

***Supervised machine learning
techniques
for the classification of
metabolic disorders
in newborns***

C. Baumgartner, C. Böhm², D.
Baumgartner, G. Marini,
K. Weinberger, B. Olgemöller, B.
Libel and A. A. Roscher

Background

- Usually blood sample that is collected during the first few days of life to screen for metabolic disorders.
- Test now simultaneously screens the concentrations of up to 50 metabolites to detect more than 20 inherited metabolic disorders .
- **The amount and complexity of the experimental data is quickly becoming unmanageable to be evaluated manually.**

Objective

- Focusing on two representative inborn errors of metabolism—
- phenylketonuria (PKU), an amino acid disorder,
- and mediumchain acyl-CoA dehydrogenase deficiency (MCADD), a fatty acid oxidation defect
- six well-established supervised machine learning techniques were evaluated to determine the ‘best’ screening model

Criteria

- discriminatory performance of the learning algorithm based on pre-classified, selected and clinically validated sub-databases of PKU and MCADD newborns.
- diagnostic prediction of constructed classifiers with optimizing sensitivity and minimizing the number of false positive results considering a large database.

Methods

Used Tandem mass spectrometry (MS/MS)

To find

- Phenylketonuria is an amino acid disorder which is caused primarily by a deficiency of phenylalanine hydroxylase
- Medium-chain acyl-CoA dehydrogenase deficiency is a fatty acid oxidation defect which leads to an accumulation of fatty acids and a decrease in cell energy metabolism.

experimental datasets were anonymously provided from the newborn screening program in Bavaria, Germany

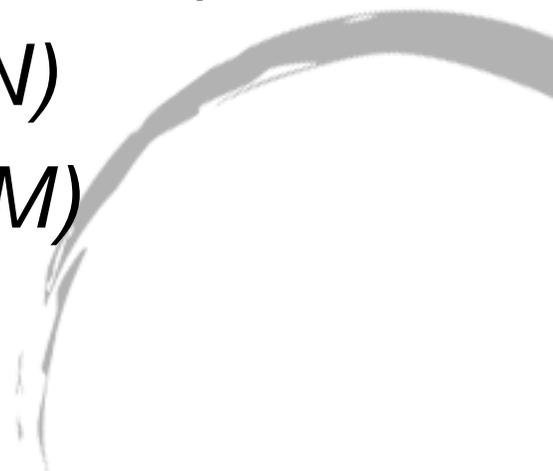
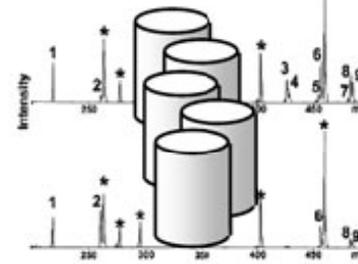
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- *Discriminate analysis (DA)*
 - *Logistic regression analysis (LRA)*
 - *Decision trees (DT)*
 - *K-nearest neighbor classifier (k-NN)*
 - *Artificial neural networks (ANN)*
 - *Support vector machines (SVM)*
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Fig 1

Anonymized NBS DB
(data collected over
several years)

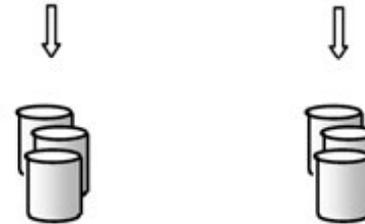
$$\chi = \{y_i, x_i\}_{i=1 \dots n}$$

$y_i \in \{2 \text{ classes}\}$
 $x_i \in \mathcal{R}^g$



Pre-selected database
of $n' = 1347$ newborns
including all PKU and
MCADD cases and a
reduced number of
randomly sampled
controls

$$\chi' = \{y_i', x_i'\}_{i=1 \dots n'}$$



Pre-selected database
of $n^* = 98411$
randomly sampled
controls

$$\chi^* = \{y_i^*, x_i^*\}_{i=1 \dots n^*}$$

Reduction of full feature
dimensionality based on
found metabolic patterns

$$\chi'' = \{y_i'', x_i''\}_{i=1 \dots n''}$$



Construction of
classification models
on mined markers by
training + X-validation

Most sensitive
screening models

Most sensitive and specific
screening model
 $f_\chi: \mathcal{R}^g \rightarrow \{\text{classes}\}$

Testing specificity
of classifiers on a
larger control database

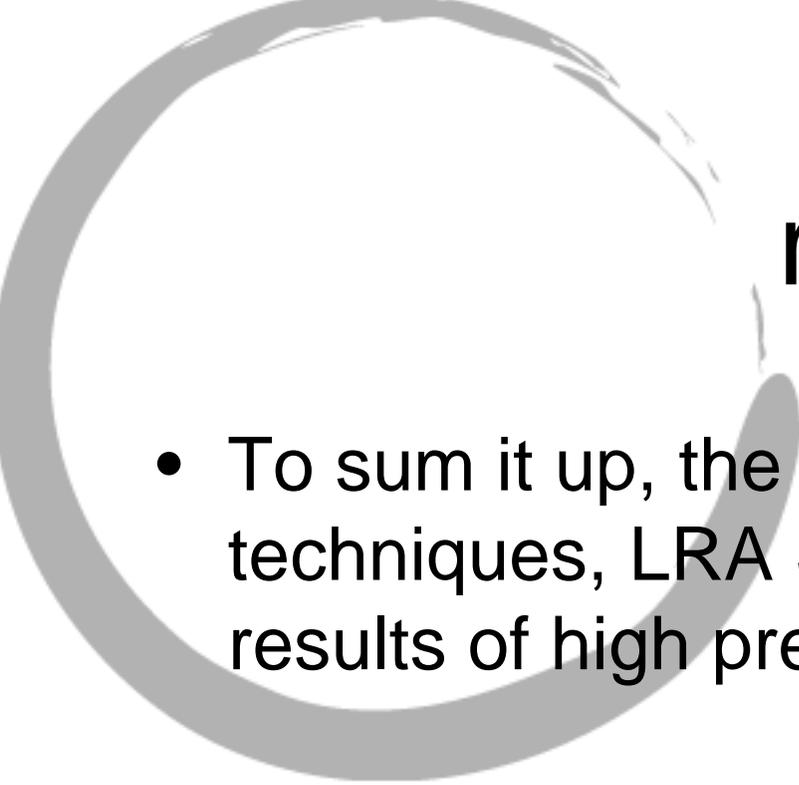
Classification result = f_χ (screened newborn)

Use WEKA

- Weka tool set and ADE-4 were used to evaluate results and perform DA and statistical analysis

Winner

- Logistic regression analysis led to superior classification rules (sensitivity >96.8%, specificity >99.98%) compared to all investigated algorithms.
- For the routine clinical screening LRA models proved particularly feasible because of their highly significant prognostic accuracy.



results

- To sum it up, the top three machine learning techniques, LRA SVM and ANN, delivered results of high predictive power
 - the DA classifier discriminated worse for both disorders
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points

- Machine learning works well in defined tasks.
- LRA and DA work in a similar manner yet one is the best one is the worst.
Lesson?
- ANN as labeled the future by many, do you think ANN will become the best