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Active Learning for Automated Visual Inspection of Manufactured Products

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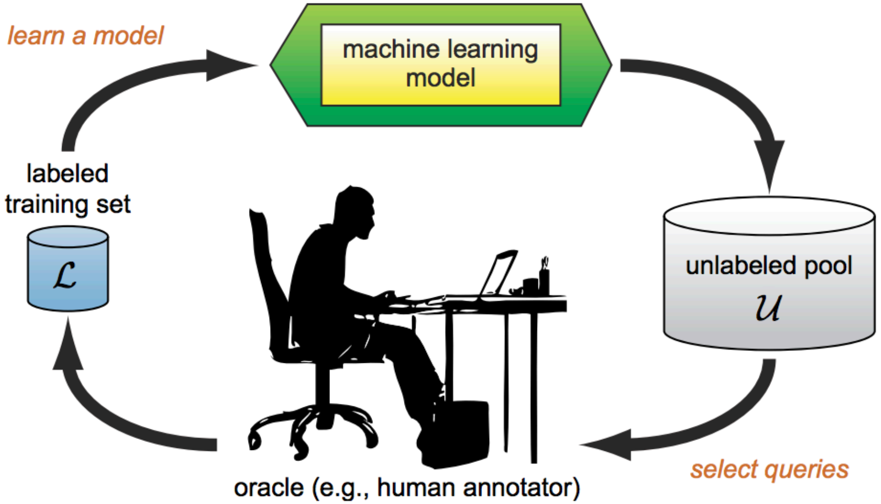
Purpose of the study

- **Automated quality control**
- **Real-world multiclass classification**
- **We compare five ML algorithms for automated defect detection** (Gaussian Näive Bayes, CART Linear SVM, MLP, and kNN)
- **We assess three active learning approaches** (stream-based classifier, pool-based sampling and pool-based sampling considering a query-by-committee strategy)

Related work

- Duan et al. : visual inspection of microdrill bits in printed circuit board production
  - Statistical features and SVM, MLP, kNN
- Gobert et al. : defect detection during metallic powder bed fusion in additive manufacturing.
  - 3D convolutional filters and SVM
- Use of labeled datasets
  - Incoming data exceeds capacity

Active learning



- Three active learning approaches:
  - **stream-based sampling**: receiving unlabeled instances one at a time, immediate decision whether to label the data or not
  - **pool-based sampling** : label most informative instances from pool of unlabeled data
  - **query-by-committee** : retrieving the unlabeled sample with the greatest variance between a set of forecasting models

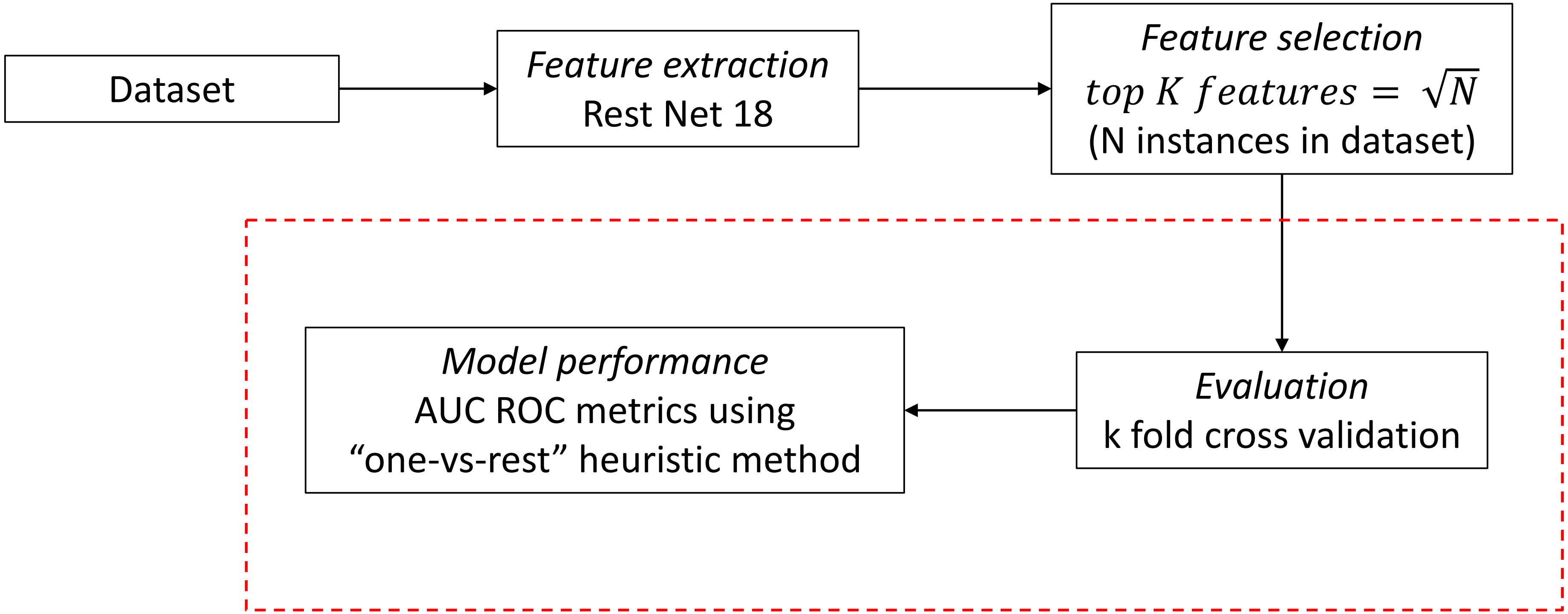
The image was taken from: SETTLES, Burr. Active learning literature survey. 2009.

Use case

- Visual inspection of shavers produced by Philips Consumer Lifestyle BV
  - detect defective printing of a logo on the shavers
- Two types of defects related to the printing quality of the logo : double printing and interrupted printing.
- Three classes of images:
  - good printing (class zero)
  - double printing (class one)
  - interrupted printing (class two)
- Limited labeled dataset

good double print interrupted print

Methodology



Three active learning approaches and five ML algorithms

Experiments

- **k fold cross validation** (k = 10)
- **Evaluate the active learning approaches**:
  - **stream-based classifier** (threshold above the 75th percentile of observed instances)
  - **pool-based sampling** selecting the instances a given model is most uncertain about
  - **pool-based sampling** considering a query-by-committee strategy
- **Metric**: AUC ROC
- **Statistical significance**: Wilcoxon signed-rank test, p value = 0.05

Results

AUC ROC values across the ten cross-validation folds

Active Learning scenario	Model	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Fold 7	Fold 8	Fold 9	Fold 10
stream-based	CART	0,8168	0,7828	0,7810	0,7694	0,8196	0,7805	0,7843	0,7970	0,8409	0,7940
	kNN	0,9289	0,9121	0,9174	0,8686	0,9024	0,9000	0,9051	0,8960	0,9282	0,9082
	MLP	**0,9900**	**0,9928**	**0,9846**	**0,9563**	**0,9804**	**0,9807**	**0,9710**	**0,9729**	0,9793	**0,9845**
	Näive Bayes	0,8818	0,8668	0,8819	0,8686	0,8829	0,8899	0,8650	0,8877	0,8864	0,9098
	SVM	0,9752	0,9828	0,9725	*0,9530*	0,9816	0,9720	0,9570	0,9412	0,9824	0,9712
pool-based	CART	0,7584	0,7904	0,7543	0,7468	0,8441	0,7730	0,8044	0,7701	0,7850	0,7412
	kNN	0,9189	0,9149	0,9161	0,8581	0,9055	0,9036	0,8961	0,8910	0,9224	0,9056
	MLP	*0,9892*	*0,9921*	*0,9845*	**0,9563**	0,9790	**0,9803**	**0,9702**	**0,9723**	0,9806	*0,9840*
	Näive Bayes	0,8800	0,8654	0,8809	0,8677	0,8813	0,8895	0,8637	0,8873	0,8850	0,9090
	SVM	0,9752	0,9819	0,9726	0,9518	*0,9806*	0,9712	0,9562	0,9412	*0,9823*	0,9722
query-by-committee		0,9774	0,9824	0,9714	0,9500	0,9723	*0,9726*	*0,9597*	*0,9571*	**0,9830**	0,9734

Results

p-values obtained for the Wilcoxon signed-rank test

Model	Active Learning scenarios		
	stream-based vs. pool-based	stream-based vs. query-by-committee	pool-based vs. query-by-committee
CART	0,0840	**0,0020**	**0,0020**
kNN	0,1309	**0,0020**	**0,0020**
MLP	0,0856	**0,0039**	**0,0039**
Näive Bayes	**0,0020**	**0,0020**	**0,0020**
SVM	0,1824	0,4316	0,6250

Conclusions and future work

- **Conclusions:**
  - Best performance : MLP model
  - No significant difference between using pool-based or stream-based active learning approaches
  - Query-by-committee performs significantly better in all cases, except for the MLPs
- **Future work:**
  - Develop data augmentation techniques
  - Seek statistically significant improvements over time for AL strategies
  - Include explainable artificial intelligence, to aid manual labeling.