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### OBJECTIVES

This study aims to

- Develop Quantitative Structure Activity Relationship (QSAR) models for predicting skin sensitization as a binary toxicity endpoint
- Assess the performance of different modeling methods and descriptor sets
- Develop consensus models
- Assess methods for defining applicability domain (AD)

**RESULTS:** Balanced Accuracies (BA %) for the Validation Set (Using Bagging Validation of the Training Set) for the Models with the Best Performing Descriptor Sets (Mean BA > 72%)

	I THE DE	SUPERI		escriptor .	Sets (iviean	0]			
Descriptors	ANN	ASNN	KNN	LibSVM	WEKA-J48	WEKA-RF	Mean	STDEV	•
MORDRED 3D	74	76	71	76	75	75	74.5	1.9	
PaDEL	73	76	71	77	75	75	74.5	2.2	
PyDescriptor 3D	73	77	70	76	73	77	74.3	2.8	
ALogPS, Estate	73	75	70	76	74	75	73.8	2.1	•
alvaDesc 3D	72	73	70	76	79	73	73.8	3.2	•
Dragon6 3D	74	74	70	74	76	72	73.3	2.1	
SIRMS	72	72	75	74	71	76	73.3	2.0	
MOLD2	73	75	69	74	76	72	73.2	2.5	•
T.E.S.T.	74	76	69	74	74	72	73.2	2.4	
CDK2	70	74	73	74	72	71	72.3	1.6	
Mean for these descriptors	72.2	73.7	70.8	75.1	74.5	73.8	73.7	2.3	F

## APPROACH

- A local lymph node assay (LLNA) dataset of 1355 chemicals was compiled from the NICEATM LLNA Database, OECD QSAR Toolbox, and eChemPortal. Records including chemical structures were curated in EPA's DSSTox Database. ٠ Using 10 different modeling methods, models were developed in the Online ٠ Chemical Database with Modeling Environment (OCHEM) with 25 descriptor sets available in OCHEM and two additional descriptor sets: PaDEL descriptors and descriptors developed for EPA's Toxicity Estimation Software Tool (T.E.S.T.). The best-performing models were used to develop consensus models. Java code was used to automate the generation of ADs covering 95% of training set compounds using different measures of distance to model. IMPACT The best-performing modeling methods -- including Associative Neural Networks (ASNN), Support Vector Machines (SVM), WEKA-J48, and WEKA-RF -- produced validation set balanced accuracies > 75%.
- T.E.S.T. and PaDEL descriptors performed comparably to the best-performing descriptor sets in OCHEM.
- Consensus models performed better than individual models.
- The assessed AD generally did not improve the results, considering the tradeoff between balanced accuracy and prediction coverage, so other methods for defining AD should be explored.
- Models will be made publicly available in OCHEM and T.E.S.T., which will contribute to improving the performance and accessibility of new approach methodologies (NAMs) for predicting skin sensitization.

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Additional Results: Balanced Accuracies (BA %) and Applicability Domain (AD) Coverage (%) for Bagging Validation Models Used to Develop Consensus Models (ensemble standard deviation was used to assess the Distance to Model (DM))

Method	Descriptors (or	Training Set BA	Validation Set (VS)	AD based on the DM that covers 95% of the training set				
	consensus type)		BA (100% coverage)	VS BA	Coverage	Product (BA X Coverage)		
ASNN	Mordred 3D	69	76	75	95	72		
ASNN	PaDEL	70	76	75	96	72		
ASNN	PyDescriptor 3D	68	77	76	94	72		
ASNN	T.E.S.T.	69	76	76	94	71		
LibSVM	ALogPS, Estate	69	76	75	97	73		
LibSVM	alvaDesc 3D	68	76	76	97	73		
LibSVM	Mordred 3D	68	76	75	97	72		
LibSVM	PaDEL	70	77	76	97	73		
LibSVM	PyDescriptor 3D	69	76	76	97	74		
WEKA-RF	PyDescriptor 3D	70	77	79	97	76		
WEKA-RF	SRMS	71	76	76	97	73		
WEKA-J48	Dragon 6 3D	70	76	76	97	73		
WEKA-J48	Mordred 3D	69	76	76	97	74		
WEKA-J48	alvaDesc 3D	70	79	75	97	73		
Consensus	(simple average)	72	79	79	95	75		
Consensus	(optimal combination of models for each property)	72	80	79	91	72		
Consensus	(weighted by model accuracy)	72	78	79	95	75		

## Additional Results: Balanced Accuracies (BA %) for the External Validation Set

(Using Five-Fold Cross-Validation of the Training Set) for the Models with the Best Performing Descriptors (Mean BA ≥ 70%)

Descriptors	ANN	ASNN	DNN	KNN	LibSVM	LSSVMG	RFR	WEKA-J48	WEKA-RF	XGBOOST	Mean	STDEV
ALogPS, Estate	72	73	73	69	76	75	71	70	72	73	72.4	2.1
T.E.S.T.	71	77	72	69	73	77	73	65	72	75	72.4	3.6
alvaDesc (3D blocks 1-30)	75	75	72	70	74	75	75	66	72	70	72.4	3.0
PaDEL	76	76	67	72	73	77	75	60	75	72	72.3	5.2
SIRMS (labels:charge+logp+hb+refractivity)	70	70	68	70	72	77	75	69	77	75	72.3	3.4
RDKIT (3D blocks: 1-11, 15-16)	73	73	73	66	73	77	74	64	76	71	72.0	4.1
MORDRED (All) 3D	72	74	67	71	74	73	75	68	71	72	71.7	2.6
Dragon6 (3D blocks 1-29)	73	70	72	68	73	72	73	66	73	72	71.2	2.4
CDK2 (cons,topol,geom,elec,hybrid) 3D	71	69	72	71	71	75	71	64	74	72	71.0	3.0
ChemaxonDescriptors (pH 0 - 14:1) 3D	72	74	70	67	67	75	72	67	73	70	70.7	3.0
RDKIT (AVALON)	69	73	68	68	72	73	72	66	74	72	70.7	2.7
PyDescriptor 3D	68	71	72	69	69	75	74	63	75	68	70.4	3.8
MOLD2	74	76	68	70	71	72	71	58	72	70	70.2	4.8
Fragmentor (length:2 - 4)	69	70	71	65	70	73	74	67	70	71	70.0	2.6
Mean for these descriptors	71.8	72.9	70.4	68.9	72.0	74.7	73.2	65.2	73.3	71.6	71.4	2.7

Models with balanced accuracies in bold were used to develop consensus models.

ANN = Artificial Neural Network; ASNN = Associative Neural Networks; DNN = Deep Neural Network; KNN = k Nearest Neighbors; LibSVM = Grid-Search Parameter Optimization Support Vector Machine; LSSVMG = Least Squares Support Vector Machine; RFR = Random Forest; WEKA-J48 = Weka C4.5 decision trees for classification; WEKA-RF = Weka Random Forest; XGBOOST = Scalable and Flexible Gradient Boosting

# Additional Results: Usefulness of Defining the Applicability Domain (AD) Based on Different Measures of Distance to Model (DM) Covering 95% of Compounds from the Training Set for ASNN Five-fold Cross-Validation Models

Descriptors	AD Covering 100% of the Training Set	PROB-STD (95%)			CLASS-LAG (95%)			ASNI	N-STDE\	/ (95%)	ASNN-CORREL (95%)		
		VS BA	VS Cov (%)	Product	VS BA (%)	VS Cov (%)	Product	VS BA (%)	VS Cov (%)	Product	VS BA (%)	VS Cov (%)	Product
	VS BA (%)	(%)											
T.E.S.T.	77	76	95	72	76	95	72	77	91	70	76	92	70
Mold2	76	76	93	71	76	93	71	77	91	70	77	91	70
PaDEL	76	76	92	69	76	91	69	75	84	63	76	91	69

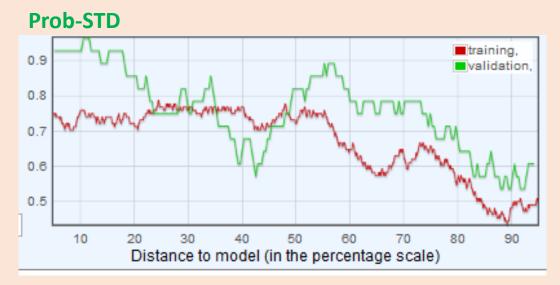
VS = Validation Set; BA = Balanced Accuracy; Cov = Coverage

Distance to Model (DM) Measures used to Calculate the Applicability Domain

- **Prob-STD:** combines information about uncertainty from CLASS-LAG and ASNN-STDEV
- **CLASS-LAG:** The absolute value of the difference between a continuous prediction value and the nearest of the binary labels [-1, 1]
- ASNN-STDEV: The sample standard deviation of an ensemble of models is used as an estimator of the model uncertainty for a given compound
- CORREL: based on the correlation of vectors of an ensemble's predictions for the target compound and compounds from the training set

Source of DM Measure definitions: Sushko et al. 2010, Applicability Domains for Classification Problems: Benchmarking of Distance to Models for Ames Mutagenicity Set, Journal of Chemical Information and Modeling 50 (12): 2094–2111. https://doi.org/10.1021/ci100253r

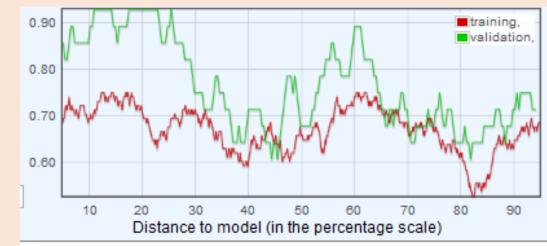
Additional Results: Accuracy vs. Four Different Measures of Distance to Model for the ASNN model developed using T.E.S.T. Descriptors and five-fold cross-validation



**CLASS-LAG** 



#### **ASNN-STDEV**



#### **ASNN-CORREL**



Graphs produced using OCHEM: https://ochem.eu/home/show.do

#### REFERENCES

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