

Data Enrichment in Fine-Grained Classification of Aquatic Macroinvertebrates

Jenni Raitoharju*, Ekaterina Riabchenko*, **Kristian Meissner**[†], Iftikhar Ahmad*, Alexandros Iosifidis*, Moncef Gabbouj* and Serkan Kiranyaz[§]

*Dept. of Signal Processing, Tampere University of Technology, Finland

[†]**Fresh Water Centre, Finnish Environment Institute SYKE, Jyväskylä, Finland**

[§]Department of Electrical Engineering, Qatar University, Doha, Qatar



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What is the need for “bug” identification?



- Used as indicators in mandatory aquatic biomonitoring (e.g. EU-WFD / MSD)
- High number of taxa to be identified (classes)
- Lot of human expert cost/time needed to classify
- Less human experts available
- Biomonitoring currently suffers from budget cuts

Image Classification

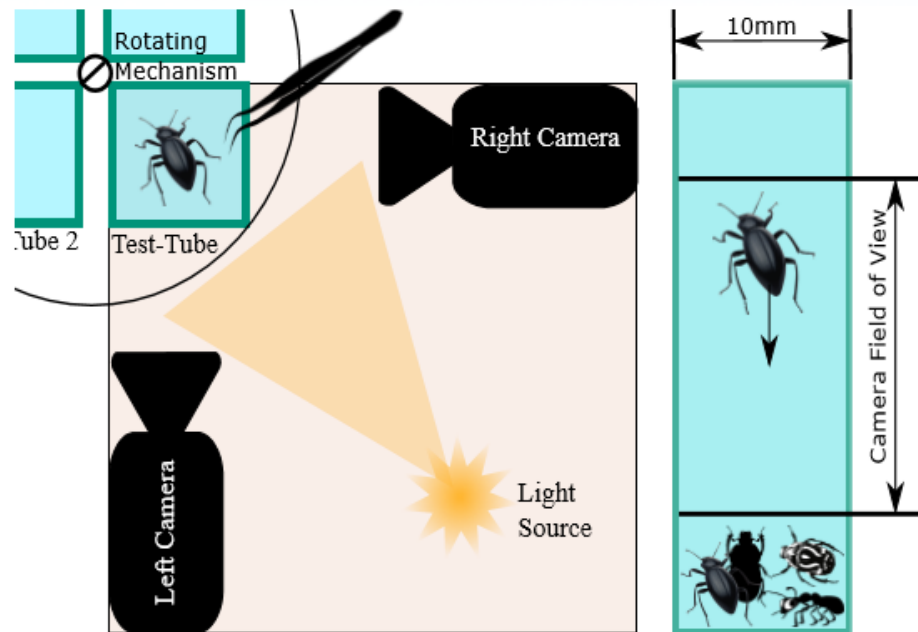
- The standard image classification pipeline is based on engineered features, e.g. SIFT, HOG, etc.
- Baseline image classification for the approach using engineered features:
 - Image description
 - Image representation
 - Image classification

Image Classification using Deep Nets

- Combined model for:
 - Image description
 - Image representation
 - Image classification
- The parameters of all processing steps are optimized for the specific task at hand

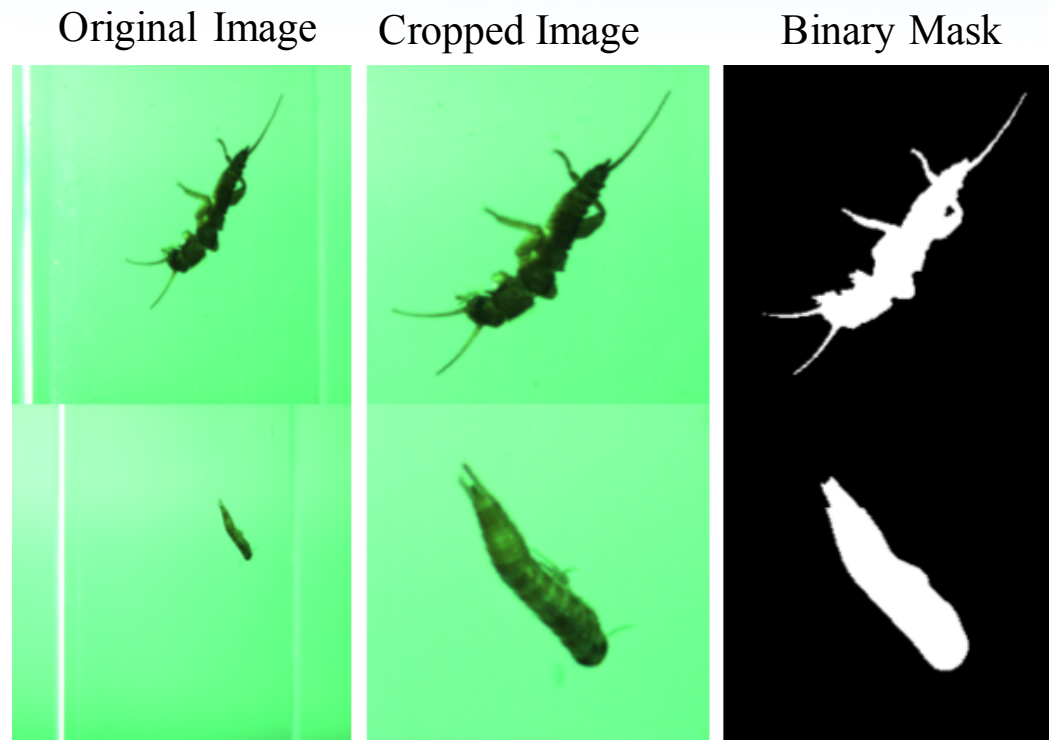
Experimental Setup

➤ Data collection



Experimental Setup

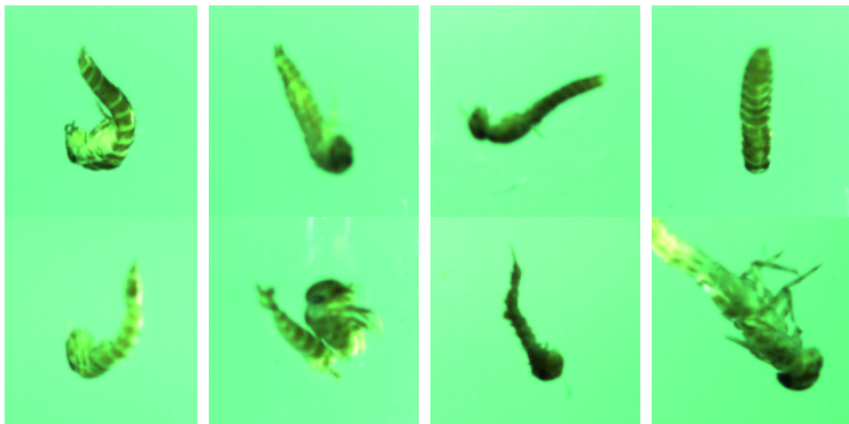
➤ Pre-processing



Experimental Setup

- Multi-class classification:
 - 29 classes
- Challenges:
 - High intra-class variations
 - Low inter-class variations

Class 5

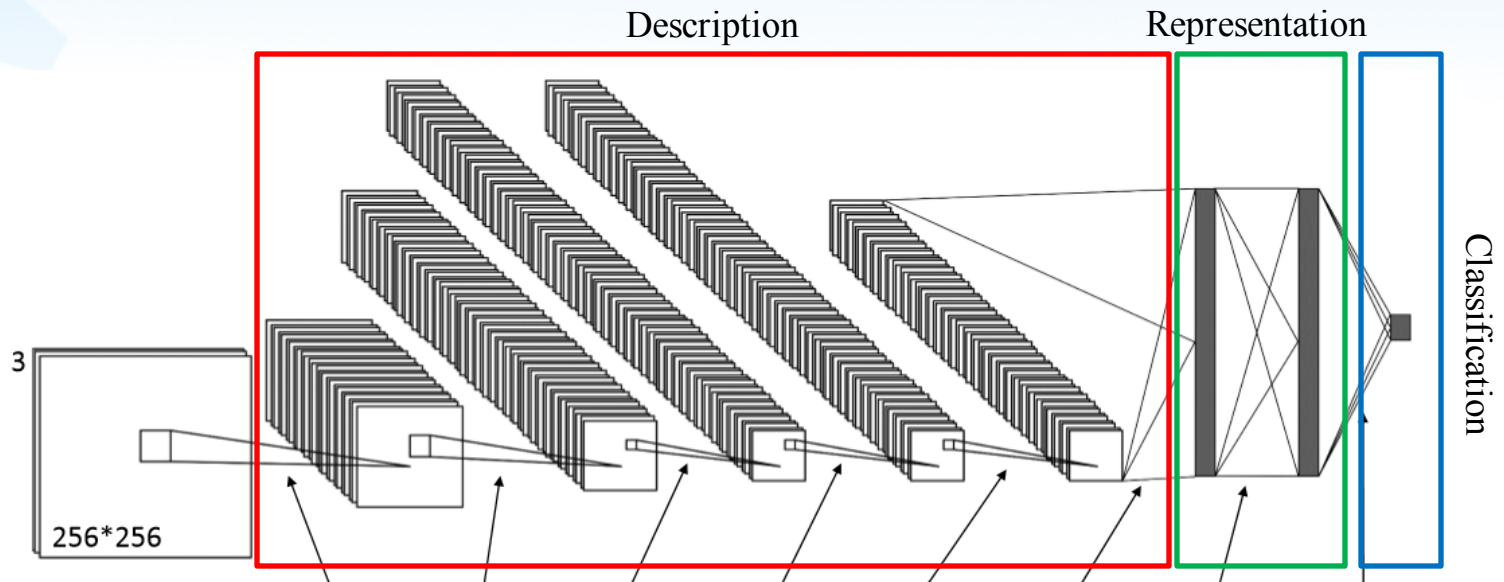


Class 1

#	Macroinvertebrate taxon	Orig. no. of images
1	<i>Ameletus inopinatus</i>	343
2	<i>Asellus aquaticus</i>	447
3	<i>Atherix ibis</i>	230
5	<i>Baetis niger</i>	455
4	<i>Baetis rhodani</i>	468
6	Ceratopogonidae	322
7	<i>Dicranota</i> sp.	367
8	<i>Elmis aenea</i>	468
9	<i>Elmis aenea</i> adult	378
10	<i>Ephemerella aroni (aurivillii)</i>	577
11	<i>Habrophlebia</i> sp.	458
12	<i>Hemerodromia</i> sp.	280
13	<i>Heptagenia dalecarlica</i>	409
14	<i>Hydraena</i> adult	436
15	<i>Isoperla</i> sp.	460
16	<i>Itytrichia lamellaris</i>	428
17	<i>Leptophlebia</i> sp.	480
18	<i>Leuctra</i> sp.	378
19	<i>Limnius volckmari</i> adult	395
20	<i>Micrasema gelidum</i>	417
21	<i>Micrasema setiferum</i>	372
22	<i>Nemoura</i> sp.	414
23	<i>Oulimnius tuberculatus</i>	465
24	<i>Oxyethira</i> sp.	438
25	<i>Philopotamus montanus</i>	330
26	Psychodiidae	408
27	<i>Protonemura</i> sp.	387
28	Simuliidae	418
29	<i>Taeniopteryx nebulosa</i>	404

Image Classification using Deep Nets

➤ AlexNet model



	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5	Layer 6	Layer 7	Layer 8
Type	conv+max+norm	conv+max+norm	conv	conv	conv+max	fully connected	fully connected	fully connected
Channels	96	256	384	384	256	4096	4096	29
Filter size	11x11	5x5	3x3	3x3	3x3			
Input size	227*227	55*55	27*27	13*13	13*13			

Data enrichment

- Data enrichment approaches have been shown to enhance the performance of classification schemes due to:
 - They provide examples that might appear in the evaluation phase
 - They provide a larger dataset that can be used in order to better estimate the parameters of the classification model (especially in neural networks having an enormous number of parameters)

Data enrichment

- We have used two types of enrichment:
 - Horizontal and vertical flipping
 - Rotation with random angles



#	Macroinvertebrate taxon	Orig. no. of images	Expansion factor
1	<i>Ameletus inopinatus</i>	343	5
2	<i>Asellus aquaticus</i>	447	4
3	<i>Atherix ibis</i>	230	8
5	<i>Baetis niger</i>	455	4
4	<i>Baetis rhodani</i>	468	4
6	Ceratopogonidae	322	5
7	<i>Dicranota</i> sp.	367	5
8	<i>Elmis aenea</i>	468	4
9	<i>Elmis aenea</i> adult	378	4
10	<i>Ephemerella aroni (aurivillii)</i>	577	3
11	<i>Habrophlebia</i> sp.	458	4
12	<i>Hemerodromia</i> sp.	280	7
13	<i>Heptagenia dalecarlica</i>	409	4
14	<i>Hydraena</i> adult	436	4
15	<i>Isoperla</i> sp.	460	4
16	<i>Itytrichia lamellaris</i>	428	4
17	<i>Leptophlebia</i> sp.	480	4
18	<i>Leuctra</i> sp.	378	5
19	<i>Limnius volckmari</i> adult	395	4
20	<i>Micrasema gelidum</i>	417	4
21	<i>Micrasema setiferum</i>	372	5
22	<i>Nemoura</i> sp.	414	4
23	<i>Oulimnius tuberculatus</i>	465	4
24	<i>Oxyethira</i> sp.	438	4
25	<i>Philopotamus montanus</i>	330	5
26	Psychodiidae	408	4
27	<i>Protonemura</i> sp.	387	5
28	Simuliidae	418	4
29	<i>Taeniopteryx nebulosa</i>	404	4

Experiments

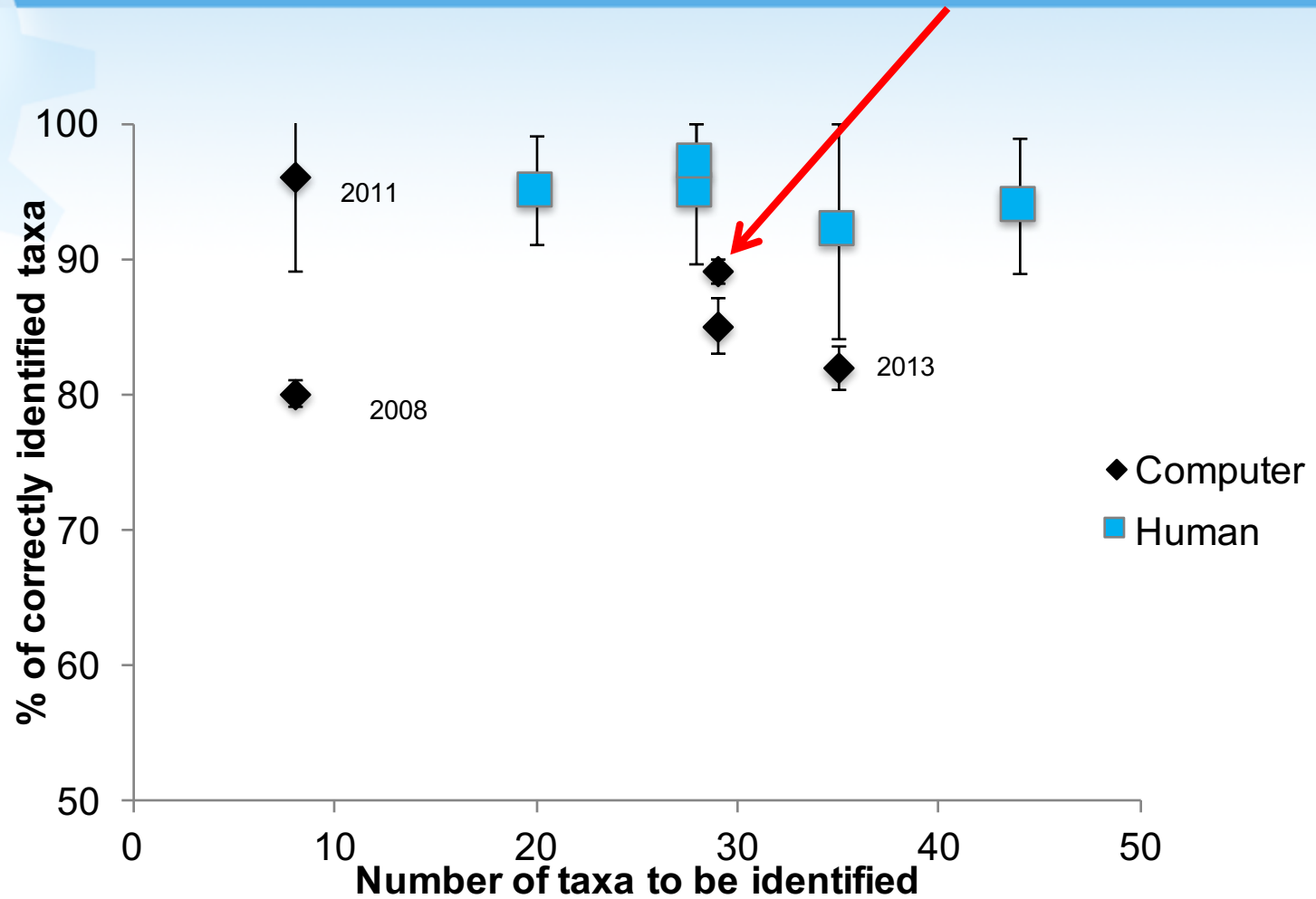
- We applied ten experiments:
 - On each experiment we split each class in 50% training, 20% validation and 30% test samples
 - We measure the performance of each method using classification rate metric
 - We report the mean classification rate and the corresponding standard deviation over all ten experiments

Experiments

➤ Results:

#	MatConvNet		Caffe		Caffe pretrained	
	orig.	enriched	orig.*	enriched	orig.*	enriched
1	81.28	84.27	77.41	79.44	85.36	88.27
2	77.58	86.95	77.47	80.98	86.35	89.04
3	80.15	86.07	75.93	80.87	86.13	87.83
4	77.19	85.53	74.56	80.43	84.76	88.65
5	81.20	85.47	79.06	82.02	86.13	88.65
6	78.56	85.53	77.69	80.48	85.42	88.27
7	79.22	85.53	76.97	78.84	86.02	88.32
8	80.92	84.81	76.70	79.99	85.47	89.09
9	76.48	84.76	76.26	80.26	84.38	87.99
10	78.84	85.31	77.69	81.47	86.40	89.31
avg	79.14	85.42	76.97	80.48	85.64	88.54
std	1.72	0.74	1.22	0.93	0.69	0.49

How do those results compare to professionals?



Summary

- Achieved error rates are acceptable and within the range of those for human experts in proficiency tests
- Data enrichment enhances performance
- Pretrained networks work better

Next step:

- 126 class data set

Thank you!

ACKNOWLEDGMENT

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