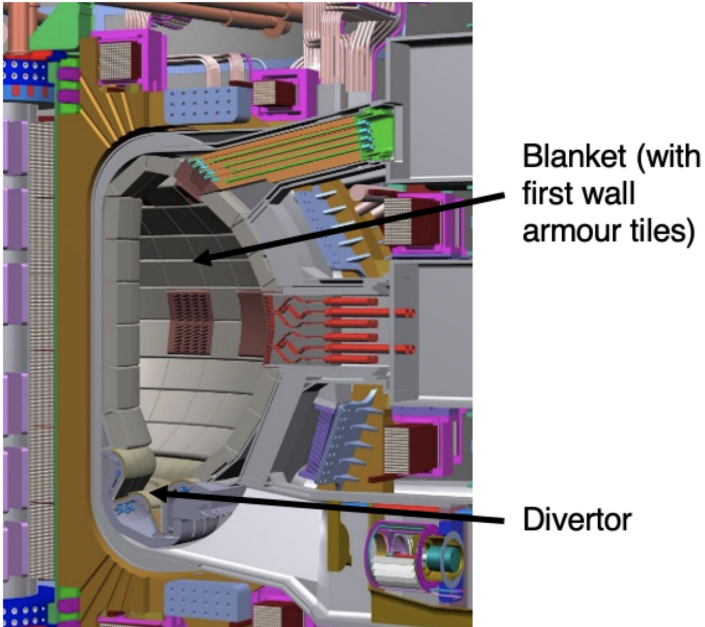


# Phase Prediction of High-Entropy Alloys

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# HEA Alloys



Unique metal alloys ideal for utilization in extreme environments due to their strength, structural stability, and resistance to corrosion and radiation

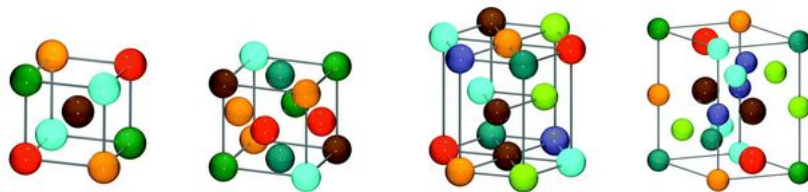
- Nuclear applications: radiation shielding

These alloys are composed of at least 5 elements with concentrations between 5 and 35 percent the atomic percentage, forming solid state solutions

# Motivation

Altering the elemental concentrations distorts the lattice structure, changing alloy resistance properties

- Can be used to an advantage
  - Achieving resistance to high temps



$\sim 10^8$  combinations of HEAs can be developed from only 64 elements in the periodic table using different weight percentages, with varying synthesis and processing routes

- Experimental process for testing characteristics is extremely time consuming
- Machine Learning models can be used to hasten the process and discover a general trend to identify alloy properties (e.g. phase prediction)

# Goals

- To be able to determine crystal structures and the properties that HEAs typically have
- Analyze and figure out techniques for better data cleaning and learning
- Optimize each model with their hyperparameters for better performance
- Benchmark against the untuned versions of each model

# Physical Parameters

Each HEA is described by a chemical composition tied to the following features:

$\Delta H_{\text{mix}}$ : Thermal Energy of the state

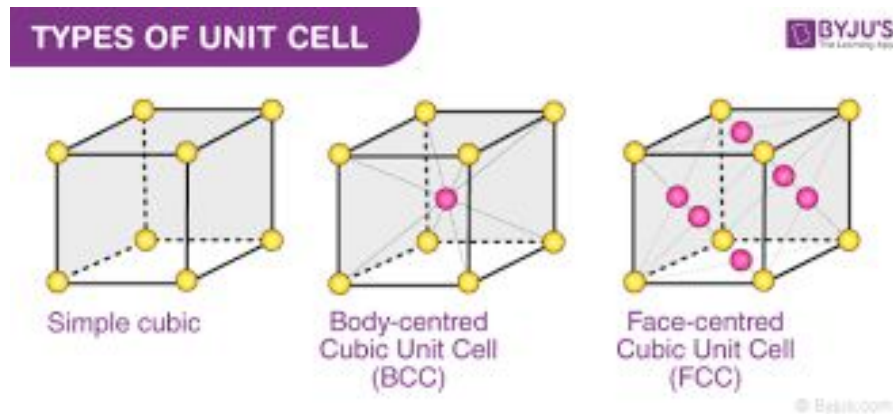
$\Delta S_{\text{mix}}$ : Deviation from perfect order of the state

$\delta$ : Atomic Size Difference

$\Delta\chi$ : General form of electron cloud

VEC: %  $e^-$  in Valence Band

Phase: FCC, BCC, IM, FCC+BCC



# Phase Determination

For a given composition, the phase is determined by the VEC value.

- BCC when  $VEC < 6.87$
- FCC when  $VEC > 8.0$
- BCC + FCC when VEC between 6.87 and 8.0

Composition	$\Delta H_{\text{mix}}$	$\Delta S_{\text{mix}}$	$\delta$	$\Delta\chi$	VEC	Phase
$\text{Al}_{0.5}\text{NbTaTiV}$	-8.395062	13.145944	3.7375048	0.0496158	4.55556	BCC
$\text{Hf}_{1.375}\text{Nb}_{0.25}\text{Ta}_{0.25}\text{Ti}_{1.75}\text{Zr}_{1.3}$ 75	0.98	11.449449	4.4954539	0.1147168	4.1	BCC
$\text{HfMo}_{0.5}\text{NbTiV}_{0.5}\text{Si}_{0.5}$	-31.11815	14.53503	9.4420482	0.2565635	4.53191	IM

# Data Set

- 1200 alloys in total
- 30 metallic elements
  - Lots of NaN values

Out[8]:

	Al	Co	Cr	Fe	Ni	Cu	Mn	Ti	V	Nb	...	Pt	Y	Pd	Au	dHmix	dSmix	$\delta$	$\Delta\chi$	VEC	Phases
0	0.111	NaN	NaN	NaN	NaN	NaN	NaN	0.222	0.222	0.222	...	NaN	NaN	NaN	NaN	-8.395	13.146	3.738	0.050	4.556	1
1	0.158	NaN	NaN	NaN	NaN	NaN	NaN	0.215	0.215	0.215	...	NaN	NaN	NaN	NaN	-9.352	13.333	3.863	0.233	4.684	1
2	0.588	NaN	NaN	NaN	NaN	NaN	NaN	0.235	0.235	0.235	...	NaN	NaN	NaN	NaN	-4.042	12.708	4.003	0.243	4.882	1
3	0.588	NaN	NaN	NaN	NaN	NaN	NaN	0.235	0.235	0.235	...	NaN	NaN	NaN	NaN	-4.817	12.708	3.832	0.050	4.647	1
4	0.476	NaN	NaN	NaN	NaN	NaN	NaN	0.239	0.239	NaN	...	NaN	NaN	NaN	NaN	-3.356	12.569	4.018	0.244	4.905	1

5 rows × 36 columns

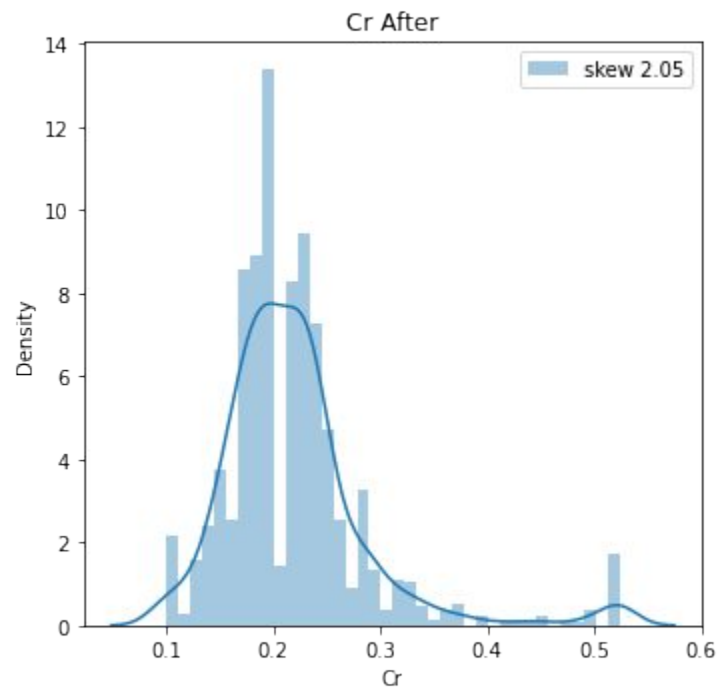
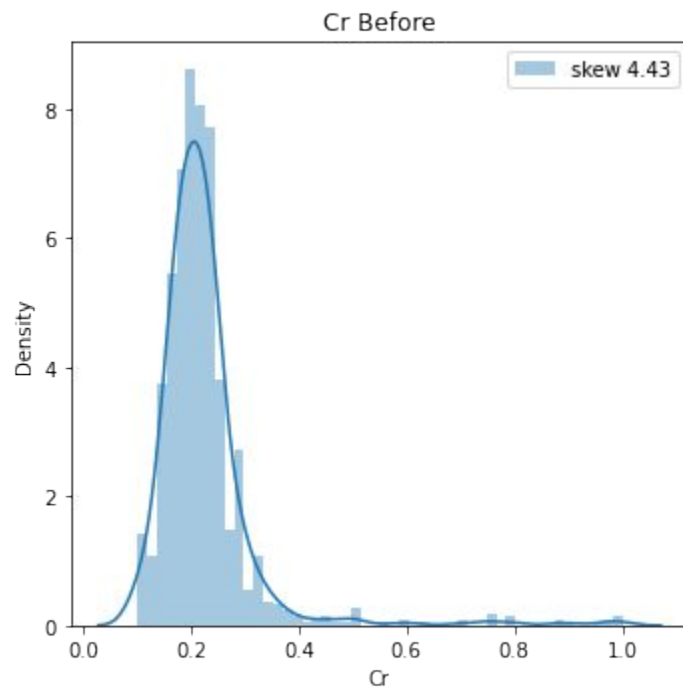
- Compiled from: Materials for Design Open Repository. High Entropy Alloys
- IM: 0, BCC: 1, FCC: 2, BCC+FCC: 3

# Data Pre-processing

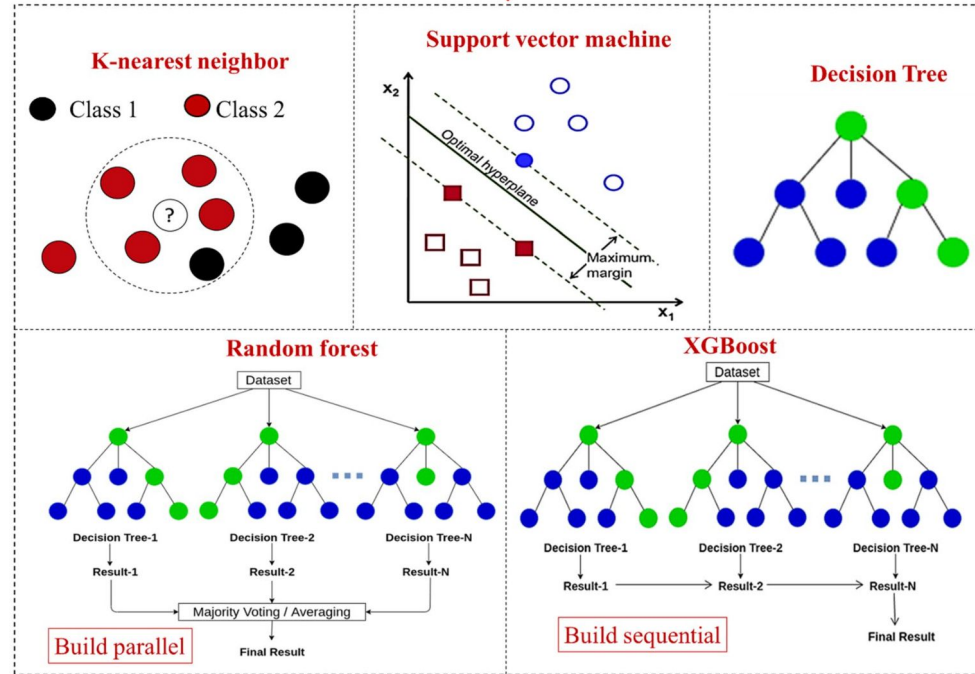
- The data is compiled from multiple sources so some values are NaN
- Data needs to be imputed
  - One technique we used is getting the closest neighbor's values and using the mean
- Feature scaling:
  - We need to minimize the skewing by introducing a cap on data points
  - One solution is to use Z-Score capping, we essentially set a max of 3 standard deviations that a data value can go up to



# Example of De-skewing



# The 5 Models:



# Methodology - K Nearest Neighbors

Hyperparameters:

- K Neighbors: between 1 and 25
- Weight: uniform vs distance
- Metric:
  - Euclidean: straight line distance
  - Manhattan: sum of total difference of each component
  - Chebyshev: max of each components difference
  - Cosine: dot product definition

# Methodology - Support Vector Machine

Hyperparameters:

- Regularization parameter: between  $1e-3$  and  $1e3$
- Kernel: linear, poly, rbf, sigmoid
- Degree (for poly): between 2 and 5
- Gamma (for poly, rbf, sigmoid): scale, auto

# Methodology - Decision Tree

## Hyperparameters:

- Max depth: how many levels (“big”) the tree is. Need to optimize for over/underfitting
- Minimum Samples Split: Threshold of samples a node has before splitting.
- Minimum Samples Leaf: Counterpart of minimum samples. When splitting stops which is important for dictating size of the tree.

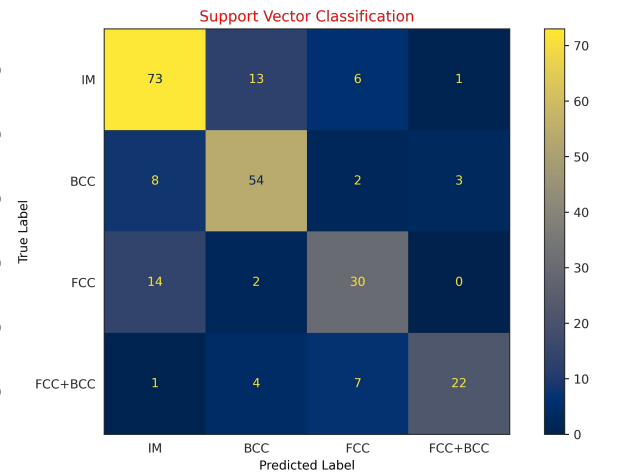
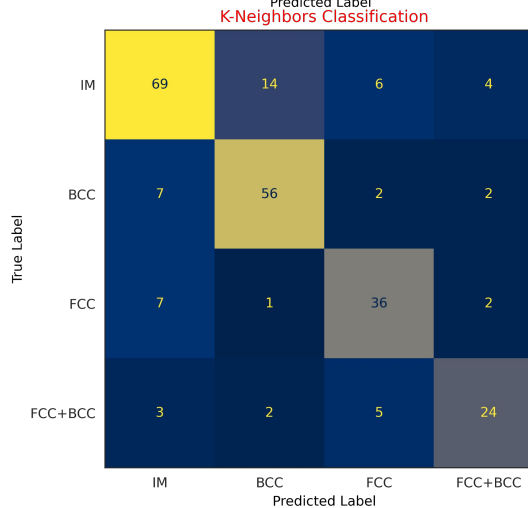
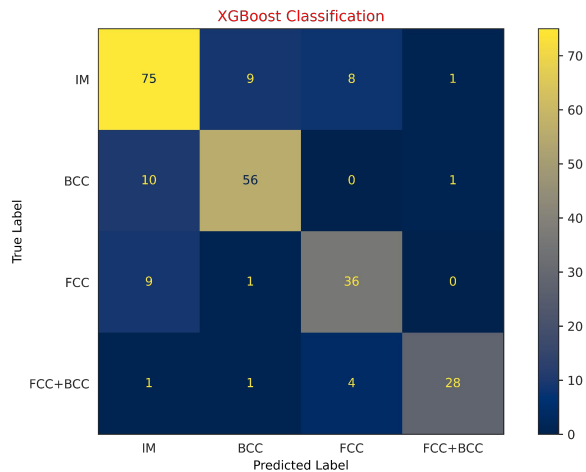
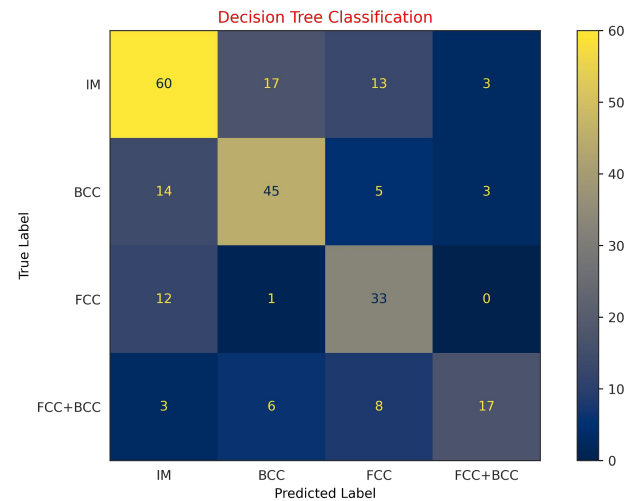
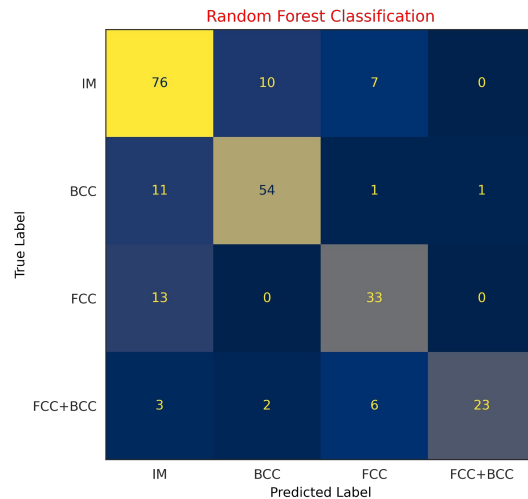
# Methodology - Extreme Gradient Boost / Random Forest

Hyperparameter:

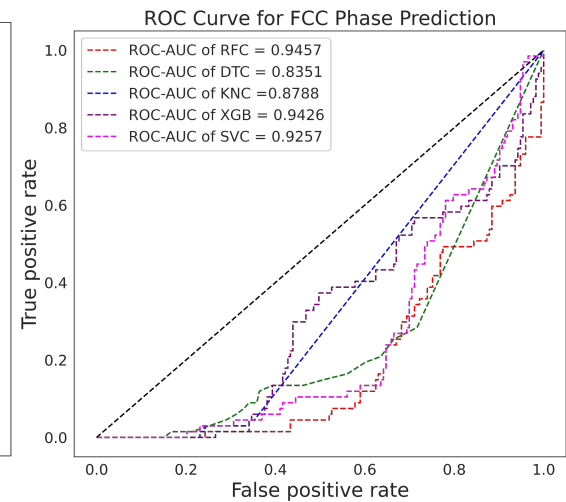
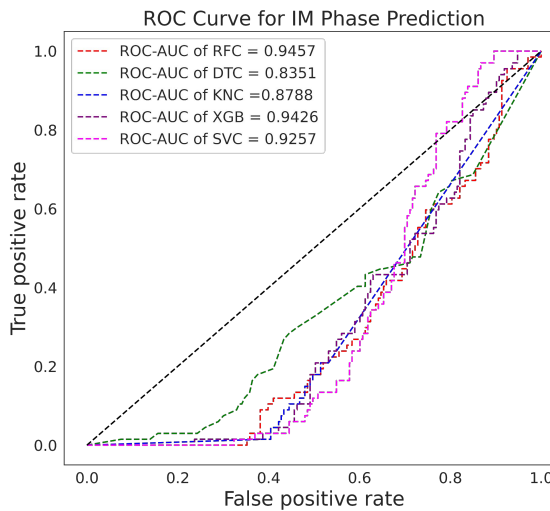
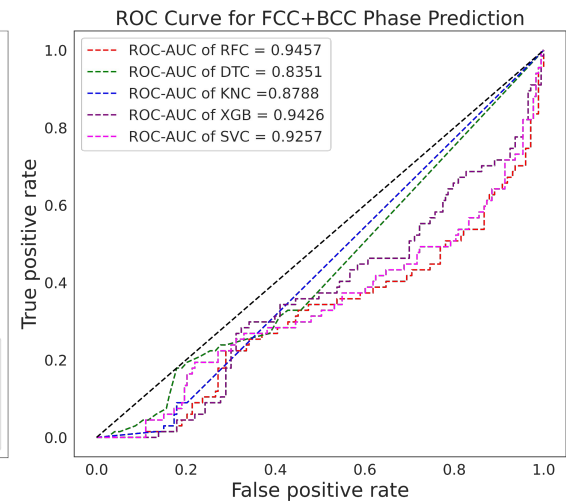
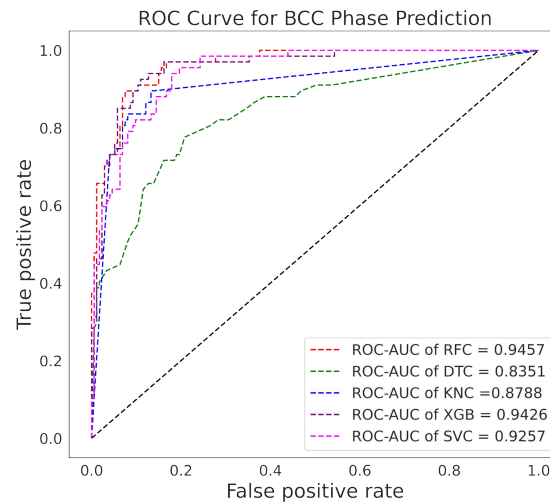
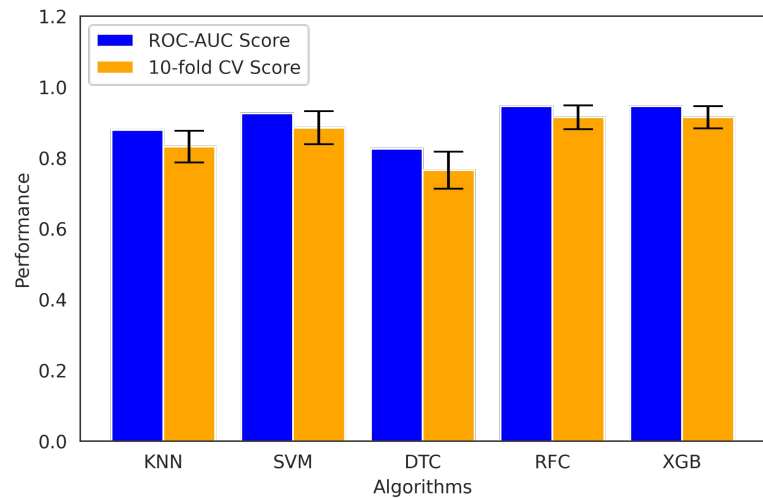
- Number of trees
- Criterion: Gini impurity
- Depth: height of the tree
- Min Sample leaf: least number of samples to be leaf node

# Results:

## Confusion Matrix



# Model Performance





# Summary

- HEA are metallic compounds with useful properties, but discovery of novel compositions is laborious and expensive experimentally
- We can use multi-classifiers to predict the phase structure of HEAs
- We clean and prepare the data by removing NaNs and substituting with synthetic values
- The resulting performance is best for the BCC phase

# Next Steps

- Future work will focus on:
  - Reduce the complexity of each model to increase prediction accuracy
  - Increase the range over which hyperparameters are queried when tuning
  - Apply the best model towards compositions outside of the dataset
- Bigger picture:
  - Raise model confidence to discover new alloys and their applications
  - Incorporate more data to expand which phases the model can classify

# Reference

Original paper:

- Singh, S., Katiyar, N.K., Goel, S. *et al.* Phase prediction and experimental realisation of a new high entropy alloy using machine learning. *Sci Rep* 13, 4811 (2023). <https://doi.org/10.1038/s41598-023-31461-7>

Data:

- Precker, C.E., Gregores Coto, A., Muíños Landín, S. (2021) Materials for Design Open Repository. High Entropy Alloys. (version 0) [Dataset]. Zenodo. <https://zenodo.org/records/5155150>