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Towards Accelerated Design of Multi-Principal Element Alloys with Optimized Hardness and Elongation Features by an Ensemble of Neural Network

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Introduction

HEA

High Entropy Alloys

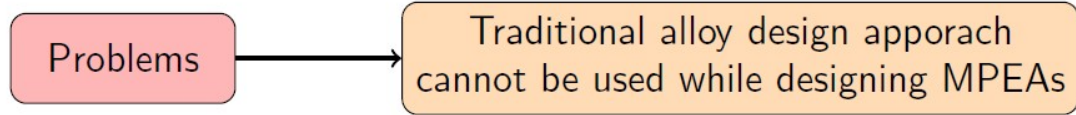
**5 or More Principal
Elements**

MEA

Medium Entropy Alloys

3 or 4 Principal Elements

Problem Statements



Literature Review

Paper	Review
[1]	Machine Learning technique to obtain new MPEAs with high hardness value in <i>Al-Co-Cr-Cu-Fe-Ni</i> alloy.
[2]	Used artificial neural network to predict the hardness of <i>AlCoCrFeMnNi</i> on 91 dataset .
[3]	Machine Learning approach to evaluate the hardness by Random forest regression on 290 Cast MPEAs .

(1)	Wen, C., Zhang, Y., Wang, C., Xue, D., Bai, Y., Antonov, S., Dai, L., Lookman, T., and Su, Y. (2019). Machine learning assisted design of high entropy alloys with desired property. <i>Acta Materialia</i> , 170:109–117.
(2)	Chang, Yao-Jen, et al. "Prediction of the composition and hardness of high-entropy alloys by machine learning." <i>Jom</i> 71.10 (2019): 3433-3442.
(3)	Xiong, J., Shi, S.-Q., and Zhang, T.-Y. (2021). Machine learning of phases and mechanical properties in complex concentrated alloys.

Research Gap



Originality of Research



Research Flow

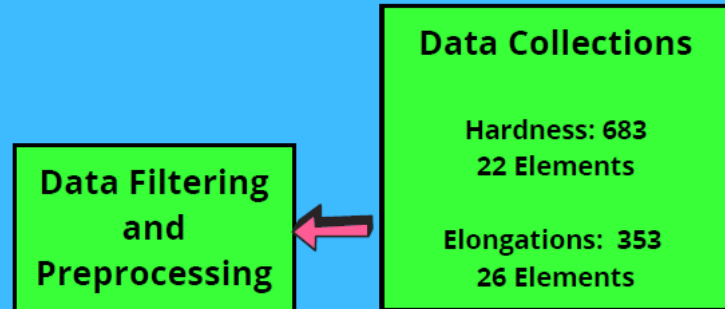
a) Datasets
of MPEA

Automatic
Featurization

(Matminer/
Pymatgen)

Properties
Calculations

Model Development



Methodology: Hyper-Parameter Tuning

Hyper-parameters
are used to
evaluate

- Weights
- Bias

SN	Hyper parameters
1	Epochs = [100, 150, 200]
2	batch size = [2,4,6]
3	layers = [4,6]
4	neuron size = [32,48,64]
5	optimizer = ['SGD','RMSprop', 'Adam', 'Nadam']
6	activation = ['relu', 'selu', 'LeakyReLU', 'PReLU']
7	loss function = [mse, msle, huberwith alpha=1.5]
8	drops = [0.05,0.075,0.08,0.1,0.15,0.2]
9	learning rate = [0.0001,0.00025,0.000375,0.0004,0.0005,0.00075,0.001,0.005,0.01]
10	Regularization : [L1,L2 & L2]
For weight initialization	
11	weight constraint = [1,2,3]
12	init weights = ['uniform', 'normal', 'he_uniform']

RandomSearchCV

**300 Hyper-Parameter
Configurations**

Model Inputs: Feature Selection Flowchart

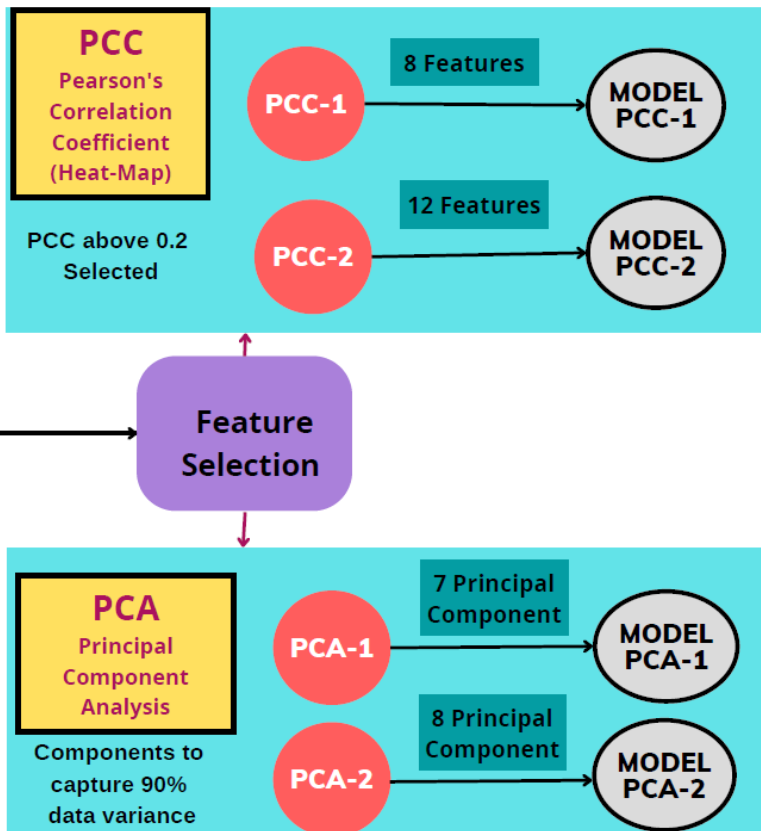
2 Feature sets from PCC
(with and without Fab
routes)

2 Feature sets from PCA
(with and without Fab
routes)

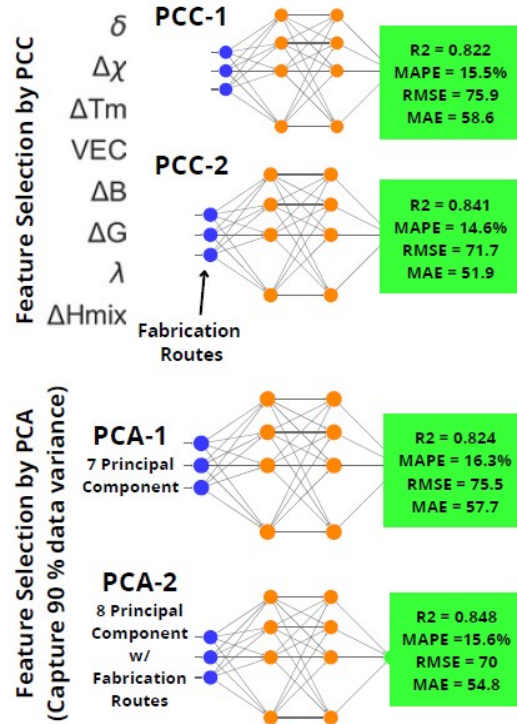
**4 Models built from 4
different feature sets**

Pool of 15 Features

1. Atomic Size Difference
2. Electronegativity
3. Melting Temp. (SD)
4. Average Melting Temp.
5. Average VEC
6. Average Atomic Number
7. Avg. Thermal Conductivity
8. Avg. Bulk Modulus
9. Bulk Modulus Assym.
10. Avg. Shear Modulus
11. Shear Modulus Assym.
12. Entropy of Mixing
13. Geometrical Parameter
14. Enthalpy of Mixing
15. Dimensionless Parameter



Results: Ensemble of 4 Models



Material Design: Approach

Medium
Entropy Alloys

(ZrHfNb)

(VNbTa)

Material Design: Significance

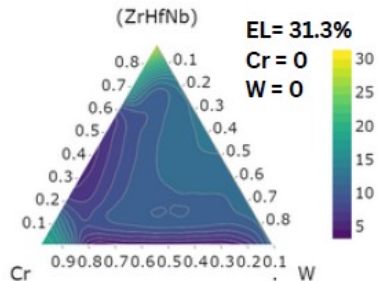
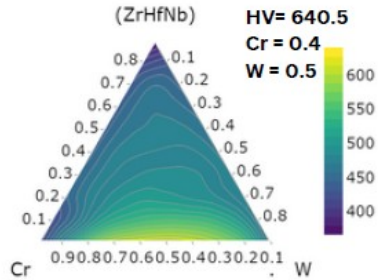
To check effect of doping, it would require fabrication of thousands of alloys physically.

Experiments can only study effect of variation of a single element.

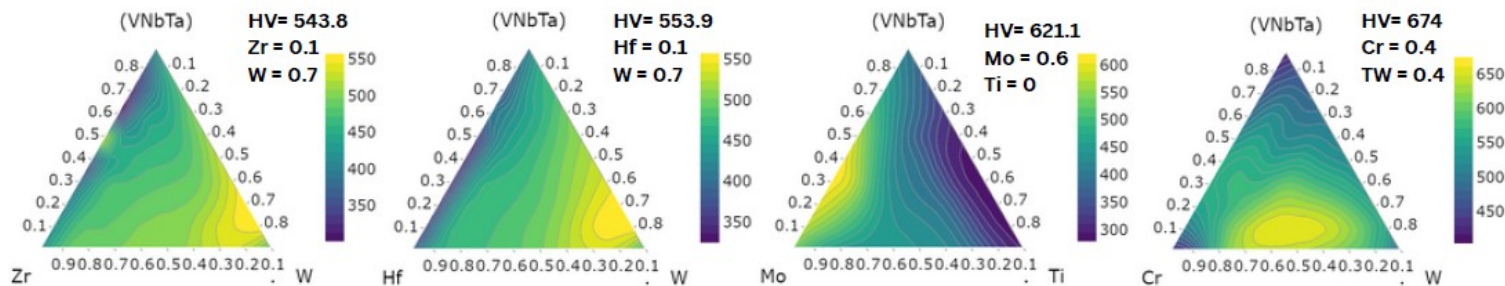
Not Possible to study the effect of two dopants in a base system.



Material Design: ZrHfNb based Alloys



Material Design: *VNbTa* based Alloys

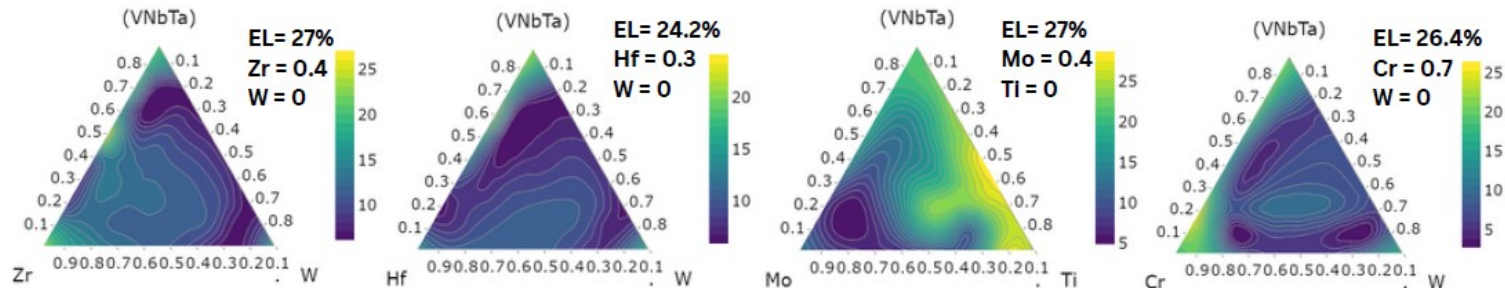


Hv = 536
EL = 27 %
Zr = 0.4
W = 0

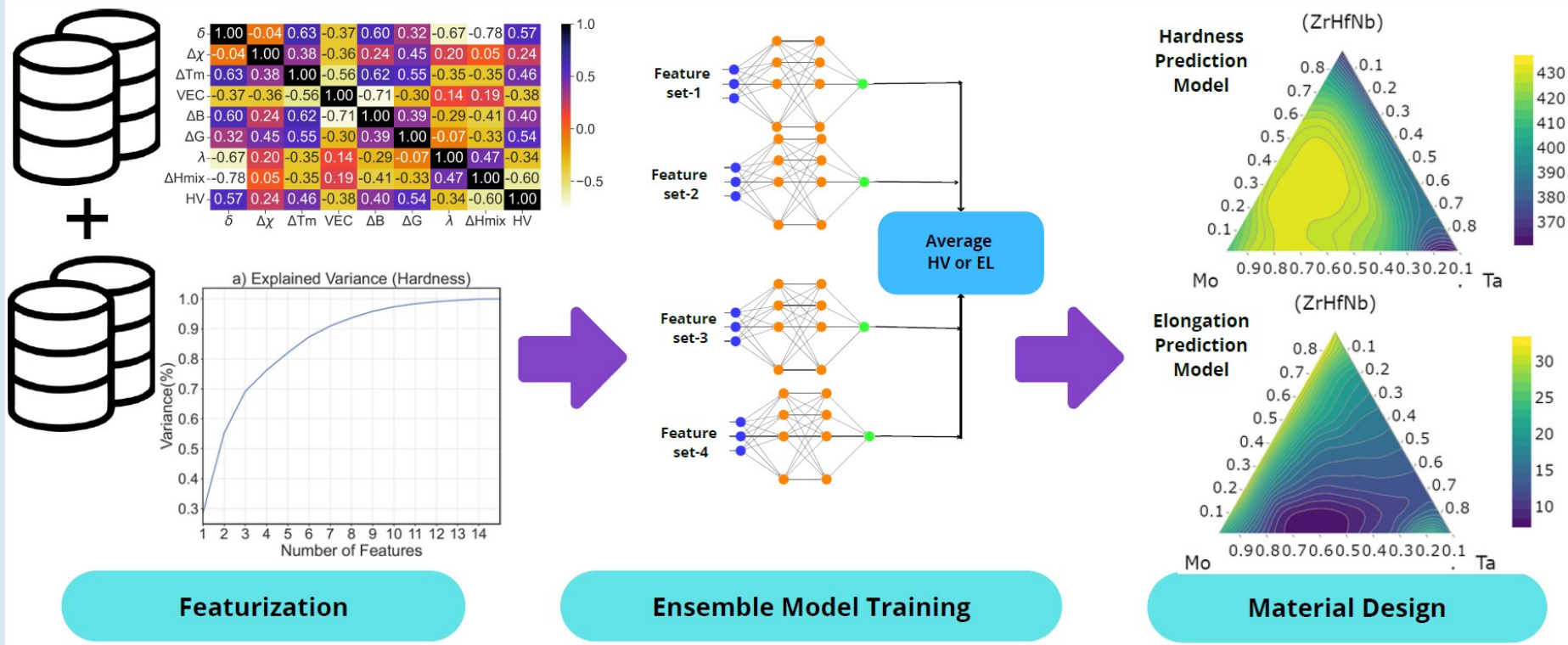
Hv = 526.4
EL = 10.9 %
Hf = 0.1
W = 0.8

Hv = 589.7
EL = 18.6 %
Mo = 0.4
Ti = 0

Hv = 563.5
EL = 20 %
Cr = 0.6
W = 0



Conclusion



Thank You

