Advances in Ensemble Learning

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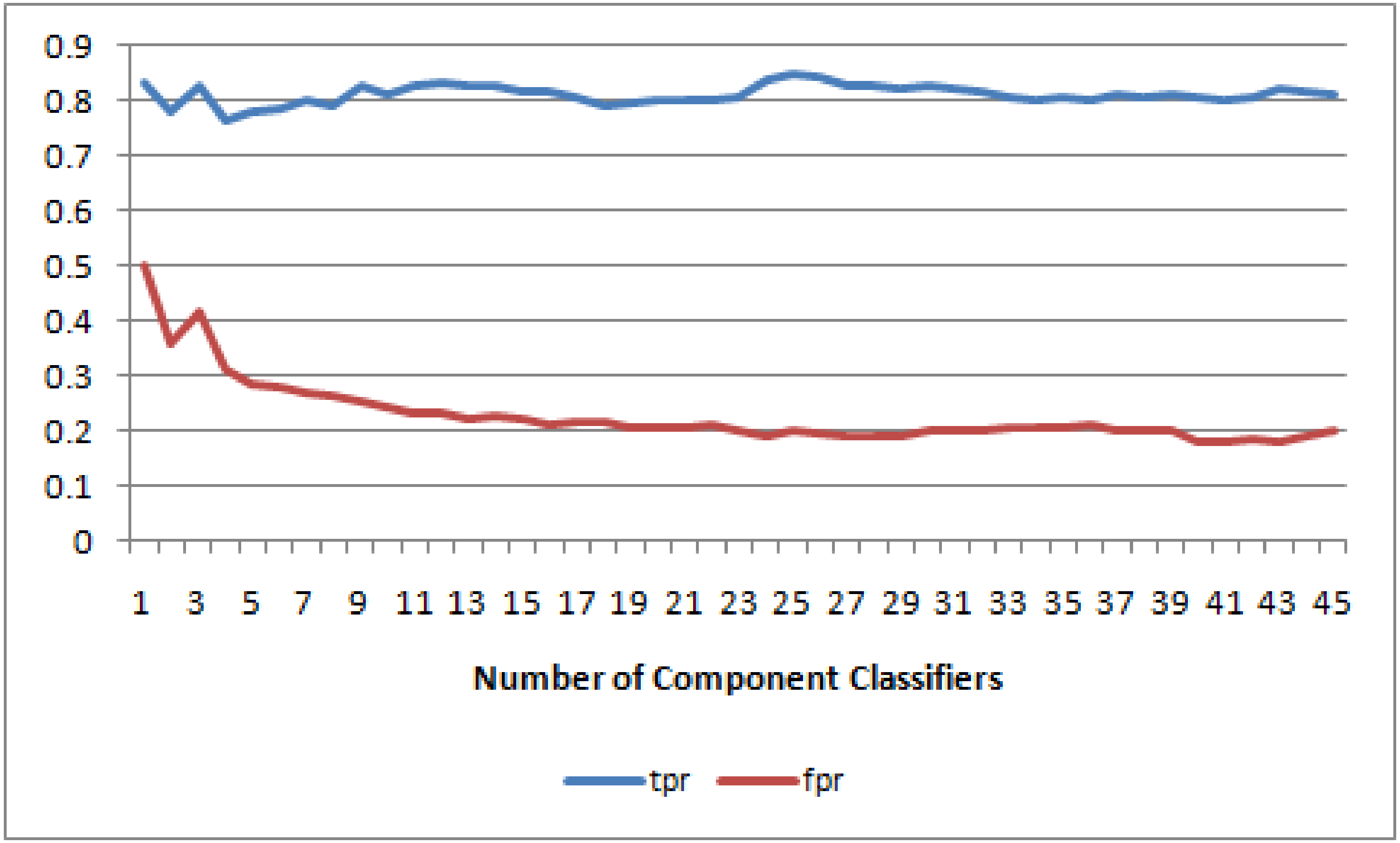
Inverse random under sampling for class imbalance problem and its application to multi-label classification

- The main idea is to severely under sample the majority class thus creating a large number of distinct training sets
- For each training set, find a decision boundary which separates the minority class from the majority class
- By combining the multiple designs through fusion, a composite boundary between the majority class and the minority class is constructed
- Significant Performance gains when applied on challenging multi-label data sets

IRUS

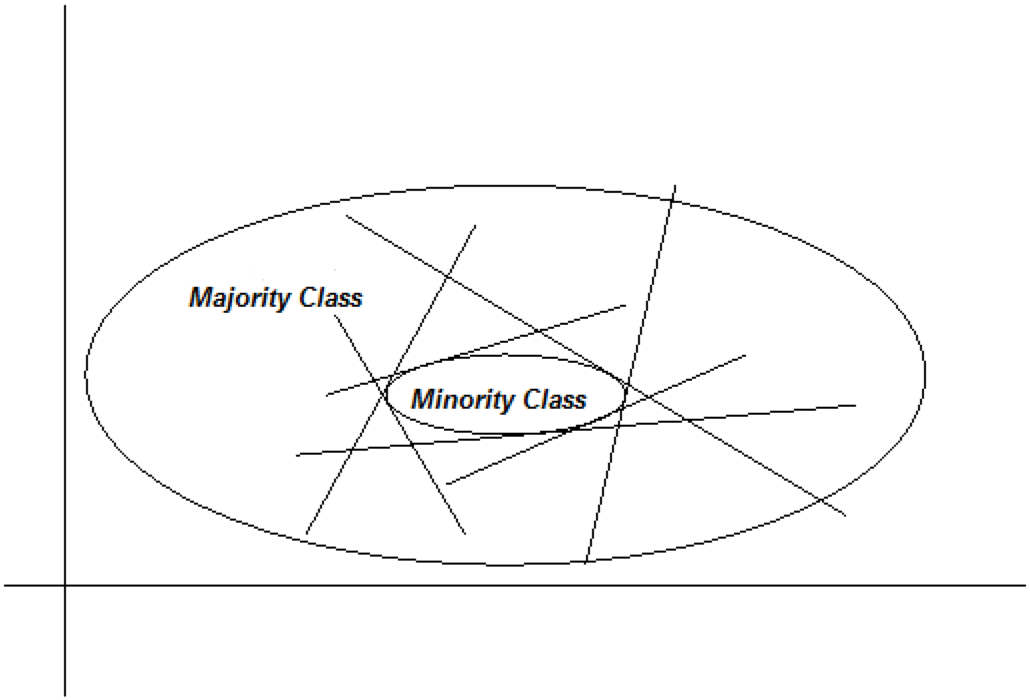
- maintain a very high true positive rate (tpr) by *imbalance inversion*
  - i.e. by making the majority class subsets have fewer examples than the minority class (positive class)
- then, control the false positive rate (fpr) by *classifier bagging*
  - i.e. by creating various subsets with each subset having all examples from the positive (minority) class and very few samples from the negative (majority) class

IRUS



0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45
Number of Component Classifiers
tpr
fpr

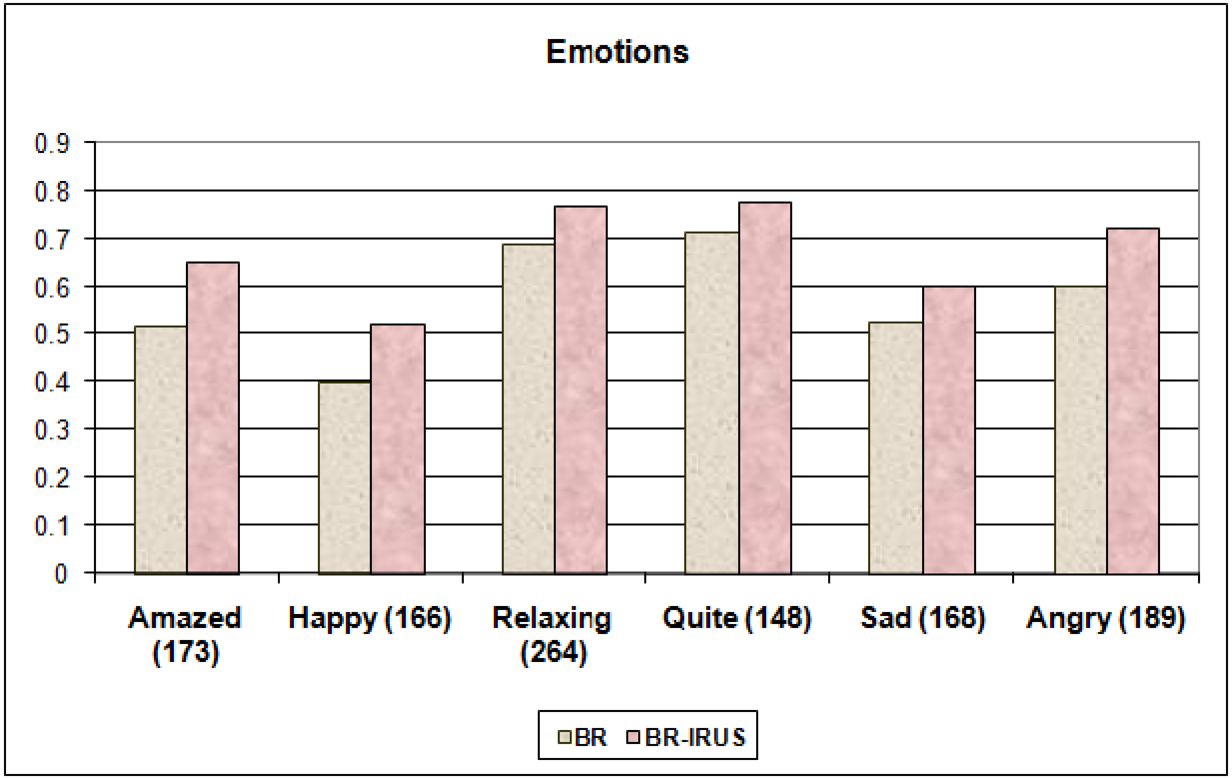
IRUS

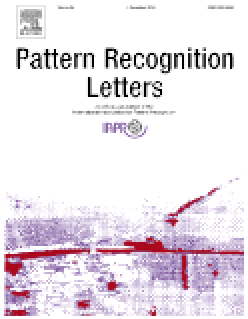


Famous Datasets

Datasets	Domain	Samples	Features	Labels	LCard
Emotions	Music	593	72	6	1.87
Scene	Vision	2407	294	6	1.07
Yeast	Biology	2417	103	14	4.24

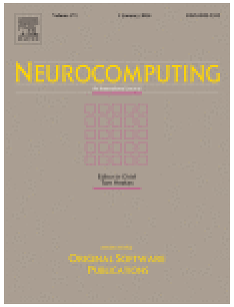
BR vs BR-IRUS (F-measure)





Multi Label classification using Heterogeneous Ensemble of Multi-label Classifiers

- The main idea is to simultaneously solve the correlation among classes and high dimensionality problems
- Use Ensemble of Multi-label Classifiers
- Individual Multi-label Classifiers to solve correlation problem while Combination of Classifiers is well known to solve dimensionality problem
- Very good performance in Image / Video Multi-label Datasets



Multi-label classification using stacked spectral kernel discriminant analysis

- The main idea is to simultaneously solve the correlation among classes problem and high dimensionality problem
- Kernel Discriminant Analysis using Spectral Regression for Dimensionality Reduction
- Stacking for finding correlation among classes
- Very good performance in Image / Video Multi-label Datasets

IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE

Multiscale local phase quantization for robust component-based face recognition using kernel fusion of multiple descriptors

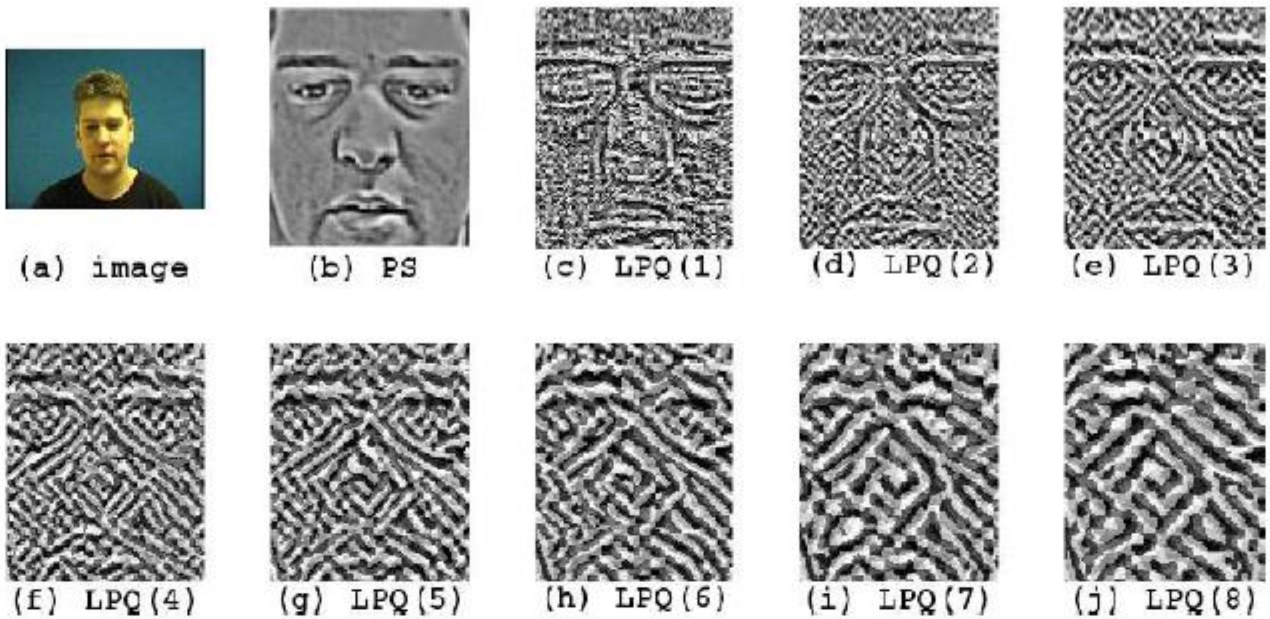


Fig. 2: a) original image, b) cropped and normalised face image, c-k) LPQ image at different scales.

IEEE TRANSACTIONS ON
INFORMATION FORENSICS
AND SECURITY

Dissimilarity Gaussian mixture models for efficient offline handwritten text-independent identification using SIFT and RootSIFT descriptors

- Writer Identification Problem through written text
- Solution of Writer Independent Task
- Combination of SIFT and ROOTSIFT Descriptors

Flood Classification using Image and Social Media Data

- Social Media Images can be effectively used for the detection of flooding events

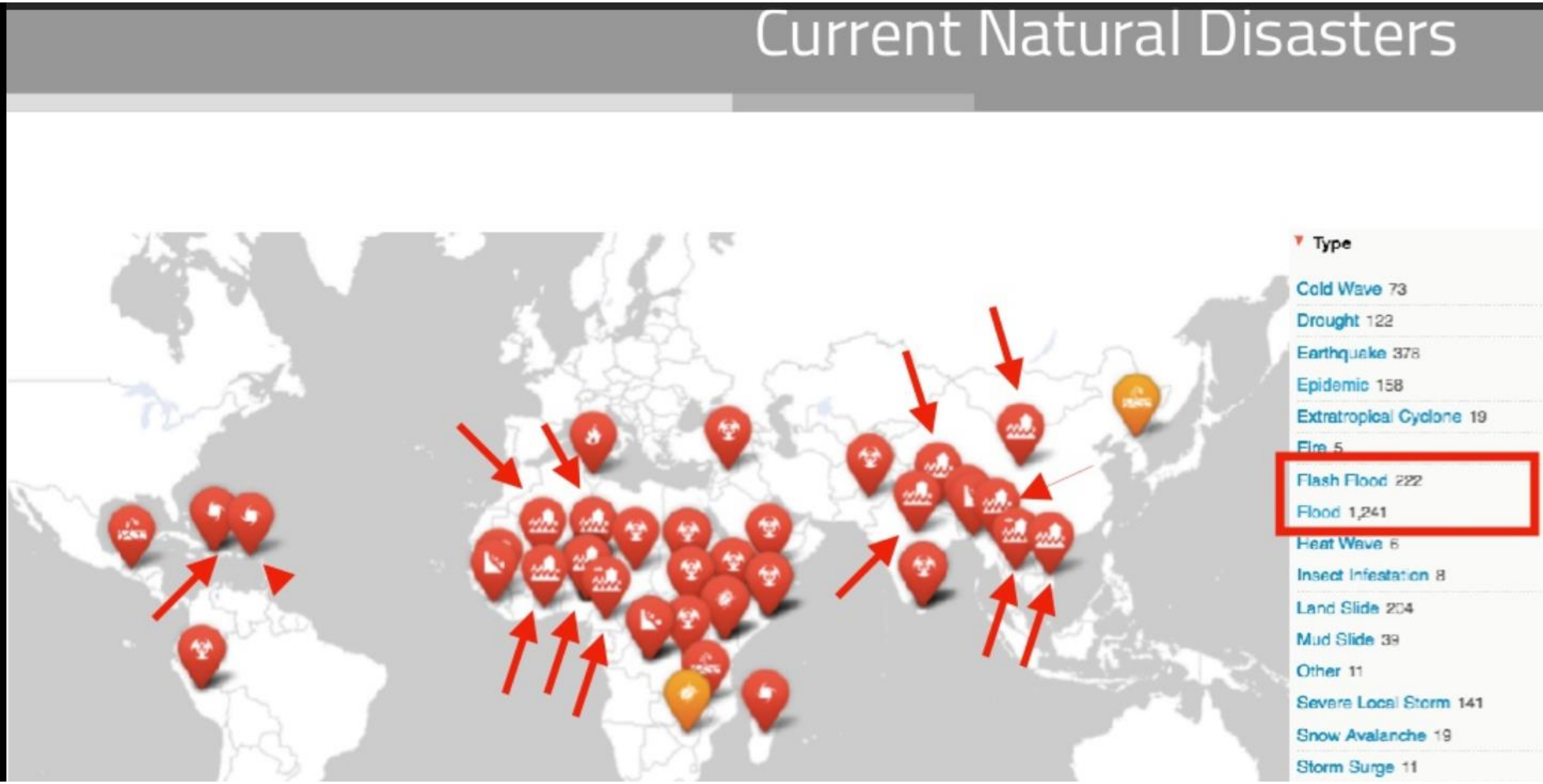



- Social Media Text for detection of flooding situation

Flood Classification using Image and Social Media Data

- Ensemble of Social Media Text and images can be effective for flood detection

MediaEval 2017 Competition (Emergency Response for Flooding Events)

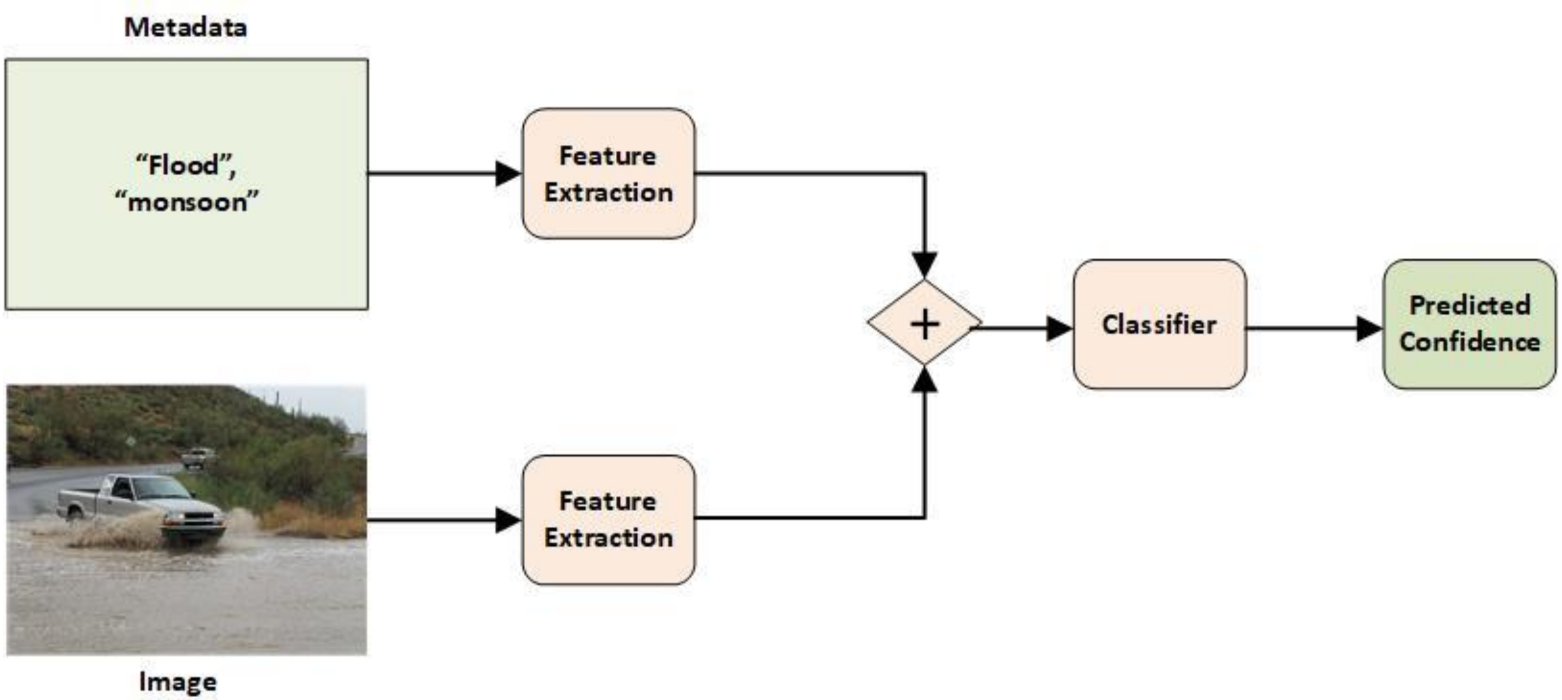


Source: MediaEval 2017 - Satellite Task: The Multimedia Satellite Task at MediaEval 2017: Emergence Response for Flooding Events (Overview)

Multimedia Satellite Task - Overview

- **Goal:** Combine Satellite Imagery with Social Multimedia
- Focus on **Flooding Events**
- Two Subtasks:
  - Disaster Image Retrieval from Social Media (DIRSM)
  - **Flood Detection in Satellite Imagery (FDSI)**

- DIRSM-Dataset:
  - 6.6k images from YFCC100M + metadata (under CC-licence)
  - Basic set of precomputed features
  - Two labels (Flooding/no Flooding)



Participants Approaches - DIRSM

- Many different approaches!
- Features:
  - Visual Features (CNN Features, Basic Features)
  - Metadata (Word Embeddings, BoW of text, title, tags)

- Classifiers:
  - Convolutional Neural Networks, Relation Networks, LSTMs
  - SVM, Random Forests, Logistic Regression
- Late-Fusion vs. Early Fusion
- Additional Data-Sources (DBPedia-Spotlight, YFCC100M)
- Spectral Regression based Kernel Discriminant Analysis

Results - DIRSM - Mean over AP@[50, 100, 150, 240, 480]

	Visual	Metadata	Visual + Metadata	Open run	Open run
MultiBrasil	87.88	62.53	85.63	91.59	41.13
WISC	62.75	74.37	80.87	81.61	81.99
CERTH-ITI	92.27	39.90	83.37	-	-
BMC	19.69	12.46	11.93	11.89	11.79
UTAOS	95.11	31.45	68.12	89.77	82.68
RU-DS	64.70	**75.74**	85.43	-	-
B-CVC	70.16	66.38	83.96	75.96	-
ELEDIA@UTB	87.87	57.12	90.39	**97.36**	-
MRLDCSE	**95.73**	18.23	**92.55**	-	-
FAST-NU-DS	80.98	71.79	80.84	-	-
DFKI	95.71	77.64	97.40	64.50	-

Experimental Results and Evaluation (2018)

- AP@480, for binary classification of flood or no-flood images

Visual Features	Meta-data	Ensemble
0.649	0.650	0.646

- Results for Detection of road and its pass-ability status

Description	F1 Score (Road Evidence)	Avg. F1 Score (Road Evidence & Pass-ability)
Visual Features	74.28%	45.04%
Text	58.30%	31.15%
Ensemble of Visual & Text	**76.61%**	45.56%

Experimental Results and Evaluation (2019)

- 2017: Ranked 8th out of 11 (Overall but 3rd in Meta-data) (No Deep Learning)
- 2018: Ranked 4th out of 9 (No Deep Learning)
- 2019: Ranked 2nd out of 11 (Use of Ensemble based Deep Learning Methods)

Papers in MediaEval 2017-2018-2019

- Flood detection using Social Media Data and Spectral Regression based Kernel Discriminant Analysis
- Detection of passable roads using ensemble of Global and Local Features
- Ensemble and Inference based Methods for Flood Severity Estimation using visual Data

Conclusion

- Ensemble Learning: Combine knowledge from different domains
- Extremely powerful and mostly improve the classification accuracy
- Various Contributions are discussed in this talk