± 3.37
BINUCLEATE	12.5 ± 8.80	10.00 ± 9.55	4.36 ± 5.26	7.00 ± 8.93
BIRDS	48.43 ± 2.70	46.97 ± 3.16	44.97 ± 3.43	47.67 ± 1.53
BREAST-CANCER	19.31 ± 3.19	16.25 ± 2.78	13.33 ± 4.49	16.53 ± 3.01
BUILDINGSAB	43.15 ± 2.07	42.32 ± 3.05	42.82 ± 2.07	41.10 ± 2.50
BUTTERFLIES	53.27 ± 2.57	52.43 ± 3.24	49.86 ± 2.39	50.66 ± 2.47
BUTTERFLIES-CLEAN	19.60 ± 1.61	17.29 ± 1.86	17.80 ± 1.41	18.47 ± 3.56
CALTECH-101	76.92	72.68	70.61	71.01
CALTECH-256	93.17 ± 0.20	89.32 ± 0.27	88.26 ± 0.26	87.45 ± 0.32
C.ELEGANS	37.86 ± 4.73	40.17 ± 4.54	38.63 ± 4.97	37.86 ± 3.40
C.ELEGANS-LIVE-DEAD	3.68 ± 4.11	7.37 ± 4.21	3.16 ± 3.49	7.37 ± 5.86
CHARS74K	75.94 ± 1.81	72.62 ± 1.66	71.16 ± 1.66	71.09 ± 1.03
CHO	4.00 ± 1.71	3.85 ± 1.85	2.62 ± 1.83	3.38 ± 1.51
CIFAR-10	62.04	50.66	48.91	47.77
COIL-100 mv1	13.32	12.21	12.15	12.0
CONVEX	8.79	8.10	8.04	8.01
ETH-80	14.82 ± 4.61	16.34 ± 6.87	16.83 ± 5.17	16.19 ± 5.96
EVENTS	36.25 ± 1.82	36.88 ± 1.42	36.04 ± 1.28	35.72 ± 2.69
FAMOUSLAND	72.75 ± 2.40	67.55 ± 2.69	66.85 ± 3.55	67.95 ± 2.07
FLOWERS17	35.47 ± 2.21	35.29 ± 1.13	33.24 ± 1.16	32.29 ± 2.78
FLOWERS102-CLEAN	59.37	57.10	57.19	56.93
GALAXYZOO	5.92 ± 0.28	4.42 ± 0.15	4.22 ± 0.17	4.03 ± 0.12
GTSRBCROP	39.81	31.11	29.01	28.14
HCC	38.93 ± 11.17	42.50 ± 9.17	33.21 ± 14.86	36.07 ± 11.40
HEP2-ICPR2012	63.35	63.08	62.67	62.67
HPA	7.62 ± 1.70	7.05 ± 3.11	6.19 ± 1.30	6.57 ± 2.19
INDOOR	88.75 ± 0.57	86.19 ± 0.52	85.09 ± 0.90	84.51 ± 0.88
IRMA2005-BALANCED	18.50	15.60	14.90	14.60
IRMA2006-BALANCED	31.50	27.0	26.40	26.80
KTH-TIPS	23.51 ± 1.80	25.05 ± 2.62	22.61 ± 1.03	23.15 ± 2.50
KTH-TIPS2	47.46 ± 9.33	49.44 ± 6.23	42.77 ± 8.41	50.60 ± 6.63
LANDUSE	31.12 ± 2.94	29.14 ± 1.62	29.21 ± 2.57	28.79 ± 1.83
LYMPHOMA	23.6 ± 3.68	22.27 ± 3.91	20.54 ± 6.86	23.6 ± 3.04
MMODALITY	29.24	26.49	26.11	26.49
MNIST	2.66	1.96	1.82	1.72
MNIST-12000	3.18	2.51	2.35	2.37
MNIST-ROTATION	13.20	10.24	9.78	9.55
MNIST-BIMG	40.27	29.80	27.35	26.02
MNIST-BRAND	29.73	16.72	14.86	13.79
MNIST-BIMG-ROT	73.94	65.21	61.60	59.84
MSTAR-S1	35.23	32.95	32.04	31.53
NATURALSCEENES	57.31 ± 0.62	51.45 ± 0.81	51.40 ± 0.62	50.64 ± 0.87
NORB-UNIFORM	10.66	5.67	5.24	5.13
NORB-JITCLUTT	52.55	44.85	43.57	42.77
OLIVA	36.00 ± 0.71	33.47 ± 0.89	33.88 ± 1.17	33.25 ± 1.31
ORL	1.25 ± 1.19	1.85 ± 0.78	1.1 ± 1.24	1.65 ± 0.74
OUTEX	1.92 ± 1.09	2.27 ± 0.64	2.01 ± 0.72	2.43 ± 0.97
PFID	76.69 ± 3.92	74.95 ± 5.88	74.40 ± 2.80	75.98 ± 3.59
POLLEN	14.46 ± 1.75	13.42 ± 0.42	13.13 ± 0.77	14.13 ± 0.77
PPMI24	90.12	88.12	86.71	86.04
PUBFIG83	91.59 ± 0.70	84.33 ± 1.10	81.99 ± 1.48	80.41 ± 0.88
RBC	32.41 ± 1.99	32.39 ± 0.58	31.27 ± 1.12	31.74 ± 1.18
RECT-BASIC	0.02	0.01	0.01	0.01
RECT-BIMG	19.76	16.25	15.78	15.54
RNAI	49.25 ± 6.99	46.0 ± 8.67	42.75 ± 6.17	45.25 ± 6.75
SERIOUS	34.95 ± 1.73	33.50 ± 1.53	31.78 ± 2.63	33.93 ± 1.78
SHAPE1	20.8 ± 4.70	17.0 ± 2.72	15.7 ± 4.56	15.3 ± 3.52
SMEAR	11.21 ± 3.18	10.11 ± 2.90	9.67 ± 2.24	9.78 ± 1.73
SOCCER	20.76 ± 2.12	20.38 ± 2.26	18.48 ± 3.69	20.00 ± 3.43
SOIL-24	9.58	0.42	0.0	0.0
SOIL-47	33.51	21.81	18.51	18.19
SPORTS	16.90 ± 1.40	15.67 ± 1.01	15.06 ± 1.35	15.07 ± 1.83
STOIC101	50.0	44.70	44.70	45.15
STOMATA	26.36 ± 12.50	26.36 ± 13.76	16.36 ± 12.06	23.64 ± 7.27
STONEFLY9	22.74	21.08	19.51	20.12
SUBCELLULAR	18.49 ± 2.67	18.84 ± 3.99	19.07 ± 3.53	20.12 ± 4.23
SUN397	97.35 ± 0.08	95.07 ± 0.08	94.22 ± 0.12	93.54 ± 0.13
SWELEAF	6.87 ± 0.55	6.71 ± 1.38	6.37 ± 0.80	6.87 ± 0.97
TERMINALBULB	65.05 ± 2.80	64.92 ± 1.11	63.56 ± 2.99	64.94 ± 1.92
TINYGRAZ03	52.65 ± 4.12	51.50 ± 3.64	47.61 ± 2.65	49.82 ± 5.13
TSG-60	2.75 ± 1.06	2.17 ± 0.67	2.25 ± 0.53	1.67 ± 0.0
UIUCTEX	33.82 ± 1.72	27.80 ± 1.20	24.92 ± 1.89	24.92 ± 1.77
WANG	15.02 ± 1.12	14.92 ± 1.46	14.52 ± 1.44	16.36 ± 0.68
XEROX-6	16.53 ± 4.25	15.20 ± 3.01	13.98 ± 2.96	16.02 ± 1.94
ZEBRATOXIC	4.17	4.17	4.17	4.17
ZUBUD	4.35	4.35	3.48	4.35

TABLE V

EVALUATION OF THE NUMBER OF TREES (T) WITH ET-DIC. OTHER PARAMETERS ARE CONSTANT: $n_{min} = 1$, $k = \sqrt{M}$, $N_{ls} = 1$ MILLION WITH BEST SIZE INTERVALS AND 16×16 DESCRIPTORS.

Datasets	2	5	10	50	100	500	1000
ACROSOMES	4.02 ± 0.31	4.13 ± 0.72	4.63 ± 1.16	6.16 ± 0.77	6.63 ± 1.23	9.57 ± 2.22	11.66 ± 1.42
AGEMAP-FAGING	47.23±3.02	47.81±4.01	49.24±3.22	52.29±3.26	59.24±4.01	60.19±2.51	61.52±3.49
ALL-IDB2	<u>0.96±1.29</u>	2.12±2.01	1.35±1.73	2.31±1.15	2.69±2.14	2.88±3.47	1.73±1.35
ALOI	22.57	22.14	22.21	24.90	27.02	34.40	39.22
ALOT	31.64±0.36	31.90±0.41	32.48±0.40	37.38±0.30	40.14±0.42	48.34±0.36	52.54±0.28
APOPTOSIS	8.14 ± 2.86	9.14 ± 3.57	9.14 ± 3.51	9.29 ± 3.95	10.00 ± 2.47	9.86 ± 4.26	8.43 ± 2.16
BINUCLEATE	4.36±5.26	6.50 ± 6.14	9.25 ± 6.43	8.25 ± 7.83	10.25 ± 6.17	12.50 ± 6.80	14.00 ± 6.24
BIRDS	44.97±3.43	47.93±3.34	48.13±2.06	47.00±2.29	47.40±2.61	47.87±3.63	48.53±2.98
BREAST-CANCER	13.33±4.49	16.53±2.44	15.97±6.34	15.28±3.51	18.33±3.22	18.19±3.59	16.39±4.72
BUILDINGSAB	42.82±2.07	43.15±2.78	43.81±2.20	45.52±1.88	45.52±2.06	50.94±2.75	53.98±2.82
BUTTERFLIES	49.86±2.39	48.15±3.36	52.11±2.25	50.07±3.96	50.98±3.14	49.89±2.80	50.37±2.21
BUTTERFLIES-CLEAN	17.80±1.41	19.89±2.14	21.22±2.97	21.78±2.08	23.58±1.75	27.18±2.35	28.89±2.22
CALTECH-101	70.61	71.11	71.16	72.31	72.29	74.28	76.96
CALTECH-256	88.26±0.26	88.13±0.34	87.92±0.38	88.34±0.21	88.87±0.39	90.15±0.28	90.57±0.21
C.ELEGANS	38.63±4.97	35.47±4.10	38.20±6.89	41.79±5.33	39.91±5.51	46.15±4.77	45.47±4.72
C.ELEGANS-LIVE-DEAD	3.16 ± 3.49	3.16 ± 4.21	4.74 ± 4.97	6.84 ± 4.11	5.26 ± 4.08	6.84 ± 5.79	5.79 ± 9.25
CHARS74K	71.16±1.66	71.28±1.32	71.08±1.25	71.70±1.18	<u>70.89±1.37</u>	73.82±1.46	74.94±1.77
CHO	2.62±1.83	4.15±3.44	3.38±2.04	4.62±2.57	4.77±3.73	7.69±2.18	7.23±3.44
CIFAR-10	48.91	48.79	48.97	50.68	51.26	54.28	56.19
COIL-100 nvl	12.15	12.55	12.47	13.23	13.48	16.30	18.30
CONVEX	8.04	7.96	7.81	8.20	8.46	9.94	10.81
ETH-80	16.83±5.17	16.70±8.29	16.04±6.31	19.12±6.98	22.13±4.51	21.65±7.59	23.63±5.00
EVENTS	36.04±1.28	35.94±2.49	<u>36.65±2.29</u>	36.17±1.62	37.54±1.45	39.63±1.04	39.40±1.46
FAMOUSLAND	66.85±3.55	68.0±2.28	68.6±2.08	71.4±2.60	73.65±2.50	74.7±2.87	76.6±1.07
FLOWERS17	33.24±1.16	<u>32.82±1.90</u>	34.03±1.76	35.62±1.59	36.76±2.45	36.59±1.69	40.35±2.28
FLOWERS102-CLEAN	57.19	<u>57.09</u>	58.01	60.31	62.62	66.92	68.68
GALAXYZOO	4.22±0.17	<u>4.19±0.11</u>	4.29±0.15	4.65±0.09	5.11±0.13	6.69±0.21	7.62±0.18
GTSRBCROP	29.01	29.45	28.67	30.79	32.23	36.47	38.23
HCC	33.21 ± 14.86	40.00 ± 8.27	42.86 ± 8.75	42.14 ± 11.04	46.79 ± 12.47	47.50 ± 13.03	54.64 ± 13.03
HEP2-ICPR2012	62.67	62.81	62.81	63.49	63.76	64.71	64.85
HPA	6.19 ± 1.30	6.76 ± 2.02	5.81 ± 2.46	7.81 ± 2.62	10.38 ± 3.03	9.81 ± 2.00	12.57 ± 2.51
INDOOR	85.09±0.90	85.07±0.86	<u>84.95±0.73</u>	85.89±1.01	86.71±0.69	87.99±0.73	88.46±0.74
IRMA2005-BALANCED	14.90	15.40	16.30	18.60	20.70	25.70	28.60
IRMA2006-BALANCED	26.40	26.70	27.10	30.20	33.00	39.10	43.70
KTH-TIPS	<u>22.61±1.03</u>	22.89±1.88	24.32±2.58	29.46±2.27	30.12±2.03	34.78±1.88	36.88±2.05
KTH-TIPS2	<u>42.77±8.41</u>	50.77±11.91	45.34±10.01	48.27±9.57	47.63±9.26	50.86±9.36	51.15±8.99
LANDUSE	29.21±2.57	29.21±2.30	30.43 ± 1.18	33.38±2.25	37.31±1.72	43.37±2.13	49.95±2.05
LYMPHOMA	20.54±6.86	22.53±4.44	25.60±5.16	26.93±3.26	28.80±5.07	32.80±5.41	35.99±6.98
MMDALITY	26.11	26.41	26.98	29.05	29.39	32.02	33.85
MINST	1.82	1.66	1.92	2.37	2.61	3.65	4.23
MINST-12000	2.35	2.42	2.44	2.99	3.48	4.91	5.81
MINST-ROTATION	9.78	9.87	9.84	11.37	12.56	16.67	19.48
MINST-BIMG	27.35	26.93	26.74	26.37	27.32	30.74	32.56
MINST-BRAND	14.86	14.47	14.24	14.44	16.26	18.64	21.16
MINST-BIMG-ROT	61.60	61.31	60.64	60.30	60.89	64.44	66.48
MSTAR-S1	32.04	31.93	30.90	33.52	35.52	37.91	40.07
NATURALSCEINES	51.40±0.62	<u>50.68±1.00</u>	52.00±0.77	54.89±0.71	56.40±0.93	59.49±1.00	62.18±1.18
NORB-UNIFORM	5.24	5.63	5.67	7.12	8.15	13.51	15.45
NORB-ITTC/LUTT	43.57	43.30	43.49	44.99	45.92	49.21	50.88
OLIVA	33.88±1.17	33.94±1.43	34.58±0.58	35.83±1.13	36.21±0.94	38.98±1.19	39.85±1.31
ORL	1.1±1.24	1.6±1.3	1.7±1.36	2.65±1.45	2.65±1.83	4.9±2.0	9.65±2.36
OUTEX	<u>2.01±0.72</u>	2.34±1.11	2.55±0.95	4.21±0.76	4.98±0.67	9.31±0.90	12.20±0.82
PFID	74.40±2.80	76.04±3.05	76.97±2.38	77.79±2.27	78.63±2.46	80.52	81.39±1.79
POLLEN	13.13±0.77	<u>12.79±1.01</u>	13.86±1.14	15.39±0.77	15.88±1.04	19.40±1.00	22.84±1.19
PPMI24	86.71	86.21	85.88	86.62	86.33	<u>85.62</u>	85.96
PUBFIG83	81.99 ± 1.48	80.78±1.36	81.48±1.28	82.77±0.52	83.05±1.27	84.93±1.10	85.82±0.89
RBC	31.27±1.12	36.19±1.26	37.31±1.30	41.08±1.59	43.03±1.50	45.62±2.33	46.99±0.92
RECT-BASIC	0.01	0.01	0.01	0.01	0.01	0.04	0.11
RECT-BIMG	15.78	15.84	16.04	17.10	17.65	19.07	19.65
RNAI	42.75±6.17	47.5±6.32	47.25±6.84	47.25±4.93	48.25±5.48	50.25±4.25	56.25±6.64
SEROUS	31.78±2.63	32.79±2.81	32.68±2.35	33.47±2.05	33.14±1.75	37.57±2.53	39.75±2.82
SHAPE1	15.7±4.56	16.8±2.82	14.5±3.14	16.2±2.75	16.6±2.29	16.8±3.28	15.7±1.79
SMEAR	<u>9.67 ± 2.24</u>	10.11 ± 2.59	<u>11.32 ± 3.51</u>	11.98 ± 4.07	9.89 ± 1.10	11.32 ± 2.74	13.52 ± 2.69
SOCCER	<u>18.48±3.69</u>	19.14±2.64	20.19±3.56	20.38±2.42	20.76±3.15	22.67±2.88	24.67±2.27
SOIL-24	0.0	0.0	0.0	0.0	0.0	4.58	7.5
SOIL-47	18.51	17.55	18.09	20.64	23.09	29.47	34.47
SPORTS	15.06±1.35	16.36±1.30	16.03±1.29	17.60±1.00	18.27±1.09	20.00±1.46	21.08±1.06
STOIC101	44.70	44.24	45.91	46.52	55.00	57.73	67.12
STOMATA	16.36 ± 12.06	20.00 ± 7.93	20.00 ± 9.79	21.82 ± 13.61	22.73 ± 14.80	25.45 ± 8.91	29.09 ± 11.35
STONEFLY9	19.51	19.34	19.95	20.56	21.08	27.00	27.35
SUBCELLULAR	19.07±3.53	18.95±3.08	19.07±4.45	21.16±3.32	21.86±3.24	25.93±3.37	30.0±3.23
SUN397	94.22±0.12	93.85±0.18	93.54±0.18	93.71±0.14	93.97±0.16	94.63±0.16	94.99±0.15
SWELEAF	6.37±0.80	7.39±0.76	7.37±0.51	8.01±0.57	7.37±0.56	9.73±1.07	10.95±0.54
TERMINALBULB	<u>63.56±2.99</u>	65.89±2.61	63.85±2.37	64.98±2.10	64.67±2.66	66.70±1.79	66.37±3.17
TINYGRAZ03	<u>47.61±2.65</u>	51.15±4.66	52.12±2.04	48.05±2.91	50.00±4.80	52.74±5.07	55.49±2.99
TSG-60	2.25±0.53	2.25±0.53	2.00±0.85	3.17±0.82	2.83±0.93	3.67±1.07	6.50±1.74
UIUCTEX	24.92±1.89	25.12±1.43	<u>27.34±2.27</u>	31.40±0.98	32.6±2.50	39.10±1.57	41.50±1.05
WANG	14.52±1.44	15.48±1.26	14.66±1.77	16.36±1.82	16.36±0.94	17.82±1.31	18.4±1.50
XEROX-6	<u>13.98±2.96</u>	15.92±2.00	14.49±3.70	16.94±2.96	18.37±3.29	18.78±3.54	20.92±1.95
ZEBRATOXIC	4.17	4.17	5.21	5.21	5.21	6.25	12.50
ZUBUD	3.48	4.35	4.35	5.22	6.96	13.91	20.0

TABLE VI

EVALUATION OF THE MINIMUM NODE SIZE (n_{min}) WITH ET-DIC.

OTHER PARAMETERS ARE CONSTANT: $T = 10$, $k = \text{sqrt}(M)$,

$N_{Is} = 1$ MILLION WITH BEST SIZE INTERVALS AND 16×16

DESCRIPTORS

TABLE VII

INFLUENCE OF THE SUBWINDOW SIZE INTERVALS WITH ET-FL.

OTHER PARAMETERS ARE CONSTANT: $n_{rain} = 5000$, $T = 10$, $k = \text{sgn}^t(N_s)$, $N_s = 1$ MILLION, 16×16 DESCRIPTORS, AND TERMINAL FREQUENCY IMAGE REPRESENTATION. IN ITALIC THE SIZE

Datasets	1 × 1	0 - 10%	0 - 25%	0 - 50%	0 - 75%	0 - 90%	0 - 100%	25 - 50%	25 - 75%	25 - 100%	50 - 75%	50 - 100%	75 - 100%	90 - 100%
ACROSOMES	36.43 ± 1.48	6.02 ± 0.58	3.28 ± 0.53	3.21 ± 0.45	3.19 ± 0.43	3.37 ± 0.85	3.80 ± 0.74	2.90 ± 0.68	3.15 ± 0.58	3.10 ± 0.78	3.84 ± 0.81	4.49 ± 0.81	4.85 ± 0.62	5.71 ± 0.85
AGEMAP-FAGING	4.19 ± 1.77	8.95 ± 3.36	16.57 ± 3.02	24.10 ± 3.54	24.10 ± 3.01	26.10 ± 5.25	25.90 ± 4.28	29.14 ± 3.08	27.81 ± 3.92	28.86 ± 3.51	27.05 ± 4.43	27.05 ± 4.31	31.24 ± 4.80	33.24 ± 3.75
ALL-IDB2	0.19 ± 0.58	0.38 ± 0.77	1.15 ± 0.94	1.35 ± 1.24	1.15 ± 1.28	0.96 ± 0.96	1.15 ± 1.15	1.73 ± 2.18	1.35 ± 1.23	2.12 ± 1.18	1.92 ± 1.92	2.31 ± 1.68	3.46 ± 1.44	12.88 ± 6.20
ALOI	70.16	58.36	47.14	32.79	26.42	25.78	27.62	23.78	23.03	25.55	26.12	28.30	32.15	35.07
ALOT	30.86 ± 0.34	24.72 ± 0.32	25.50 ± 0.29	26.62 ± 0.29	27.36 ± 0.43	27.71 ± 0.32	27.05 ± 0.38	26.10 ± 0.29	26.62 ± 0.51	26.80 ± 0.25	26.69 ± 0.49	26.73 ± 0.36	26.63 ± 0.38	27.54 ± 0.50
APOPTOSIS	40.71 ± 7.09	8.00 ± 3.39	3.71 ± 1.71	4.71 ± 2.56	5.71 ± 2.56	5.71 ± 1.81	5.57 ± 3.35	5.71 ± 2.12	5.71 ± 2.86	5.00 ± 3.21	7.86 ± 1.84	7.29 ± 2.59	10.00 ± 3.26	12.29 ± 2.32
BINUCLEATE	26.16 ± 5.79	3.0 ± 2.45	1.25 ± 2.02	2.50 ± 3.35	2.75 ± 3.58	5.00 ± 3.35	1.75 ± 3.17	2.00 ± 3.32	3.25 ± 4.88	3.75 ± 5.15	5.00 ± 4.03	6.00 ± 6.34	10.00 ± 8.06	10.25 ± 6.56
BIRDS	65.23 ± 2.13	60.43 ± 2.33	54.4 ± 1.64	49.60 ± 1.61	45.13 ± 2.22	43.53 ± 3.21	44.77 ± 1.80	46.37 ± 3.03	44.0 ± 2.08	43.17 ± 2.82	41.23 ± 2.85	42.0 ± 2.27	43.43 ± 1.89	47.7 ± 3.17
BREAST-CANCER	11.53 ± 2.78	7.08 ± 3.59	9.31 ± 3.11	8.47 ± 2.10	12.22 ± 2.83	12.22 ± 2.39	12.64 ± 1.01	10.83 ± 2.47	11.94 ± 4.22	12.22 ± 3.82	12.08 ± 2.24	14.31 ± 4.21	14.17 ± 3.77	18.47 ± 5.12
BUILDINGSAB	70.11 ± 2.51	54.36 ± 2.73	52.09 ± 2.83	53.92 ± 2.39	55.91 ± 2.75	54.92 ± 2.28	58.18 ± 1.42	51.27 ± 3.97	55.64 ± 2.88	55.97 ± 2.99	60.33 ± 2.62	68.67 ± 2.88	81.33 ± 2.88	81.33 ± 2.88
BUTTERFLIES	65.54 ± 2.30	57.62 ± 1.33	53.07 ± 2.34	48.81 ± 3.07	43.62 ± 3.42	44.21 ± 3.36	43.32 ± 3.09	44.37 ± 3.04	41.97 ± 2.73	41.42 ± 3.58	39.61 ± 2.80	39.22 ± 2.17	42.75 ± 3.93	46.89 ± 3.48
BUTTERFLIES-CLEAN	33.56 ± 1.80	31.69 ± 1.98	25.27 ± 2.27	21.6 ± 2.30	20.42 ± 2.20	20.98 ± 2.72	21.09 ± 2.19	15.62 ± 2.34	17.31 ± 1.60	16.93 ± 2.45	16.93 ± 1.36	19.78 ± 1.99	20.91 ± 1.44	24.56 ± 2.79
CALTECH-101	84.16	83.25	80.15	78.56	76.43	75.78	74.96	75.20	73.95	72.80	72.49	72.74	73.63	76.04
CALTECH-256	94.11 ± 0.37	93.81 ± 0.16	92.36 ± 0.31	90.79 ± 0.35	90.13 ± 0.30	89.95 ± 0.29	89.77 ± 0.26	89.29 ± 0.21	89.09 ± 0.27	88.88 ± 0.41	88.76 ± 0.33	89.11 ± 0.43	89.78 ± 0.29	91.26 ± 0.21
C.ELEGANS	65.21 ± 3.46	26.15 ± 3.36	27.78 ± 4.78	34.53 ± 4.53	38.55 ± 4.50	44.96 ± 1.95	41.63 ± 4.12	40.68 ± 4.24	41.45 ± 5.10	43.59 ± 4.98	44.79 ± 2.60	46.24 ± 3.83	52.39 ± 4.43	54.87 ± 4.45
C.ELEGANS-LIVE-DEAD	21.58 ± 4.97	1.58 ± 2.41	3.16 ± 3.49	2.63 ± 2.63	4.74 ± 3.68	4.21 ± 6.57	3.16 ± 3.49	2.63 ± 2.63	3.16 ± 3.49	3.16 ± 4.21	3.16 ± 3.49	3.16 ± 4.82	4.74 ± 3.68	13.68 ± 7.52
CHARS7-138	96.85 ± 0.56	92.51 ± 0.92	90.51 ± 0.92	87.78 ± 1.38	84.82 ± 1.24	83.09 ± 0.97	83.03 ± 1.30	85.49 ± 1.01	81.62 ± 1.55	77.76 ± 0.97	77.54 ± 1.29	75.34 ± 1.50	78.66 ± 0.63	78.66 ± 0.63
CHO	7.99 ± 3.76	4.77 ± 3.73	2.92 ± 1.28	2.31 ± 1.24	3.23 ± 2.43	3.54 ± 3.00	4.77 ± 2.33	5.23 ± 2.68	5.69 ± 2.84	5.85 ± 2.65	7.99 ± 3.14	6.77 ± 3.01	16.0 ± 3.01	31.54 ± 5.85
CIFAR-10	74.44	68.31	63.47	60.42	58.57	57.05	57.05	61.22	58.05	54.95	54.33	53.24	55.75	55.75
COIL-100 nvl	23.11	32.15	27.63	25.04	26.55	26.99	26.65	23.35	23.79	25.33	33.52	41.14	60.42	67.35
CONVEX	50.10	33.93	21.01	15.76	12.55	11.29	11.35	12.53	10.35	10.23	8.96	9.93	13.28	17.30
ETH-80	17.67 ± 5.57	18.45 ± 6.95	20.41 ± 9.08	16.62 ± 7.16	17.82 ± 5.86	16.45 ± 5.92	17.10 ± 7.62	16.94 ± 5.24	17.07 ± 7.63	16.43 ± 5.69	18.61 ± 8.39	17.01 ± 6.62	17.59 ± 5.91	18.49 ± 6.51
EVENTS	48.48 ± 2.23	36.99 ± 2.54	37.13 ± 1.16	35.33 ± 1.96	35.17 ± 2.41	35.48 ± 1.86	37.08 ± 1.89	35.625 ± 1.09	36.89 ± 2.27	36.54 ± 2.90	38.04 ± 2.23	37.52 ± 2.48	40.85 ± 2.05	43.44 ± 1.29
FAMOUSLAND	82.55 ± 2.15	76.8 ± 1.65	74.7 ± 2.23	70.55 ± 1.94	72.55 ± 1.94	72.3 ± 2.24	72.15 ± 2.16	69.25 ± 3.04	71.35 ± 2.29	72.05 ± 2.35	70.45 ± 2.83	72.65 ± 4.58	73.95 ± 2.70	77.4 ± 2.57
FLOWERS17	47.47 ± 1.85	37.5 ± 1.82	34.97 ± 2.30	34.06 ± 2.60	33.38 ± 2.40	33.06 ± 2.08	34.56 ± 2.10	33.08 ± 2.08	33.29 ± 1.91	34.88 ± 1.56	33.82 ± 1.69	34.38 ± 1.70	37.15 ± 1.37	40.5 ± 1.61
FLOWERS102-CLEAN	78.30	63.06	61.78	62.08	62.08	62.08	62.08	59.64	59.09	60.16	58.01	59.69	62.88	67.02
GALAXYZOO	17.26 ± 0.18	19.39 ± 0.27	14.62 ± 0.16	11.49 ± 0.15	10.30 ± 0.24	9.31 ± 0.11	8.48 ± 0.27	9.66 ± 0.26	9.15 ± 0.19	7.61 ± 0.15	8.23 ± 0.17	6.71 ± 0.16	4.96 ± 0.23	3.88 ± 0.15
GTSRBCROP	78.71	72.84	67.90	59.34	51.21	47.07	43.24	51.08	45.66	38.69	37.89	33.29	29.69	28.19
HCC	13.21 ± 8.53	11.79 ± 7.24	17.86 ± 10.71	20.36 ± 11.36	15.00 ± 8.72	16.79 ± 12.22	20.00 ± 11.43	21.43 ± 13.36	22.14 ± 8.72	22.14 ± 9.01	21.07 ± 8.89	21.43 ± 8.45	22.50 ± 8.23	27.50 ± 13.03
HEP2-ICPR2012	74.80	61.85	59.54	60.08	60.49	60.08	61.04	57.22	58.72	60.63	60.08	62.53	65.53	67.57
HPA	4.76 ± 2.92	3.14 ± 1.13	3.43 ± 1.06	3.81 ± 1.81	4.95 ± 1.94	5.71 ± 1.54	7.62 ± 1.81	5.43 ± 2.17	5.52 ± 3.15	8.95 ± 3.02	7.52 ± 2.71	9.71 ± 2.58	12.57 ± 4.08	16.57 ± 2.22
INDOOR	89.05 ± 0.76	85.13 ± 0.90	84.13 ± 0.63	84.45 ± 0.87	84.20 ± 0.84	84.12 ± 0.45	84.52 ± 1.06	84.27 ± 0.96	84.84 ± 0.96	84.72 ± 0.82	85.21 ± 1.05	85.44 ± 0.55	86.95 ± 1.30	88.95 ± 0.68
IRMA2005	54.9	26.90	21.10	16.50	13.90	13.5	13.90	14.40	13.30	13.10	14.40	15.40	16.20	19.40
IRMA2006	66.5	40.3	30.9	26.2	23.9	23.1	23.5	23.1	22.8	25.1	24.0	23.8	25.70	27.5
KTH-TIPS	51.07 ± 2.97	7.44 ± 1.86	7.44 ± 1.39	8.66 ± 1.87	8.12 ± 0.88	10.41 ± 1.43	10.22 ± 2.03	8.10 ± 1.11	8.98 ± 1.69	10.46 ± 1.61	10.71 ± 1.63	12.05 ± 1.69	16.24 ± 2.23	24.39 ± 1.55
KTH-TIPS2	55.79 ± 8.30	48.38 ± 6.68	46.90 ± 8.20	47.87 ± 6.27	48.42 ± 9.01	50.09 ± 7.74	46.67 ± 8.29	49.39 ± 7.13	49.73 ± 8.59	51.88 ± 7.38	52.87 ± 8.38	52.21 ± 9.63	54.52 ± 9.37	51.49 ± 9.54
LANDUSE	23.71 ± 2.18	21.88 ± 1.74	21.48 ± 1.38	21.55 ± 2.12	23.17 ± 2.73	25.90 ± 2.17	27.74 ± 1.37	23.33 ± 1.00	25.07 ± 2.10	28.52 ± 2.40	26.74 ± 1.87	33.05 ± 1.53	41.71 ± 2.17	50.81 ± 2.34
LYMPHOMA	11.35 ± 5.64	7.84 ± 3.90	5.95 ± 3.97	8.65 ± 3.97	10.27 ± 3.15	8.38 ± 5.85	7.87 ± 3.18	8.38 ± 5.85	11.08 ± 5.19	11.02 ± 4.80	11.62 ± 4.69	12.43 ± 5.43	11.35 ± 4.32	11.35 ± 4.32
MMODALITY	49.73	23.51	23.32	26.03	26.68	26.41	26.87	26.80	26.76	29.01	29.81	29.85	32.37	36.15
MNIST	77.19	52.29	14.74	3.65	2.96	2.58	2.49	2.4	2.36	1.87	1.86	1.77	1.64	1.98
MNIST-12000	78.77	65.69	36.86	6.59	4.09	3.48	3.27	3.29	2.87	2.75	2.41	2.30	2.63	3.28
MNIST-ROTATION	78.46	78.92	20.90	42.16	28.65	22.98	20.90	26.69	20.41	16.35	14.82	13.18	12.65	16.00
MNIST-BIMG	85.72	78.65	69.06	48.24	38.58	32.87	29.55	36.39	31.90	26.91	27.24	23.41	22.10	24.91
MNIST-BRAND	85.69	78.65	70.20	42.03	29.83	21.22	16.70	24.73	21.27	13.03	14.23	11.00	9.15	12.15
MNIST-BIMG-ROT	86.84	86.94	78.23	74.216	70.57	72.60	72.60	69.63	62.56	64.90	58.93	57.31	61.07	61.07
MSTAR-S1	43.03	41.61	35.40	30.56	30.11	30.85	23.16	25.55	25.61	27.09	24.42	19.72	17.36	17.36
NATURALSCENES	86.50 ± 0.59	40.17 ± 0.56	40.04 ± 1.11	43.89 ± 0.63	47.18 ± 1.05	49.72 ± 0.57	52.60 ± 0.81	46.98 ± 0.57	50.87 ± 0.88	55.94 ± 1.10	56.09 ± 0.60	59.97 ± 0.87	65.82 ± 0.84	71.02 ± 0.77
NORB-UNIFORM	66.35	54.47	37.23	27.67	23.54	19.51	17.83	22.21	19.83	15.32	12.49	15.72	13.28	14.88
NORB-JITTCLUTT	80.04	78.36	71.00	58.39	50.23	44.93	43.07	51.85	45.73	40.03	40.46	35.38	31.68	32.96
OLIVA	51.99 ± 1.30	33.97 ± 1.12	29.99 ± 1.21	29.74 ± 1.43	31.27 ± 0.85	32.56 ± 0.95	34.37 ± 1.25	30.63 ± 1.05	32.93 ± 0.99	35.31 ± 1.45	35.59 ± 1.18	38.49 ± 0.78	43.43 ± 1.64	49.35 ± 1.43
ORL	7.1 ± 1.45	1.35 ± 1.10	2.25 ± 1.08	7.95 ± 1.07	2.05 ± 1.33	2.1 ± 1.53	2.2 ± 1.05	2.05 ± 1.39	1.95 ± 1.42	2.5 ± 1.57	3.2 ± 2.11	3.4 ± 1.51	3.65 ± 1.47	5.75 ± 2.88
OUTEX	1.04 ± 0.28	2.06 ± 1.09	1.46 ± 0.55	4.33 ± 1.28	4.70 ± 1.54	6.71 ± 1.16	7.89 ± 0.87	5.60 ± 1.03	8.52 ± 1.19	10.39 ± 1.04	10.99 ± 1.50	15.09 ± 0.94	24.05 ± 1.89	38.22 ± 2.56
PFID	77.02 ± 2.12	75.82 ± 0.92	74.73 ± 2.36	72.73 ± 3.12	75.00 ± 2.27	74.43 ± 2.49	74.97 ± 2.23	76.00 ± 2.99	74.73 ± 2.98	76.42 ± 3.45	77.87 ± 2.28	79.64 ± 3.05	81.37 ± 2.68	81.37 ± 2.68
POLLEN	33.13 ± 1.88	12.48 ± 1.24	9.42 ± 0.93	6.21 ± 0.88	6.32 ± 1.17	5.36 ± 0.97	5.							

Datasets	1000	2500	5000	10000	25000	50000
ACROSOMES	2.77 ± 0.49	2.52 ± 0.29	2.90 ± 0.68	3.26 ± 0.71	4.34 ± 0.79	5.86 ± 0.70
AGEMAP-FAGING	6.29±2.18	4.29±0.88	4.19±1.77	<u>3.90±1.24</u>	4.86±1.56	5.24±0.98
ALL-IDB2	0.38±0.77	0.96±0.96	<u>0.19 ± 0.58</u>	<u>0.96±1.29</u>	0.96±1.97	0.96±1.29
ALOI	23.15	22.74	23.03	24.51	25.85	26.97
ALOT	28.88±0.36	<u>23.92±0.41</u>	24.72±0.32	26.27±0.35	29.96±0.50	34.82±0.41
APOPTOSIS	3.43 ± 1.46	<u>4.00 ± 2.10</u>	3.71 ± 1.71	4.57 ± 3.05	5.00 ± 2.58	7.14 ± 2.47
BINUCLEATE	<u>0.25±0.75</u>	1.25±3.01	1.25±2.02	2.00±2.18	0.75±1.15	0.75±2.25
BIRDS	41.63±2.66	41.0±3.08	41.23±2.85	43.1±2.45	43.9±2.70	48.27±2.57
BREAST-CANCER	10.14±2.71	9.17±3.73	<u>7.08±3.59</u>	8.89±2.26	9.31±2.33	10.14±3.73
BUILDINGSAB	47.62±2.68	49.99±3.43	<u>52.09±2.83</u>	54.92±3.19	52.98±3.24	52.38±2.66
BUTTERFLIES	43.32±2.94	41.05±2.37	<u>39.22±2.17</u>	40.05±3.44	40.23±3.13	42.38±1.88
BUTTERFLIES-CLEAN	<u>14.13±1.22</u>	15.93±1.82	<u>15.62±2.34</u>	16.49±2.03	18.78±2.26	20.6
CALTECH-101	71.27	72.91	72.49	73.64	75.33	76.95
CALTECH-256	<u>87.96±0.22</u>	88.32±0.33	88.76±0.33	89.59±0.44	90.52±0.19	91.08±0.38
C.ELEGANS	27.52±4.72	27.09±3.27	<u>26.15±3.36</u>	27.35±2.65	27.69±2.87	30.09±3.33
C.ELEGANS-LIVE-DEAD	4.21±3.94	3.16 ± 3.49	<u>1.58 ± 2.41</u>	3.16 ± 3.49	4.74 ± 5.49	3.68 ± 2.41
CHARS74K	73.76±1.17	<u>73.71±1.77</u>	75.34±1.50	77.09±1.43	78.33±1.41	79.95±1.09
CHO	3.08±1.95	<u>2.92±2.33</u>	<u>2.31±1.24</u>	4.46±2.33	6.31±2.96	8.77±2.39
CIFAR-10	55.60	55.28	<u>53.24</u>	54.78	55.93	58.83
COIL-100 nv1	25.46	24.83	<u>23.35</u>	19.79	22.48	25.48
CONVEX	9.56	8.41	8.96	10.49	10.27	11.00
ETH-80	17.65±6.39	17.35±7.15	16.43±5.69	16.19±6.56	15.70±3.93	17.83±5.51
EVENTS	<u>34.27±1.79</u>	35.73±2.37	37.46±1.48	40.08±1.49	<u>42.46±2.54</u>	43.17±1.60
FAMOUSLAND	67.75±2.76	68.75±3.51	69.25±3.04	71.05±3.19	72.8±2.91	75.0±2.25
FLOWERS17	33.32±3.44	<u>32.41±3.29</u>	33.06±2.08	33.62±2.09	36.74±1.72	39.99±1.61
FLOWERS102-CLEAN	59.54	<u>56.90</u>	58.01	59.83	62.93	64.58
GALAXYZOO	<u>2.84±0.13</u>	3.49±0.19	3.88±0.15	4.09±0.22	4.84±0.42	5.97±0.31
GTSRBCROP	<u>24.44</u>	25.55	28.19	29.20	33.52	38.03
HCC	17.14 ± 6.93	10.71 ± 10.71	11.79 ± 7.24	13.21 ± 9.92	16.07 ± 9.55	16.43 ± 9.61
HEP2-ICPR2012	58.04	59.54	57.22	59.13	60.08	61.31
HPA	2.95 ± 1.50	<u>2.38 ± 0.98</u>	3.14 ± 1.13	3.62 ± 1.80	4.48 ± 1.65	6.00 ± 2.04
INDOOR	85.11±0.64	<u>84.03±0.88</u>	84.12±0.45	85.07±0.91	86.74±0.68	87.19±1.30
IRMA2005	11.3	12.60	13.10	13.90	15.70	16.80
IRMA2006	23.10	22.40	22.80	23.60	25.60	26.90
KTH-TIPS	9.24±1.54	7.29±1.00	7.44±1.86	7.78±1.47	7.76±1.59	8.80±0.94
KTH-TIPS2	52.44±10.32	54.55±9.35	<u>46.67±8.29</u>	52.83±6.25	52.76±9.29	53.15±7.50
LANDUSE	17.76±1.90	17.55±1.60	<u>21.48±1.38</u>	19.31±1.70	22.79±2.01	26.90±2.00
LYMPHOMA	9.19±4.71	8.38±4.90	<u>5.95±3.97</u>	7.57±3.38	10.00±4.53	11.08±4.59
MMODALITY	22.06	<u>21.79</u>	23.32	24.05	28.89	28.28
MNIST	1.44	1.4	1.64	1.88	2.66	3.64
MNIST-12000	2.72	2.18	2.30	2.90	3.51	5.05
MNIST-ROTATION	9.42	10.58	12.65	15.83	19.62	24.25
MNIST-BIMG	<u>20.39</u>	21.65	22.10	24.29	26.46	26.12
MNIST-BRAND	<u>8.21</u>	8.40	9.15	11.77	14.08	12.76
MNIST-BIMG-ROT	<u>55.05</u>	58.22	57.31	60.232	60.67	60.26
MSTAR-S1	16.73	18.10	17.36	20.15	26.64	26.35
NATURALSCENES	40.00±0.69	<u>39.31±0.81</u>	40.04±1.11	41.91±1.09	45.13±0.77	48.21±0.78
NORB-UNIFORM	9.95	10.67	12.49	14.74	19.75	23.47
NORB-JITTCLUETT	<u>24.71</u>	28.65	31.68	35.20	40.02	43.83
OLIVA	<u>28.01±0.68</u>	28.36±0.86	29.74±1.43	31.90±1.03	34.81±1.33	38.49±1.38
ORL	2.1 ± 1.66	1.75±0.78	1.35±1.10	1.45±1.11	1.3±1.17	1.8±1.58
OUTEX	1.20±0.62	0.90±0.59	1.04±0.28	1.46±0.57	2.66±1.08	3.01±0.88
PFID		72.87±2.43	72.73±3.12	73.72±3.00	75.57±2.67	74.67±2.78
POLLEN	3.88±0.66	3.53±0.55	<u>3.42±0.37</u>	3.95±0.45	5.37±0.59	5.81±0.90
PPMI24	<u>85.00</u>	85.33	85.79	86.83	87.75	86.96
PUBFIG83	78.54	<u>78.08±0.89</u>	79.45±0.64	81.27 ± 1.09	83.16 ± 1.17	85.04 ± 0.91
RBC	28.76±1.18	<u>30.04±1.28</u>	32.95±1.82	36.88±1.20	42.91±1.20	41.15±0.70
RECT-BASIC	<u>0.09</u>	0.21	0.14	0.20	0.19	0.27
RECT-BIMG	17.78	20.07	22.16	20.95	20.76	20.90
RNAI	14.25±5.48	<u>9.5±3.67</u>	14.5±3.32	5.5±4.15	11.75±4.34	15.5±7.14
SEROUS	24.04±2.44	<u>27.57±2.52</u>	27.65±2.09	30.27±1.93	32.76±1.52	31.94±2.08
SHAPE1	17.5±4.59	16.1±3.99	<u>15.4±2.69</u>	16.6±3.75	18.3±3.93	16.9±3.01
SMEAR	7.58±2.43	7.25 ± 2.32	<u>6.26±1.91</u>	8.57 ± 2.73	9.45 ± 3.34	12.20 ± 2.11
SOCCER	<u>17.52±2.86</u>	20.0±2.33	<u>20.86±2.90</u>	22.10±4.30	24.38±2.77	27.05±4.47
SOIL-24	<u>9.58</u>	19.17	20.83	31.25	35.0	55.0
SOIL-47	48.72	53.19	52.21	57.02	64.04	65.85
SPORTS	9.46±1.02	8.94±1.00	9.40±0.97	9.61±0.95	12.35±1.03	13.66±1.31
STOIC101	31.67	27.58	<u>25.76</u>	25.76	29.55	33.48
STOMATA	20.91 ± 11.54	20.91 ± 7.10	<u>20.00 ± 12.73</u>	25.45 ± 11.35	23.64 ± 12.33	25.45 ± 10.60
STONEFLY9	14.98	15.42	14.72	15.77	16.73	16.03
SUBCELLULAR	11.86±2.84	13.02±3.32	11.63±2.90	<u>11.63±2.49</u>	16.51±3.63	15.35±2.98
SUN397	95.18±0.19	94.91±0.13	95.07±0.09	<u>95.45±0.15</u>	95.42±0.16	95.48±0.19
SWELEAF	4.25±0.55	4.43±0.96	3.33±0.84	4.33±1.02	5.03±0.74	6.11±0.68
TERMINALBULB	55.20±1.41	54.23±1.61	54.87±2.61	<u>53.86±1.47</u>	55.08±1.88	56.26±1.80
TINYGRAZ03	53.89±1.65	54.16±3.51	55.84±3.27	<u>53.54±2.28</u>	62.21±2.69	68.05±1.88
TSG-60	3.58±1.49	8.83±1.72 ?	4.08±1.51	<u>3.92±1.24</u>	4.58±1.13	6.08±1.40
UIUCTEX	13.38±1.54	12.5±1.47	12.32±1.53	<u>11.82±1.0</u>	12.5±0.93	13.84±0.96
WANG	<u>11.44±0.77</u>	11.7±1.50	12.0±0.83	<u>12.0±0.69</u>	14.8±0.85	16.68±1.06
XEROX-6	11.43±2.18	10.41±1.50	<u>7.35±2.08</u>	11.84±2.29	15.51±1.63	14.29±3.87
ZEBRATOXIC	3.12	4.17	4.17	5.21	8.33	8.33
ZUBUD	9.57	11.30	<u>6.96</u>	7.83	7.83	9.57

TABLE VIII

INFLUENCE OF THE n_{min} FOR ET-FL (LARGE VALUES), OTHER PARAMETERS ARE CONSTANT: $T = 10$, $k = \sqrt{rT(M)}$, $N_{fs} = 1$ MILLION, 16×16 DESCRIPTORS, BEST SUBWINDOW SIZE INTERVALS, AND TERMINAL FREQUENCY IMAGE REPRESENTATION, THE NUMBER OF VISUAL WORDS IS DECREASING FROM LEFT TO RIGHT.

Datasets	2	10	100	500	1000
ACROSOMES	3.68 ± 0.70	3.41 ± 0.47	<u>2.50 ± 0.55</u>	2.79 ± 0.82	2.68 ± 0.62
AGEMAP-FAGING	42.29±3.52	38.10±2.69	<u>18.95±3.00</u>	7.62±0.95	<u>4.86±1.44</u>
ALL-IDB2	1.15±1.54	0.77±1.28	1.15±0.94	0.38±0.77	0.38±0.77
ALOI	n/a	n/a	n/a	n/a	n/a
ALOT	44.21±0.28	38.43±0.42	30.92±0.33	<u>28.49±0.24</u>	28.88±0.36
APOPTOSIS	12.57 ± 3.31	12.14 ± 3.34	6.14 ± 1.44	5.71 ± 2.47	3.86 ± 1.81
BINUCLEATE	12.0±6.96	6.50±5.61	3.00±3.50	1.50±3.20	<u>0.25±0.75</u>
BIRDS	47.0±2.97	46.27±3.05	40.33±2.47	39.9±2.92	40.13±1.37
BREAST	13.61±6.11	13.33±6.34	12.64±3.75	<u>9.44±3.27</u>	9.44±3.28
BUILDINGSAB	41.71±2.39	41.77±2.45	43.31±5.53	44.53±2.50	43.31±2.06
BUTTERFLIES	<u>52.27±2.24</u>	49.06±2.44	44.14±2.54	41.12±2.65	<u>40.78±3.12</u>
BUTTERFLIES-CLEAN	19.53±6.96	17.8±1.79	13.98±1.45	<u>12.13±4.19</u>	12.18
CALTECH-101	74.12	71.75	70.35	69.74	70.48
CALTECH-256	89.76±0.44	88.68±0.29	87.77±0.31	88.17±0.33	88.53±0.36
C.ELEGANS	40.09±4.84	41.97±14.49	30.17±4.17	30.17±5.32	26.58±3.71
C.ELEGANS-LIVE-DEAD	8.42 ± 5.37	4.74 ± 4.37	1.58 ± 2.41	3.16 ± 3.49	<u>3.68 ± 3.37</u>
CHARS74K	73.43±1.30	73.29±1.94	71.83±1.44	71.24±2.05	71.96±1.81
CHO	4.46±1.45	5.23±2.59	3.69±3.31	<u>2.92±2.70</u>	<u>2.46±2.09</u>
CIFAR-10	50.71	<u>49.93</u>	50.26	53.66	<u>55.60</u>
COIL-100	22.83	<u>22.0</u>	22.31	25.31	27.0
CONVEX	10.54	10.37	8.79	7.72	7.47
ETH-80	22.36±8.18	23.09±7.88	18.22±6.83	17.44±6.75	14.01±6.71
EVENTS	43.31±1.17	39.77±1.18	33.23±2.26	32.56±1.14	32.73±2.86
FLOWERS17	37.03±2.39	33.91±1.79	29.59±1.99	29.59±2.00	29.0±1.88
FLOWERS102-CLEAN	58.55	55.83	51.96	52.00	53.31
FAMOUS	72.95±2.14	68.6±3.38	63.2±2.40	62.25±2.70	<u>60.95±2.13</u>
GALAXYZOO	3.79±0.16	3.62±0.12	2.82±0.06	<u>2.69±0.10</u>	2.84±0.13
GTSRBCROP	28.86	27.86	25.24	25.10	25.00
HCC	43.93 ± 12.43	37.86 ± 13.57	24.29 ± 9.95	19.29 ± 8.48	14.99 ± 7.11
HEP2-ICPR2012	62.67	61.17	61.58	59.67	<u>59.40</u>
HPA	13.90 ± 3.16	10.67 ± 3.09	5.52 ± 2.51	<u>3.62 ± 1.58</u>	3.71 ± 2.02
INDOOR	87.33±0.92	85.22±0.82	<u>84.46±0.64</u>	<u>84.55±0.79</u>	85.11±0.64
IRMA2005	21.3	17.3	13.6	11.5	11.3
IRMA2006	39.5	31.1	24.5	22.8	22.4
KTH-TIPS	23.51±1.46	18.68±2.31	11.49±1.93	8.46±2.95	7.66±1.79
KTH-TIPS2	50.99±9.29	50.05±9.92	49.61±9.20	47.71±9.27	50.76±11.39
LANDUSE	32.5±1.89	27.69±1.97	20.33±1.96	<u>17.14±1.77</u>	17.19±1.58
LYMPHOMA	27.2±4.31	21.2±8.31	12.53±3.38	<u>9.33±3.27</u>	9.60±4.37
MMODALITY	25.76	24.50	21.64	<u>21.64</u>	22.06
MNIST	1.64	1.47	1.28	<u>1.22</u>	1.42
MNIST-12000	2.56	2.32	<u>1.89</u>	1.90	1.92
MNIST-ROTATION	10.25	9.61	8.14	8.57	9.24
MNIST-BIMG	28.572	26.28	20.98	<u>19.36</u>	20.39
MNIST-BRAND	14.63	13.14	8.48	<u>7.94</u>	8.21
MNIST-BIMG-ROT	64.06	62.02	54.46	54.91	55.05
MSTAR-S1	41.32	38.99	22.20	16.79	17.47
NATURALSCEANES	50.89±1.45	47.66±0.60	42.77±0.76	40.21±0.83	39.44±0.65
NORB-UNIFORM	8.56	7.99	8.07	9.21	9.95
NORB-JITCLUTT	19.68	<u>18.57</u>	19.66	22.69	24.71
OLIVA	36.44±1.64	33.78±0.51	28.08±0.89	26.42±1.06	27.13±1.23
ORL	1.35±1.25	1.2±1.12	<u>0.95±0.79</u>	1.45±1.33	1.35±0.79
OUTEX	3.33±1.04	2.25±0.94	0.83±0.48	0.79±0.47	<u>0.74±0.42</u>
PFID	75.66±1.62	74.84±3.15	71.09±3.06	69.56±3.29	69.73±4.50
POLLEN	12.04±0.97	10.24±1.34	5.32±0.97	4.23±0.87	4.19±0.83
PPM124	87.79	85.54	84.83	<u>84.25</u>	85.00
PUBFIG83	41.12±1.10	81.05 ± 1.70	77.48 ± 0.92	77.81 ± 1.35	78.54 ± 1.00
RBC		38.55±2.22	32.19±1.54	29.80±0.81	<u>29.80±0.87</u>
RECT-BASIC	0.04	<u>0.03</u>	0.03	0.04	0.07
RECT-BIMG	15.81	15.60	14.91	15.88	16.83
RNAI	42.75±3.78	38.75±4.22	24.25±4.04	18.25±5.81	16.75±5.37
SEROUS	34.91±0.93	33.31±1.86	27.90±1.40	<u>27.19±2.20</u>	27.38±2.59
SHAPE1	21.0±7.95	21.4±3.20	19.2±7.74	<u>16.2±6.97</u>	16.1±6.24
SMEAR	13.41±2.98	11.87 ± 2.64	8.13 ± 2.10	6.37 ± 2.19	7.47 ± 2.35
SOCCER	19.33±7.30	21.14±3.32	14.76±4.13	<u>16.0±3.09</u>	17.43±3.16
SOIL-24	5.0	4.58	6.67	11.25	16.67
SOIL-47	<u>29.26</u>	34.26	35.32	43.62	48.08
SPORTS	18.14±1.24	14.54±4.91	10.65±3.72	8.87±3.08	<u>8.51±1.17</u>
STOIC101	62.12	46.06	30.91	23.48	<u>21.52</u>
STOMATA	25.45 ± 11.35	30.00 ± 15.77	<u>21.82 ± 7.27</u>	26.36 ± 16.98	22.73 ± 10.16
STONEFLY9	25.17	20.30	<u>16.03</u>	16.03	16.11
SUBCELLULAR	20.58±5.72	17.91±4.07	13.60±4.19	14.19±2.19	13.26±3.79
SUN397	n/a	94.38±0.12	94.09±0.10	94.21±0.13	94.45±0.10
SWELEAF	12.03±0.84	9.88±1.06	5.27±0.85	4.07±0.78	4.08±0.66
TERMINALBULB	64.63±2.47	63.01±2.55	57.89±1.87	<u>55.35±2.01</u>	55.38±1.70
TINYGRAZ03	60.97±4.69	59.38±2.75	<u>54.96±3.78</u>	61.33±3.24	59.73±7.3
TSG-60	n/a	1.83±1.38	1.17±0.76	1.33±1.0	2.33±1.53
UIUCTEX	25.54±1.62	20.70±1.39	15.9±1.29	13.82±1.42	<u>12.46±1.62</u>
XEROX-6	18.06±3.26	15.31±2.19	12.04±1.70	9.08±2.43	9.90±4.01
WANG	15.68±0.99	14.32±1.90	12.1±1.65	<u>10.07±1.93</u>	10.04±1.39
ZEBRATOXIC	6.25	7.29	5.21	5.21	<u>3.12</u>
ZUBUD	<u>6.96</u>	8.70	7.83	7.83	9.56

TABLE IX

INFLUENCE OF LOWER n_{min} FOR FT-FL (SMALL VALUES). OTHER PARAMETERS ARE CONSTANT: $T = 10$, $k = \text{sqrt}(M)$, $N_s = 1$ MILLION, 16×16 DESCRIPTORS, BEST SUBWINDOW SIZE INTERVALS, AND TERMINAL FREQUENCY IMAGE REPRESENTATION. THE NUMBER OF VISUAL WORDS IS DECREASING FROM LEFT TO RIGHT. FINAL CLASSIFIER WAS LINEAR.

Datasets	1	\sqrt{M}	$M/8$	$M/4$	$M/2$	M
ACROSOMES	2.97 ± 0.51	2.90 ± 0.68	2.95 ± 0.67	2.86 ± 0.68	3.23 ± 0.56	3.12 ± 0.79
AGEMAP-FAGING	3.62 ± 1.94	4.19 ± 1.77	4.10 ± 1.21	4.67 ± 2.11	4.19 ± 1.77	4.19 ± 1.77
ALL-IDB2	1.54 ± 1.68	0.19 ± 0.58	1.54 ± 1.88	1.54 ± 1.88	1.54 ± 1.88	1.54 ± 1.88
ALOI	31.58	23.03	22.25	21.39	20.27	20.18
ALOT	32.33 ± 0.43	24.72 ± 0.32	25.32 ± 0.42	25.66 ± 0.45	25.69 ± 0.34	25.62 ± 0.36
APOPTOSIS	4.00 ± 2.10	3.71 ± 1.71	4.29 ± 3.00	4.29 ± 2.39	5.23 ± 2.13	4.43 ± 2.51
BINUCLEATE	2.25 ± 3.78	1.25 ± 2.02	3.0 ± 2.69	5.00 ± 3.16	4.75 ± 3.78	4.17 ± 3.99
BIRDS	47.4 ± 2.15	41.23 ± 2.85	41.83 ± 2.30	39.97 ± 1.78	39.10 ± 2.70	38.37 ± 2.04
BREAST-CANCER	10.14 ± 3.17	7.08 ± 3.59	9.44 ± 2.96	10.55 ± 2.86	9.99 ± 3.21	17.92 ± 2.74
BUILDINGSAB	49.89 ± 2.07	52.09 ± 2.83	52.38 ± 2.22	50.99 ± 2.53	51.44 ± 2.29	52.76 ± 2.07
BUTTERFLIES	54.21 ± 1.66	39.22 ± 2.17	34.85 ± 3.23	36.34 ± 1.70	33.99 ± 3.44	30.92 ± 2.45
BUTTERFLIES-CLEAN	21.58 ± 2.74	15.62 ± 2.34	15.20 ± 2.26	13.87 ± 1.35	16.11 ± 2.00	15.04 ± 1.65
CALTECH-101	71.89	72.49	72.28	72.79	72.71	72.30
CALTECH-256	88.29 ± 0.31	88.76 ± 0.33	88.93 ± 0.36	88.73 ± 0.34	88.70 ± 0.30	88.95 ± 0.26
C.ELEGANS	27.69 ± 4.57	26.15 ± 3.36	26.58 ± 3.55	25.47 ± 3.84	30.59 ± 5.67	28.80 ± 6.10
C.ELEGANS-LIVE-DEAD	2.63 ± 4.85	1.58 ± 2.41	3.68 ± 4.11	2.63 ± 4.85	3.16 ± 3.49	3.16 ± 3.49
CHARS74K	76.87 ± 1.44	75.34 ± 1.50	75.54 ± 1.75	75.56 ± 1.64	76.26 ± 1.61	74.25 ± 1.74
CHO	2.77 ± 2.04	2.31 ± 1.24	3.85 ± 3.25	3.23 ± 2.62	3.23 ± 1.88	2.92 ± 1.75
CIFAR-10	56.29	53.24	53.19	52.80	53.48	53.72
COIL-100 nv1	28.51	23.35	24.20	24.13	25.58	28.85
CONVEX	12.49	8.96	8.88	8.91	8.79	8.88
ETH-80	15.70 ± 6.49	16.43 ± 5.69	17.38 ± 9.06	15.63 ± 8.51	15.66 ± 5.27	n/a
EVENTS	35.08 ± 2.19	35.17 ± 2.41	35.46 ± 2.39	37.42 ± 1.66	36.77 ± 2.55	35.83 ± 2.65
FAMOUSLAND	63.7 ± 2.39	69.25 ± 3.04	70.75 ± 1.74	71.25 ± 5.42	71.17 ± 2.35	71.05 ± 2.41
FLOWERS17	34.32 ± 1.57	33.06 ± 2.08	33.38 ± 1.57	33.21 ± 2.94	34.62 ± 2.43	32.76 ± 1.99
FLOWERS102-CLEAN	57.82	58.01	57.83	57.44	56.99	57.55
GALAXYZOO	9.65 ± 0.39	3.88 ± 0.15	3.28 ± 0.14	3.10 ± 0.08	2.90 ± 0.12	2.90 ± 0.09
GTSRBCROP	45.30	28.19	24.18	23.02	21.92	20.32
HCC	17.86 ± 8.89	11.79 ± 7.24	16.79 ± 8.23	15.36 ± 9.66	14.29 ± 8.14	15.58 ± 8.24
HEP2-ICPR2012	60.90	57.22	58.45	57.77	56.95	58.72
HPA	3.33 ± 1.3	3.14 ± 1.13	3.71 ± 1.31	4.29 ± 1.36	3.71 ± 2.19	3.49 ± 1.05
INDOOR	83.13 ± 0.72	84.12 ± 0.45	84.22 ± 0.62	83.99 ± 0.55	83.84 ± 0.54	84.36 ± 0.95
IRMA2005	13.80	13.10	13.10	14.10	13.90	13.4
IRMA2006	24.2	22.8	23.5	23.90	23.20	25.4
KTH-TIPS	9.05 ± 0.74	7.44 ± 1.86	8.37 ± 1.26	7.46 ± 1.02	6.75 ± 1.51	8.02 ± 0.93
KTH-TIPS2	52.96 ± 10.11	46.67 ± 8.29	54.26 ± 11.04	51.83 ± 7.96	50.96 ± 7.94	52.13 ± 9.23
LANDUSE	18.62 ± 1.31	21.48 ± 1.38	17.24 ± 0.95	18.07 ± 1.81	18.43 ± 1.22	16.74 ± 1.53
LYMPHOMA	6.76 ± 4.72	5.95 ± 3.97	8.13 ± 2.42	8.93 ± 2.92	7.60 ± 2.67	7.60 ± 2.07
MMODALITY	22.71	23.32	23.44	22.90	23.32	23.74
MNIST	1.98	1.64	1.63	1.56	1.81	1.71
MNIST-12000	2.49	2.30	2.39	2.61	2.58	2.67
MNIST-ROTATION	14.31	12.19	12.36	12.16	12.18	11.93
MNIST-BIMG	47.06	22.10	20.30	18.59	18.26	17.54
MNIST-BRAND	19.52	9.15	8.44	8.63	8.51	8.33
MNIST-BIMG-ROT	74.65	57.31	57.35	55.69	54.16	50.16
MSTAR-S1	16.28	17.36	15.82	13.49	17.99	15.48
NATURALSCENES	43.35 ± 0.75	40.04 ± 1.11	39.62 ± 1.04	38.84 ± 0.63	38.75 ± 0.74	38.54 ± 0.78
NORB-UNIFORM	14.88	12.49	12.35	13.24	13.61	14.89
NORB-JITCLUTT	48.97	31.68	29.21	28.16	27.08	26.54
OLIVA	27.90 ± 0.85	29.74 ± 1.43	29.54 ± 1.14	30.54 ± 0.81	30.56 ± 0.94	30.60 ± 0.97
ORL	2.95 ± 1.21	1.35 ± 1.10	2.7 ± 2.12	2.4 ± 1.71	2.45 ± 1.25	2.3 ± 1.27
OUTEX	1.18 ± 0.33	1.04 ± 0.28	1.34 ± 0.64	2.04 ± 0.91	1.43 ± 0.51	1.04 ± 0.28
PFID	74.45 ± 3.11	72.73 ± 3.12	75.41 ± 2.58	74.67 ± 2.66	73.88 ± 3.75	73.88 ± 3.75
POLLEN	4.77 ± 0.75	3.42 ± 0.37	4.57 ± 0.65	5.06 ± 0.64	5.01 ± 0.86	5.23 ± 1.00
PPM124	88.33	85.79	85.04	85.62	85.71	85.83
PUBFIG83	81.34 ± 1.05	79.45 ± 0.64	78.70 ± 1.33	79.90 ± 1.12	79.94 ± 1.42	80.59 ± 1.26
RBC	45.57 ± 1.62	32.95 ± 1.82	32.64 ± 1.18	30.74 ± 0.96	29.50 ± 1.43	30.30 ± 1.97
RECT-BASIC	0.22	0.14	0.20	0.19	0.20	0.23
RECT-BIMG	23.89	22.16	22.15	22.18	21.90	21.73
RNAI	17.5 ± 6.52	14.5 ± 3.32	11.0 ± 5.15	13.0 ± 4.97	10.83 ± 3.33	15.25 ± 5.96
SEROUS	26.78 ± 1.98	27.65 ± 2.09	26.09 ± 2.35	25.55 ± 1.66	26.67 ± 1.42	28.17 ± 1.81
SHAPE1	17.0 ± 3.44	15.4 ± 2.69	19.8 ± 2.99	17.7 ± 3.07	17.8 ± 4.49	19.3 ± 2.45
SMEAR	8.68 ± 2.88	6.26 ± 1.91	7.36 ± 2.36	8.68 ± 3.16	9.45 ± 1.85	7.69 ± 1.84
SOCCER	24.29 ± 5.51	20.86 ± 2.90	19.14 ± 2.23	20.76 ± 5.07	18.66 ± 2.49	18.86 ± 4.17
SOIL-24	52.08	20.83	22.5	24.58	19.58	23.75
SOIL-47	61.06	52.21	54.36	54.68	53.94	54.89
SPORTS	10.49 ± 0.70	9.40 ± 0.97	9.30 ± 1.14	8.99 ± 1.18	8.77 ± 0.77	8.71 ± 0.97
STOIC101	30.76	25.76	26.97	26.36	25.91	24.09
STOMATA	21.82 ± 10.91	20.00 ± 12.73	25.45 ± 9.79	22.73 ± 6.10	24.55 ± 10.00	25.45 ± 14.55
STONEFLY9	15.16	14.72	14.46	14.98	15.16	15.42
SUBCELLULAR	14.19 ± 3.11	11.63 ± 2.90	13.72 ± 3.56	13.60 ± 3.72	15.0 ± 4.04	13.72 ± 1.93
SWELEAF	3.24 ± 0.37	3.33 ± 0.84	4.91 ± 0.96	5.27 ± 0.82	5.76 ± 1.01	4.29 ± 0.72
SUN397	94.83 ± 0.18	95.07 ± 0.09	95.18 ± 0.19	95.16 ± 0.13	95.25 ± 0.17	95.19 ± 0.12
TERMINALBULB	55.28 ± 1.84	54.87 ± 2.61	53.37 ± 2.07	55.22 ± 1.71	55.28 ± 1.22	53.85 ± 1.74
TINYGRAZ03	61.50 ± 2.66	55.84 ± 3.27	61.15 ± 4.52	60.53 ± 4.95	60.80 ± 3.36	59.03 ± 5.37
TSG-60	5.25 ± 1.40	4.08 ± 1.51	n/a	n/a	n/a	n/a
UIUCTEX	11.82 ± 1.47	12.32 ± 1.53	11.38 ± 1.10	12.16 ± 1.09	12.06 ± 1.13	12.18 ± 0.58
WANG	10.74 ± 0.89	12.0 ± 0.83	12.14 ± 1.62	12.2 ± 1.41	12.66 ± 1.56	11.95 ± 1.58
XEROX-6	9.59 ± 3.07	7.35 ± 2.08	9.69 ± 1.95	11.22 ± 4.33	10.92 ± 3.76	11.43 ± 3.95
ZEBRATOXIC	5.21	4.17	4.17	3.12	5.21	4.17
ZUBUD	8.70	6.96	8.70	8.70	7.83	7.83

TABLE X
 INFLUENCE OF THE NUMBER OF RANDOM TESTS FOR ET-FL. OTHER
 PARAMETERS ARE CONSTANT: $T = 10$, $n_{min} = 5000$, $N_{fs} = 1$
 MILLION, 16×16 DESCRIPTORS, BEST SUBWINDOW SIZE INTERVALS,
 AND TERMINAL FREQUENCY IMAGE REPRESENTATION.

Datasets	TF	TB	HF	HB
ACROSOMES	2.90 ± 0.68	2.68 ± 0.71	3.30 ± 0.51	3.84 ± 0.73
AGEMAP-FAGING	4.19 ± 1.77	13.24 ± 2.81	4.10 ± 1.42	12.38 ± 2.95
ALL-IDB2	0.19 ± 0.58	0.77 ± 0.94	0.96 ± 0.96	2.31 ± 1.44
ALOI	23.03	95.04	23.20	99.90
ALOT	24.72 ± 0.32	24.46 ± 0.37	24.02 ± 0.44	24.12 ± 0.36
APOPTOSIS	3.71 ± 1.71	5.86 ± 3.41	3.57 ± 1.32	6.86 ± 3.25
BINUCLEATE	1.25 ± 2.02	41.75 ± 6.13	1.50 ± 3.00	32.75 ± 11.64
BIRDS	41.23 ± 2.85	41.0 ± 2.47	43.03 ± 2.54	41.3 ± 3.64
BUILDINGSAB	52.09 ± 2.83	69.17 ± 2.73	55.64 ± 2.84	72.76 ± 3.37
BREAST-CANCER	7.08 ± 3.59	18.61 ± 3.63	9.72 ± 3.23	18.06 ± 3.51
BUTTERFLIES	39.22 ± 2.17	45.59 ± 2.62	39.34 ± 3.08	45.29 ± 4.22
BUTTERFLIES-CLEAN	15.62 ± 2.34	23.56 ± 1.21	17.4 ± 2.57	23.6 ± 1.48
CALTECH-101	72.49	74.38	73.73	73.38
CALTECH-256	88.76 ± 0.33	88.28 ± 0.39	89.26 ± 0.30	88.34 ± 0.40
C.ELEGANS	26.15 ± 3.36	28.72 ± 3.16	25.90 ± 3.65	30.09 ± 2.78
C.ELEGANS-LIVE-DEAD	1.58 ± 2.41	6.32 ± 3.16	0.0 ± 0.0	7.37 ± 5.86
CHARS74K	75.34 ± 1.50	75.18 ± 1.53	77.95 ± 1.71	76.24 ± 1.19
CHO	2.31 ± 1.24	30.62 ± 5.90	3.54 ± 3.37	23.85 ± 5.60
CIFAR-10	53.24	55.61	54.14	60.29
COIL-100 nv1	23.35	87.66	24.25	83.61
CONVEX	8.96	8.15	9.16	8.95
ETH-80	16.43 ± 5.69	14.95 ± 7.77	19.41 ± 6.79	20.58 ± 5.43
EVENTS	35.17 ± 2.41	37.35 ± 2.24	36.94 ± 1.18	38.79 ± 1.59
FAMOUSLAND	69.25 ± 3.04	73.15 ± 2.18	72.05 ± 2.33	75.7 ± 1.49
FLOWERS17	33.06 ± 2.08	33.68 ± 2.28	36.15 ± 1.82	33.79 ± 1.82
FLOWERS102-CLEAN	58.01	58.82	59.63	60.26
GALAXYZOO	3.88 ± 0.15	4.48 ± 0.19	3.97 ± 0.18	4.30 ± 0.16
GTSRBCROP	28.19	29.99	28.50	28.43
HCC	11.79 ± 7.24	37.50 ± 14.08	15.00 ± 8.42	39.29 ± 11.63
HEP2-ICPR2012	57.22	61.99	79.29	63.22
HPA	3.14 ± 1.13	3.62 ± 1.33	4.00 ± 1.75	4.19 ± 1.22
INDOOR	84.12 ± 0.45	84.47 ± 0.75	84.39 ± 0.39	85.01 ± 1.06
IRMA2005	13.10	23.0	13.70	22.60
IRMA2006	22.8	36.90	22.20	37.5
KTH-TIPS	7.44 ± 1.86	22.07 ± 1.50	7.39 ± 1.33	21.51 ± 1.98
KTH-TIPS2	46.67 ± 8.29	46.38 ± 6.59	53.26 ± 8.06	54.41 ± 6.71
LANDUSE	21.48 ± 1.38	25.67 ± 1.82	19.62 ± 2.03	24.79 ± 2.11
LYMPHOMA	5.95 ± 3.97	12.97 ± 5.38	6.49 ± 3.24	14.59 ± 5.43
MMODALITY	23.32	24.31	23.36	25.15
MNIST	1.64	2.2	1.61	2.53
MNIST-12000	2.30	2.48	2.70	2.73
MNIST-ROTATION	12.65	14.57	13.46	16.45
MNIST-BIMG	22.10	22.00	23.04	24.03
MNIST-BRAND	9.15	9.55	11.04	11.95
MNIST-BIMG-ROT	57.31	59.36	59.67	63.27
MSTAR-S1	17.36	19.46	24.36	21.91
NATURALSCENES	40.04 ± 1.11	43.63 ± 1.00	41.51 ± 0.77	44.90 ± 0.77
NORB-UNIFORM	12.49	17.88	12.89	19.83
NORB-JITTLUTT	31.68	57.25	31.73	50.09
OLIVA	29.74 ± 1.43	33.84 ± 0.94	30.50 ± 1.07	34.60 ± 0.88
ORL	1.35 ± 1.10	6.2 ± 2.01	2.15 ± 2.00	8.25 ± 1.01
OUTEX	1.04 ± 0.28	1.97 ± 0.61	1.50 ± 0.66	2.80 ± 0.43
PFID	72.73 ± 3.12	75.66 ± 2.54	73.17 ± 2.58	75.25 ± 4.60
POLLEN	3.42 ± 0.37	3.79 ± 1.07	3.88 ± 0.33	4.32 ± 0.73
PPM124	85.79	85.92	86.42	85.50
PUBFIG83	79.45 ± 0.64	81.10 ± 1.04	79.71 ± 1.19	81.47 ± 1.57
RBC	32.95 ± 1.82	32.39 ± 1.73	33.79 ± 0.85	32.93 ± 0.76
RECT-BASIC	0.14	0.60	0.14	0.79
RECT-BIMG	22.16	24.81	22.94	23.80
RNAL	14.5 ± 3.32	25.75 ± 4.34	13.0 ± 4.0	28.5 ± 6.34
SEROUS	27.65 ± 2.09	28.06 ± 2.20	29.67 ± 2.13	29.04 ± 1.89
SHAPE1	15.4 ± 2.69	23.6 ± 4.8	17.8 ± 2.6	15.9 ± 4.83
SMEAR	6.26 ± 1.91	9.45 ± 2.75	8.02 ± 2.83	8.24 ± 1.13
SOCCER	20.86 ± 2.90	34.48 ± 4.42	21.62 ± 5.41	30.67 ± 3.09
SOIL-24	20.83	69.58	32.08	69.58
SOIL-47	52.21	78.94	68.19	80.32
SPORTS	9.40 ± 0.97	9.75 ± 1.10	9.22 ± 1.19	9.95 ± 0.82
STOIC101	25.76	56.97	28.64	57.42
STOMATA	20.00 ± 12.73	23.64 ± 11.64	28.18 ± 8.58	20.91 ± 14.69
STONEFLY9	14.72	17.16	78.72	77.00
SUBCELLULAR	11.63 ± 2.90	15.0 ± 4.04	14.07 ± 2.52	12.91 ± 1.42
SUN397	95.07 ± 0.09	95.42 ± 0.15	95.26 ± 0.21	95.29 ± 0.11
SWELEAF	3.33 ± 0.84	11.29 ± 1.68	4.47 ± 1.32	11.67 ± 1.29
TERMINALBULB	54.87 ± 2.61	56.63 ± 1.17	54.62 ± 1.81	57.19 ± 1.20
TINYGRAZ03	55.84 ± 3.27	54.34 ± 2.05	58.32 ± 3.83	56.46 ± 3.87
TSG-60	4.08 ± 1.51	75.5 ± 2.92	3.33 ± 1.18	70.08 ± 3.32
UIUCTEX	12.32 ± 1.53	25.78 ± 1.89	13.34 ± 1.05	25.30 ± 1.40
WANG	12.0 ± 0.83	13.0 ± 1.43	23.98 ± 1.22	23.66 ± 0.77
XEROX-6	7.35 ± 2.08	11.84 ± 2.63	9.99 ± 3.19	13.67 ± 3.33
ZEBRATOXIC	4.17	7.29	8.17	7.29
ZUBUD	6.96	12.17	7.83	12.17

TABLE XI

INFLUENCE OF THE GLOBAL FEATURE REPRESENTATION FOR ET-FL: TERMINAL FREQUENCIES (TF) OR BINARY (TB), HIERARCHICAL FREQUENCY (HF) OR BINARY (HB). OTHER PARAMETERS ARE CONSTANT: $T = 10$, $k = \text{sqrt}(M)$, $n_{min} = 5000$, $N_{fs} = 1$ MILLION, 16×16 DESCRIPTORS, BEST SUBWINDOW SIZE INTERVALS.

Datasets	1	5	10	20	40
ACROSOMES	5.91 ± 0.70	3.68 ± 0.88	2.90 ± 0.68	2.92 ± 0.69	2.72 ± 0.55
AGEMAP-FAGING	6.19±1.15	4.29±1.87	4.19±1.77	3.71±1.50	3.81±2.09
ALL-IDB2	1.15±1.76	0.96±1.29	0.19±0.58	0.58±1.23	0.96±1.29
ALOI	46.41	26.54	23.03	21.96	21.05
ALOT	39.57±0.63	27.76±0.30	24.72±0.32	22.54±0.34	21.28±0.19
APOPTOSIS	8.14 ± 2.31	2.57 ± 1.67	3.71 ± 1.71	4.43 ± 2.34	4.29 ± 2.21
BINUCLEATE	4.50±5.10	5.25±3.61	1.25±2.02		2.5±2.50
BIRDS	55.03±2.22	45.8±2.16	41.23±2.85	45.03±2.88	44.0±2.72
BREAST-CANCER	13.06±2.42	7.50±1.78	7.08±3.59	6.39±3.12	9.58±3.37
BUILDINGSAB	52.43±1.92	52.04±2.15	52.09±2.83	52.15±2.42	52.76±2.14
BUTTERFLIES	49.57±3.42	42.13±2.78	39.22±2.17	40.07±1.74	38.03±3.25
BUTTERFLIES-CLEAN	20.96±1.28	16.64±1.85	15.62±2.34	14.78±1.76	15.13±1.49
CALTECH-101	80.57	75.22	72.49	71.46	71.18
CALTECH-256	92.81±0.31	90.12±0.30	88.76±0.33	88.25±0.25	87.71±0.29
C.ELEGANS	30.17±3.12	25.47±4.50	26.15±3.36	28.55±3.92	27.69±4.34
C.ELEGANS-LIVE-DEAD	3.68 ± 3.37	1.05 ± 3.16	1.58 ± 2.41	2.11 ± 2.58	1.58 ± 2.41
CHARS74K	84.18±1.30	76.59±1.55	75.34±1.50	71.45±0.77	69.68±1.36
CHO	6.46±2.46	3.23±1.45	2.31±1.24	2.46±2.09	2.77±1.79
CIFAR-10	62.27	54.98	53.24	54.76	55.69
COIL-100 nv1	28.42	24.24	23.35	23.06	21.62
CONVEX	10.92	10.32	8.96	8.13	7.41
ETH-80	22.84±7.26	19.0±7.03	16.43±5.69	15.11±5.81	15.38±7.46
EVENTS	44.85±1.72	36.90±2.22	35.17±2.41	35.42±2.11	34.08±2.04
FAMOUSLAND	77.1±2.3	70.3±2.59	69.25±3.04	68.35±3.07	67.7±2.72
FLOWERS17	42.03±2.95	36.03±2.5	33.06±2.08	33.35±1.97	31.82±3.52
FLOWERS102-CLEAN	67.92	59.48	58.01	57.38	56.62
GALAXYZOO	5.73±0.41	4.18±0.11	3.88±0.15	3.70±0.10	3.65±0.13
GTSRBCROP	45.86	33.01	28.19	23.32	21.00
HCC	18.93 ± 10.17	11.79 ± 10.66	11.79 ± 7.24	16.79 ± 8.53	15.36 ± 8.83
HEP2-ICPR2012	58.17	58.86	57.22	58.04	57.90
HPA	5.52 ± 2.55	3.14 ± 0.96	3.14 ± 1.13	2.95 ± 1.97	2.57 ± 1.65
INDOOR	89.73±0.62	86.26±0.93	84.12±0.45	83.02±0.88	81.88±1.07
IRMA2005	21.5	14.7	13.1	12.0	11.8
IRMA2006	27.70	23.10	22.80	22.90	22.40
KTH-TIPS	12.22±1.73	7.95±1.20	7.44±1.86	7.46±1.36	7.24±1.34
KTH-TIPS2	53.44±7.87	50.27±7.91	46.67±8.29	53.29±8.60	47.25±9.36
LANDUSE	32.17±1.65	22.69±1.79	21.48±1.38	17.83±2.43	17.10±0.69
LYMPHOMA	10.81±4.19	6.22±4.84	5.95±3.97	4.05±3.02	6.93±3.20
MMDALITY	33.40	26.41	23.32	21.41	20.95
MINIST	6.87	2.26	1.64	1.26	1.06
MINIST-12000	7.32	3.18	2.30	2.20	1.94
MINIST-ROTATION	29.75	17.04	12.65	10.01	8.61
MINIST-BIMG	36.89	27.69	22.10	18.19	15.55
MINIST-BRAND	25.13	12.76	9.15	7.75	6.59
MINIST-BIMG-ROT		57.31	55.38	54.81	50.06
MSTAR-S1	27.43	24.70	17.36	18.84	16.62
NATURALSCENES	51.94±0.81	41.82±0.74	40.04±1.11	39.22±0.91	38.36±0.90
NORB-UNIFORM	26.93	15.37	12.49	10.49	8.77
NORB-JITCLUTT	49.75	36.90	31.68	26.36	21.05
OLIVA	39.58±1.08	31.94±1.10	29.74±1.43	28.08±1.05	27.75±1.06
ORL	2.45±1.82	2.15±1.76	1.35±1.10	0.9±0.86	1.7±1.35
OUTEX	2.04±0.47	1.69±0.80	1.04±0.28	1.32±0.65	1.30±0.91
PFID	76.28±1.02	77.08±3.55	72.73±3.12	70.57±3.81	69.89±3.96
POLLEN	9.89±1.36	5.28±0.74	3.42±0.37	3.37±0.69	3.10±0.83
PPMI24	89.54	87.75	85.79	87.21	87.17
PUBFIG83	88.96 ± 0.94	83.01 ± 1.22	79.45 ± 0.64	77.02 ± 2.06	75.81 ± 1.36
RBC	47.16±1.67	37.17±1.14	32.95±1.82	31.65±1.25	29.14±1.03
RECT-BASIC	1.11	0.34	0.14	0.12	0.09
RECT-BIMG	22.94	21.59	22.16	20.79	17.25
RNAI	13.5±5.02	14.25±4.48	14.5±3.32	12.25±4.93	13.0±5.57
SEROUS	34.89±2.01	30.76±2.02	27.65±2.09	26.48±2.59	25.19±1.90
SHAPE1	21.9±3.33	16.2±3.82	15.4±2.69	13.6±3.61	16.3±4.03
SMEAR	12.42 ± 3.26	8.24 ± 2.96	6.26±1.91	6.15 ± 1.85	6.04 ± 1.65
SOCER	25.81±2.57	20.95±1.28	20.86±2.90	19.52±2.60	17.90±3.58
SOIL-24	42.92	17.08	20.83	29.58	20.83
SOIL-47	65.64	56.17	52.21	55.53	55.53
SPORTS	15.74±1.52	10.38±0.59	9.40±0.97	8.48±0.97	7.71±0.90
STOIC101	35.00	27.88	25.76	25.76	26.67
STOMATA	20.91 ± 10.79	27.27 ± 9.96	20.00 ± 12.73	15.45 ± 8.18	24.55 ± 14.11
STONEFLY9	21.08	15.42	14.72	15.33	14.11
SUBCELLULAR	16.98±4.60	14.30±3.33	11.63±2.90	12.79±2.49	13.84±3.31
SUN397	96.21±0.12	95.76±0.13	95.07±0.09	94.26±0.19	93.09±0.16
SWELEAF	5.71±1.11	4.16±0.63	3.33±0.84	3.92±0.33	4.77±0.72
TERMINALBULB	59.07±2.48	54.57±1.24	54.87±2.61	53.04±1.93	53.79±2.09
TINYGRAZ03	66.99±4.39	58.94±4.64	57.17±4.53	54.69±5.05	53.89±3.72
TSG-60	7.08±4.12	4.25±0.95	4.08±1.51	4.33±1.22	
UIUCTEX	16.84±1.02	12.72±1.40	12.32±1.53	12.04±1.57	11.50±1.33
WANG	15.82±1.14	11.50±1.41	12.0±0.83	11.42±1.53	11.98±1.14
XEROX-6	14.29±3.16	10.61±2.20	7.35±2.08	10.61±3.33	11.22±3.53
ZEBRATOXIC	14.58	5.21	4.17	4.17	4.17
ZUBUD	8.70	8.70	6.96	6.96	8.70

TABLE XII

INFLUENCE OF THE NUMBER OF TREES FOR ET-FL. OTHER PARAMETERS ARE CONSTANT: $k = \text{sqrt}(M)$, $n_{min} = 5000$, $N_{Is} = 1$ MILLION, 16×16 DESCRIPTORS, BEST SUBWINDOW SIZE INTERVALS, AND FREQUENCY TERMINAL IMAGE REPRESENTATION.

B. Results with simple optimizations

In the main paper, we mentioned optimizations that can improve results. We provide more details below and then report results in Table XIII using these simple optimizations. In the Table, DIFFTWOPIXNEIGH means Extremely Randomized Trees are built with node tests that threshold the difference of one pixel with one of its 8 direct neighbor (chosen randomly). Filters (nb_{fil}) means we applied nb_{fil} filters (389 in grey images, for color images filters are applied on each RGB channel so a total of 1167 filtered images) and then described subwindows by $16 \times 16 \times nb_{fil}$ intensity values corresponding to pixel values of all these filtered images. In-depth analysis and extension of these optimizations will be subject of future study.

1) *Extending parameter ranges:* A first, straightforward way, to try to improve results, is to simultaneously enlarge ensembles of trees (ie. more than 40 used in previous sections) and the number of extracted subwindows for both learning (i.e. more than 1 million training subwindows used in previous sections) and prediction. Increasing these parameters and tuning the n_{min} value in ET-FL can lead to millions of features as input of the final linear classifier that turned out to be effective for some datasets. In addition, increasing the number of random tests evaluated in each tree node could also help.

2) *Synthetic data:* Instead of simply increasing the number of extracted subwindows, augmenting the original training sets with image or subwindow variations can help to improve results. For red-blood cell recognition, right and straight angle rotated and mirrored subwindows improved recognition rates while only increasing the number of extracted training subwindows to 10 millions but without transformation did not bring improvement. Other variations such as spatially-variant blurring, or adding noise, might also be investigated, depending on the application.

3) *Normalizing random subwindow descriptors:* Normalizing the pixel value distributions within each subwindow for each RGB channel independently (by subtracting the mean and then dividing by the standard deviation) improves significantly results (compared to HSV encoding) on several datasets where strong illumination variations occur (including the traffic signs and characters recognition benchmarks).

4) *Evaluating different node tests in Extra-Trees:* More complex node tests can be implemented in decision tree nodes [68], [69], [70]. Instead of single pixel thresholding, we evaluated node tests that threshold the difference of a pixel and one of its 8 direct neighbours (chosen randomly). It improved results on various datasets, including for the recognition of traffic signs, X-Rays, and acrosomes. We hypothesize such improvement is due to the fact that tests on difference of pixel intensities allow to better capture contrast (edges) in images, enable invariance to linear intensity changes, and they also potentially reduce individual decision tree bias [71]. In future work, we are interested to evaluate if performances could be improved if the tree induction algorithm can choose tests among different test

types at each node, e.g. linear combination of neighboring pixels, which somehow generalizes the following variant.

5) *Applying filters to original images :* On a web-scale object recognition dataset, we applied various filters (linear combination of neighboring pixels to detect oriented lines and contours) and spatial pooling operations (maximum and mean statistics over 3×3 , 5×5 , 7×7 , 9×9 , 11×11 neighborhoods) to original images in each RGB color channel independently, somewhat in the same way as first filter bank layers in convolutional network approaches [72]. Then we extracted random subwindows and describe them by raw pixel intensity values from all these filtered images, then build our tree models. On that dataset it improves results very significantly while increasing the number of training subwindows extracted in the original image space to 10 millions did not bring such improvement. It also improved results on two datasets of natural scenes and X-rays, although less dramatically.

6) *Describing subwindows with statistical features:* Several approaches combine many statistical features, and let the learning algorithm select the most relevant ones for each problem (such as in [73], [74]). Combining raw pixel descriptors with the default 328 features of [74]) computed within each subwindow yields significant error rate decrease on the red-blood cell dataset, but with a very important computational burden. Alternatively, one might rely on performances of subwindow size intervals to select a priori the type of features to include: if small subwindows yields the best results then texture features might help to improve results, while shape features or pooling of local features within larger spatial regions might perform best if large subwindows yield better results. For example, on dataset of cells in immunofluorescence, small to medium subwindows perform best in our evaluations in line with the best performing method on this dataset using a descriptor that encodes spatial relations among adjacent LBP texture features. However, in the future, we seek to enable decision trees to automatically generate such kind of features by combining previous optimizations in order to improve the versatility of the method.

7) *Other sources of data:* Whenever possible, one could combine visual data with other sources of information, such as textual data, or spectral data invisible to the human eye. In [75], we obtained on the dataset of biomedical imaging modalities a significant improvement by combining ET-FL with bags of textual terms extracted from image descriptions. In [76], we used hyperspectral data to better detect materials in outdoor scenes. In a preliminary study on classification of protein crystallization experiments, we obtained better classification results by describing subwindows with pixels from additional images obtained by a rotating-polarizer microscope (data not shown).

TABLE XIII
ERROR RATE RESULTS USING SIMPLE OPTIMIZATIONS

Datasets	Best	Best with optimizations	Description of optimizations
ACROSOMES	2.50±0.55	1.48±0.49	Align images horizontally, DIFFTWOPIXNEIGH, ET-FL
ALOT	21.28	14.32	10 millions training subwindows, ET-FL
CHARS74K	69.68 ± 1.36	52.10±1.44	TRGB, DIFFTWOPIXNEIGH, ET-FL, $T = 100$
CIFAR10	46.33	25.69	Filters (1167), $T=750$, $k=1$, ET-FL
GTSRB	18.73	1.19	10 million training subwindows, TRGB, DIFFTWOPIXNEIGH, $T = 100$, $k = 28$, $n_{min} = 10000$, ET-FL
HEP2	56.95	43.5	8,6 million training subwindows (15%-45% size intervals + rotation + mirroring), TRGB, $T = 80$, $n_{min} = 6000$, $k = 28$, DIFFTWOPIXNEIGH, ET-FL
IRMA-2005	11.3	5.90	Filters (190), DIFFTWOPIXNEIGH, 5 million training subwindows, $T = 100$, $n_{min} = 25000$, ET-FL
IRMA-2006	22.2	14.80	10 million training subwindows, DIFFTWOPIXNEIGH, $T = 100$, $n_{min} = 10000$, ET-FL
LANDUSE	16.74±1.53	13.31±1.60	10 million training subwindows, $T = 100$, $k = 1$, $n_{min} = 50000$, ET-FL
MMODALITY	20.95	10.00	ET-FL, Combination with bags of textual descriptions [75]
NATURALSCENES	38.36±0.90	31.35 ± 0.41	Filters (389), 150000 training subwindows, $T = 100$, $k = 28$, $n_{min} = 1000$, ET-FL
NORB-JITTCLUTT	18.57	12.94	10 million training subwindows, $T = 40$, $n_{min} = 100$, ET-FL
RBC	29.14	19.31	Subwindows described by raw pixels and WND-CHARM features (328), ET-DIC

C. Comparison with other methods

1) *Comparison with Extremely Randomized Trees on global pixel image representation:* In Table XIV we compare on several datasets (with fixed image sizes) our approach to the direct application of Extra-Trees without subwindow extraction, ie. where each image is represented by a single input vector encoding all its pixel values. These results show the benefits of using variants with random subwindow extraction as they clearly outperforms the global approach on datasets with variabilities such as translation (CONVEX, HPA, LANDUSE, OUTEX, RECT-BASIC), in-plane rotation (MNIST-ROTATION), and view-point changes (COIL-100). On MNIST-BIMG-ROT, increasing the number of trees with ET-DIC actually yields results comparable to ET-Global. Moreover, it has to be noted that through the optimization of ET-DIC and ET-FL parameters, one obtains very significant improvements for some datasets (e.g. 12.94% on NORB-JITTCLUTT with ET-FL, while optimizing decision trees parameters for ET-Global could not bring such improvements). Still, ET-Global is only slightly inferior on some datasets where optimal size intervals with ET-DIC and ET-FL are large (e.g. GALAXYZOO, CIFAR-10).

TABLE XIV
 COMPARISON OF ET-DIC ($T = 10$, $K = \sqrt{M}$, $n_{min} = 1$, OPTIMAL SIZE INTERVALS), ET-FL ($T = 10$, $K = \sqrt{M}$, $n_{min} = 5000$), AND EXTREMELY RANDOMIZED TREES ($T = 500$, $K = \text{sqrt}$, $n_{min} = 1$) ON GLOBAL IMAGE PIXELS ON SEVERAL DATASETS WITH FIXED-SIZE IMAGES.

Datasets	ET-DIC	ET-FL	ET-Global
APOPTOSIS	8.14 ± 2.86	3.71 ± 1.71	15.42 ± 3.55
CIFAR-10	<u>48.91</u>	<u>49.93</u>	49.13
COIL-100	<u>12.15</u>	23.35	32.61
CONVEX	<u>8.04</u>	8.96	19.67
GALAXYZOO	4.22 ± 0.17	3.88 ± 0.15	4.23 ± 0.11
LANDUSE	29.21 ± 2.57	21.48 ± 1.38	47.12 ± 3.67
HPA	6.19 ± 1.30	3.14 ± 1.13	16.29 ± 2.90
MNIST-12000	2.35	<u>1.89</u>	4.36
MNIST-ROTATION	9.78	12.65	14.48
MNIST-BIMG-ROT	61.60	57.31	<u>55.11</u>
NORB-UNIFORM	<u>5.24</u>	12.49	8.47
NORB-JITTCLUTT	43.57	<u>31.68</u>	38.90
ORL	1.1 ± 1.24	1.35 ± 1.10	1.25 ± 1.68
OUTEX	2.01 ± 0.72	1.04 ± 0.28	65.05
RECT-BASIC	<u>0.01</u>	0.14	4.59
RECT-BIMG	<u>15.78</u>	22.16	20.74
STOMATA	16.36 ± 12.06	20.00 ± 12.73	28.18 ± 14.35

2) *Comparison with baseline methods:* In Table XV we compared our results with previously published baselines on 24 datasets for which baseline results were provided once the dataset was first released. These baselines are either global approaches using various classifiers on down-scaled image versions, or approaches using orientations filters (GIST [39] and V1S [77]), or methods based on color histograms.

3) *Detailed comparisons:* Here we first provide result comparisons in our preferred field of application (bioimaging data). Then we propose comparisons on a subset of other datasets. Overall these comparisons suggest to consider our approach as a first try on new datasets as it performs better than many published methods, although obviously not reaching state-of-the-art performances on every dataset.

a) Detailed comparisons on bioimaging datasets: On ACROSOMES, we perform better (1.48%) than a neural network classifier using 20 texture features [1] that yields 3.93% error rate. On APOPTOSIS, we obtain 2.57 ± 1.67 while [6] yields 1.6% error rate by extracting 295 features, then follow an iterative process (called CARTA) that involves a human user in order to apply a genetic algorithm for feature selection, and finally use a SVM classifier. On STOMATA, [6] states that the original CARTA features were not sufficient so they included 130 additional rotation-invariant features to better separate the two classes into different cluster regions, but no final classification rate is provided. On the HPA dataset, we obtain 2.38% error rate while [28] evaluated 6 approaches and obtain between 33.40% (using GLCM features and a SVM classifier) down to 10% (using hundreds of features from CHARM [74] combined with PCA and LDA). On SMEAR we perform better than an nearest-neighbor classifier using 20 nuclear/cytoplasmic features but worse than an optimized approach using genetic algorithm to perform feature selec-

tion before applying the nearest neighbor classifier [48]. On HCC, we obtain 10.71% error rate (???) while a SVM classifier using SIFT features yields 63.93% error rate, but our approach is not as good than the best variant of [26] that uses wavelet-based covariance descriptors (published results vary from 22.1% down to 0.7%). On BINUCLEATE, C.ELEGANS, CHO, RNAi, SUBCELLULAR, TERMINALBULB, and LYMPHOMA, our ET-FL results using similar test protocols are on par with the computationally intensive WND-CHARM method [74] which computes a large set (> 1000) of features and compounds of image transforms. On AGEMAP dataset we perform much better (3.62% error rate) than WND-CHARM (51%). Additional experiments (not included) also show excellent results with our method on the two other liver gender datasets (with caloric restriction diet and ad-libitum diet) of the IICBU 2008 benchmark. During the IRMA-2005 challenge, 41 runs were submitted with error rates ranging from 73.3% down to 12.6% [30], while we now obtain 5.90% using optimizations. On IRMA-2006, 27 runs were submitted with results ranging from 31.7% (using weighted k-nearest neighbor on rescaled images of 16×16 pixels) down to 16.2% (with sparse histogram of image patches and a maximum entropy classifier) [80], while we now obtain 14.80% using optimizations. During the HEP2 ICPR 2012 challenge, 28 recognition algorithms were submitted, error rate results varied from 81.5% down to 31.5% (using SVM with descriptors that encode spatial relations among adjacent LBP features) while we obtain 43.5% error rate with optimizations and rank 9th. On RBC, our optimized 19.31% error rate is better than expected human error rate ($> 20\%$) and than various approaches using gaussian mixture densities or nearest neighbor classifiers, but less good than the best variants of [45] (using combination of gaussian mixtures and LDA, or combination of nearest neighbors with several processing steps) where results vary from 31% error rate down to 15.3%. On MMODALITY ImageCLEF 2010 challenge, our best run using optimizations yielded 10% error rate and ranked 6th among 45 runs (ranging from 88% error rate down to 6%). On ZEBRATOXIC we obtain better results than a phenotype recognition model that implements various intensity and texture descriptors and a support vector machine classifier, following the same two protocols [62]: internal cross-validation on the training set ($1.12\% \pm 1.09$ vs $2.6\% \pm 0.95$ error rate), and evaluation on an independent test set (3.12% vs 6.25% error rate).

b) Detailed comparisons on other datasets: On NORB-UNIFORM we obtain better results than a combination of Convolutional Nets and SVM [38], restricted Boltzman machines [83], and a huge convolutional network with five hidden layers and hundreds of maps per layer [84] although their result is better than ours when adding a translation and contrast-extracting layer. On NORB-JITTCLUTT, we obtain comparable results to Convolutional Network "LeNet7" but lower results than a combination of unsupervised Convolutional Nets and SVM. On MNIST variants, our results are comparable with 3 hidden layer Deep Belief Network and 3 hidden layer Stacked

TABLE XV
COMPARISON WITH BASELINE METHODS ON SEVERAL DATASETS (CH: COLOR HISTOGRAMS, NNL1/2: NEAREST NEIGHBOR WITH L1/2 NORM, MLR: MULTINOMIAL LOGISTIC REGRESSION, SVM: SUPPORT VECTOR MACHINES).

Datasets	Our best error rate	Baseline error rate	Baseline method
CALTECH-101	69.74±	42.45±0.74	VIS [77]
CALTECH-256	87.71±	92.4±0.7 / 76	NNL1 / VIS [77]
CIFAR-10	25.69	58.87 / 45.3	MLR on 32 × 32 / Gist [78]
COIL-100	12.0	> 34.69	NNL1 [79]
CONVEX	7.41	19.13	SVM RBF [18]
INDOOR	81.88±1.07	79	Gist + RBF SVM [29]
IRMA2005	5.90	22.8	NNL2 on 32 × 32 [30]
IRMA2006	14.80	32.1	NNL2 on 32 × 32 [80]
LANDUSE	13.31±1.60	18.81	CH (HLS) [81]
MNIST	1.06	5.0	NNL2 on 28 × 28 [35]
MNIST-12000	1.89	3.03	SVM RBF on 28 × 28 [18]
MNIST-ROTATION	8.14	11.11	SVM RBF on 28 × 28 [18]
MNIST-BIMG	15.55	22.61	SVM RBF on 28 × 28 [18]
MNIST-BRAND	6.59	14.58	SVM RBF on 28 × 28 [18]
MNIST-BIMG-ROT	50.06	55.18	SVM RBF on 28 × 28 [18]
NORB-UNIFORM	5.13	18.4 / 11.6	NNL2 / SVM Gaussian on 32 × 32 [38]
NORB-JITTCLUTT	12.94	43.3	SVM Gaussian on 108 × 108 [38]
OLIVA	26.42	17.3	Gist [39]
PFID	69.56	88.7	CH [42]
RECT-BASIC	0.01	2.15	SVM RBF [18]
RECT-BIMG	14.91	24.04	SVM RBF [18]
SUN-397	93.54	94.5 / 91.8 / 83.7	Tinyimages / CH / Gist [55]
WANG	10.04	47.2 / 16.9	NNL2 32 × 32 / CH [82]
ZUBUD	3.48	27.0 / 7.8	NNL2 32 × 32 / CH [82]

Autoassociator Network [18], but lesser than the best results on the regular MNIST benchmark. On SPORTS, our ET-DIC and ET-FL results (less than 10% misclassification error rate and average class error rate) are much better than the bag-of-features model (about 55% average class error rate) used in [50] (using a combination of DoG, MSER, and affine-Harris detectors, SIFT descriptor, K-means clustering, and a linear SVM classifier) and also compared to their specific method using various types of features and selective hidden random field (about 35% average class error rate), a result probably explained by the fact that they discard too much information (color information is not used in their bag-of-feature model, and their specific method only computes a few color features for super-pixels). On SWELEAF, our results are slightly better than an extension of shape contexts with inner-distance and matching with dynamic programming [85] and much better than the original work using specifically designed features and neural networks [56]. We obtain better results than the local affine frame method [86] using only one training view on COIL-100, and we tied on SOIL-24 (perfect recognition). We are slightly inferior on ZUBUD (4 misclassified images while they obtain perfect classification when they represent local appearance by low-frequency coefficients of the discrete cosine transformation) on which several other methods perform worst (results range from 59% error rate by the first published method [87] down to 0%). On CHARS74KEIMG, we obtain better results than nearest neighbors and SVM approaches using SIFT, Spin images, MR8 descriptors, Shape Contexts and a commercial OCR system, results on par with nearest neighbors

and Geometric Blur descriptors [14] but slightly inferior results than SVM and a combination of all descriptors. On PFID, we obtain significantly better results than a bag of SIFT features + SVM, and our results are on par with a specific method using pixel segmentation combined with statistics of pairwise local features [42]. On the recent GTSRB dataset, our results with optimizations (98.81%) are better than combining histograms of oriented with LDA (95.68%) and random forests (96.14%), slightly better than multi-scale convolutional neural networks (98.31%), comparable to human performance (98.84%), but slightly inferior to a committee of large convolutional neural networks (99.46%) [25]. On several other datasets (KTH-TIPS, UIUCTEX, XEROX6), we obtain with ET-FL results competitive with other approaches where various interest point detectors, invariant descriptors, and SVM kernels were combined and optimized [88], and for the two texture datasets we obtain better results than other methods specifically designed for texture classification cited in [88] although not reaching the state of the art. On EVENTS, ET-DIC and ET-FL are slightly better than the “scene only” model of [20] (ie. a dense grid sampling scheme, the use of rotation invariant SIFT descriptor to represent patches as well as some geometry/layout information, and K-Means clustering). On SHAPE1, our classification accuracy results are competitive with a localized bag-of-features model using shape features [47]. On LANDUSE, we obtain significantly better results (86.69% recognition rate) than variants of spatial pyramid image representations involving co-occurrence of visual words obtained by K-means clustering of SIFT features (77.38% recogni-

tion rate) [33], and than simpler HSL color histograms (81.19%) [81]. On some other problems (such as BIRDS, BUTTERFLIES, CALTECH-101, CALTECH-256, CIFAR-10, EVENTS, FLOWERS102-CLEAN, INDOOR, KTH-TIPS2, NATURALSCENES, PUBFIG83, SUN397) our results using raw pixel values from original images are significantly inferior than more elaborated approaches, e.g. architectures that combine various steps of normalization, filtering and spatial pooling ([37], [89], [29], [55], [84]), or methods combining numerous image descriptors [73]. Our optimizations improve performances as discussed in main text but still do not yield state-of-the-art recognition rates.

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