

# Artificial Neural Networks for the Rapid Prediction of Possible Ferroptosis Inducers Using the GPx4 Enzyme

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# Outline

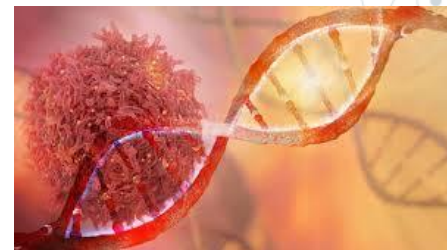
1. Introduction
2. Methodology
3. Results & Discussion
4. Conclusions



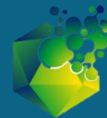
# Cancer in the World



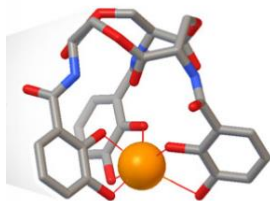
- The fight against cancer represents one of the most significant challenges in the field of global health;
- Cancer is a major contributor to global mortality, causing about 1 in every 6 deaths and affecting nearly every household.
- Globally, there were an estimated **20 million new cases of cancer and 9.7 million deaths from cancer in 2022** (WHO 2022)
- **With its increasing prevalence and the urgent need to discover effective treatments, the search for new drugs has become a research priority**



# New treatments for cancer: Chelation Therapy and Ferroptosis

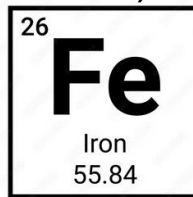


Chelation Therapies:  
remove metals from cells



Enterobactin and Iron

Iron (Fe) essential to  
various cellular reactions  
(ferric ion)

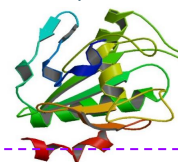


Excess of **Iron** ⇒  
participation in reactions  
that generates oxidative  
stress (OE)

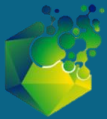


PROPOSE: inhibits the **GPx4**  
**enzyme** has emerged  
as a promising approach to  
therapy -> ferroptosis

One important  
system against OE  
is the **GPx4**  
**enzyme**

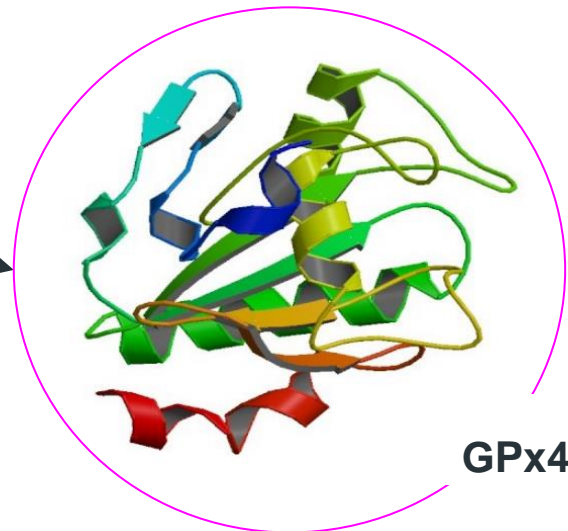
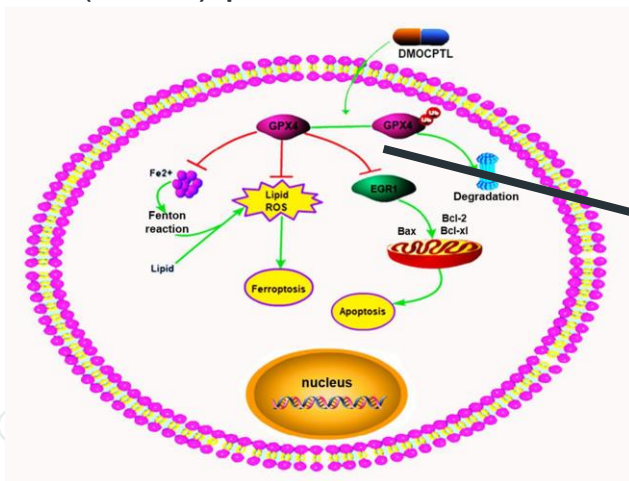


OE can cause  
**Ferroptosis**  
Type of prograded  
cell death



# GPx4 Enzyme

- The reactivation of cell death induced by the accumulation of iron-dependent lipid peroxides (Ferroptosis) is a potential mechanism for cancer treatment.
- One pathway to trigger Ferroptosis involves the inactivation of the glutathion-dependent peroxidase (GPx4) protein.

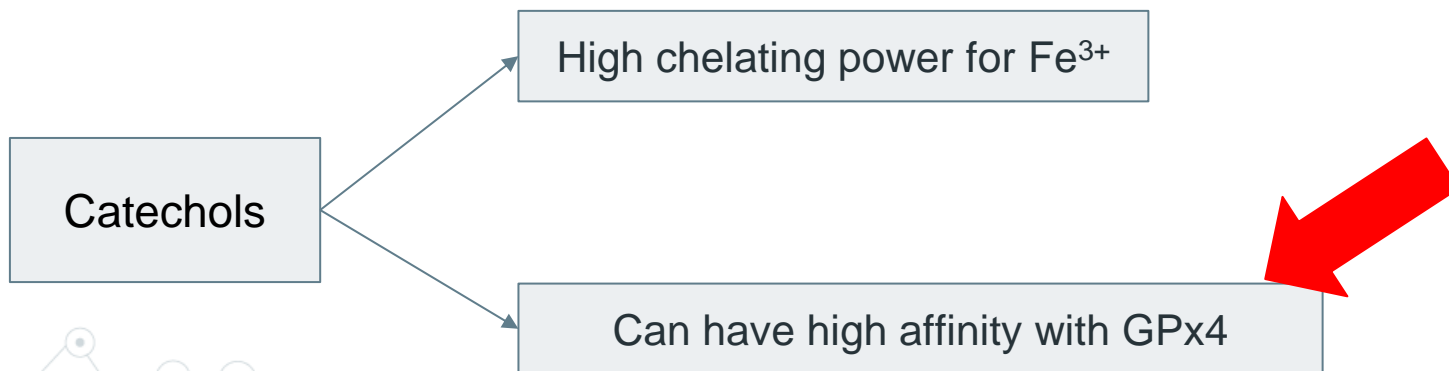


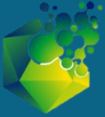
GPx4

# Siderophores - catechols



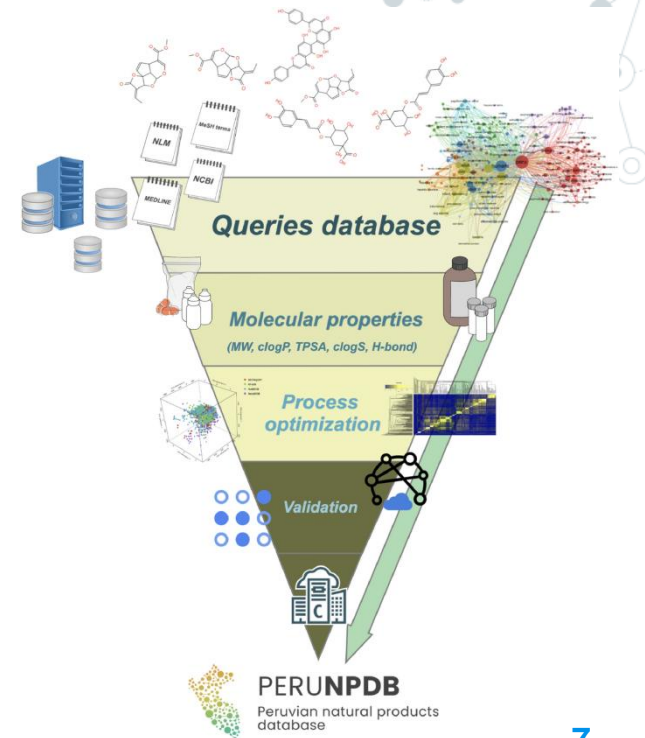
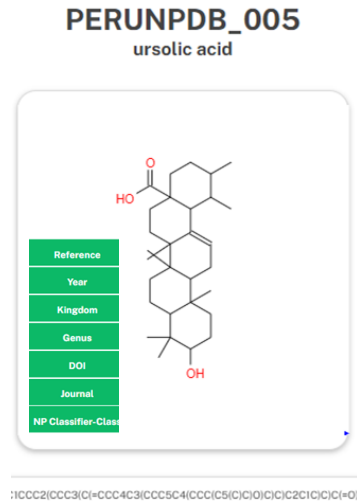
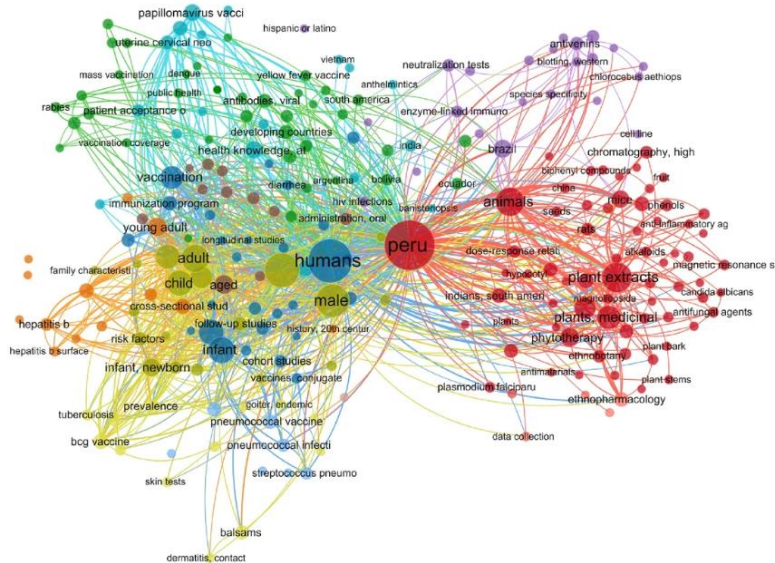
- Siderophores are low molecular weight organic molecules
- Its chelation power to  $\text{Fe}^{3+}$  has been studied for chelation in cancer therapy
- Catechols -> common iron-binding functional groups within siderophores





# Natural Products in Peru

- The first version of PeruNPDB, a compound database of NPs from Peru that includes 280 compounds from plant and animal sources.



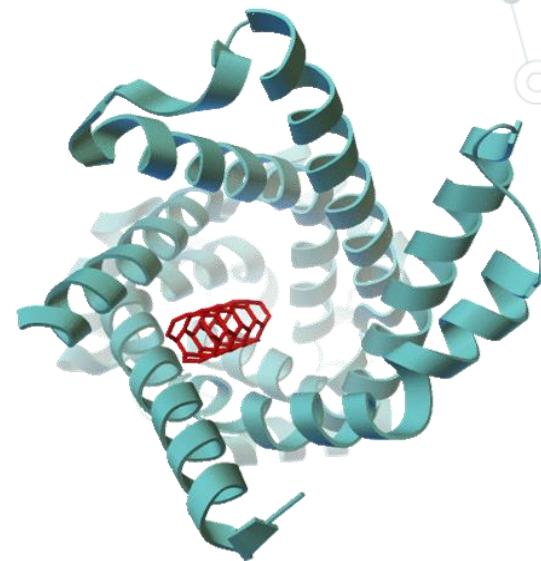


# Molecular docking and Scoring Functions

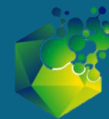


Predict the best orientation and conformation of a ligand (small molecule) in a binding site of a receptor (Protein);

Estimate the binding affinity score with a scoring function







# Molecular docking and Scoring Functions

## PHYSICS BASED (Force Field)

Derived from mechanics force fields to calculate protein-ligand binding

## KNOWLEDGE-BASED

- utilize knowledge derived from experimentally determined complexes
- obtains the score from summing pairwise statistical potentials between protein and ligand

## EMPIRICAL

- Based on empirical observations;
- Calculates the affinity through the sum of terms that represent factors such as hydrogen bonding, van der Waals, electrostatic and hydrophobic interactions;

## MACHINE LEARNING

Trains scoring functions using features obtained from known protein-ligand binding experiments

### Scoring Functions

#### Physics-based

$$\text{DOCK: } E_{bind} = \sum_{i=1}^L \sum_{j=1}^R \left( \frac{A_{ij}}{r_{ij}^{12}} - \frac{B_{ij}}{r_{ij}^6} + \frac{q_i q_j}{\epsilon(r_{ij}) r_{ij}} \right) \quad (1)$$

#### Empirical

$$\text{X-Score: } E_{bind} = w_0 + w_1 \Delta G_{vdw} + w_2 \Delta G_{Hbond} + w_3 \Delta G_{rot} + w_4 \Delta G_{hydro} \quad (2)$$

#### Knowledge-based

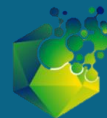
$$\text{PMF: } E_{bind} = \sum_{i=1}^L \sum_{j=1}^R -k_B T \ln[g(r)] \quad (3)$$

#### Machine learning-based

$$\begin{aligned} \text{RF-Score: } E_{bind} &= f_{RF}(x_m) \\ x_{ij} &= \sum_{i=1}^L \sum_{j=1}^R \theta[d_{cutoff} - d_{ij}] \end{aligned} \quad (4)$$

**Previous Work -> RFL-Score**

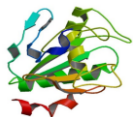
# Objective



Proposes a GPx4 target-specific scoring function for molecular docking

Training Set

PERUNPDB.



ML algorithm

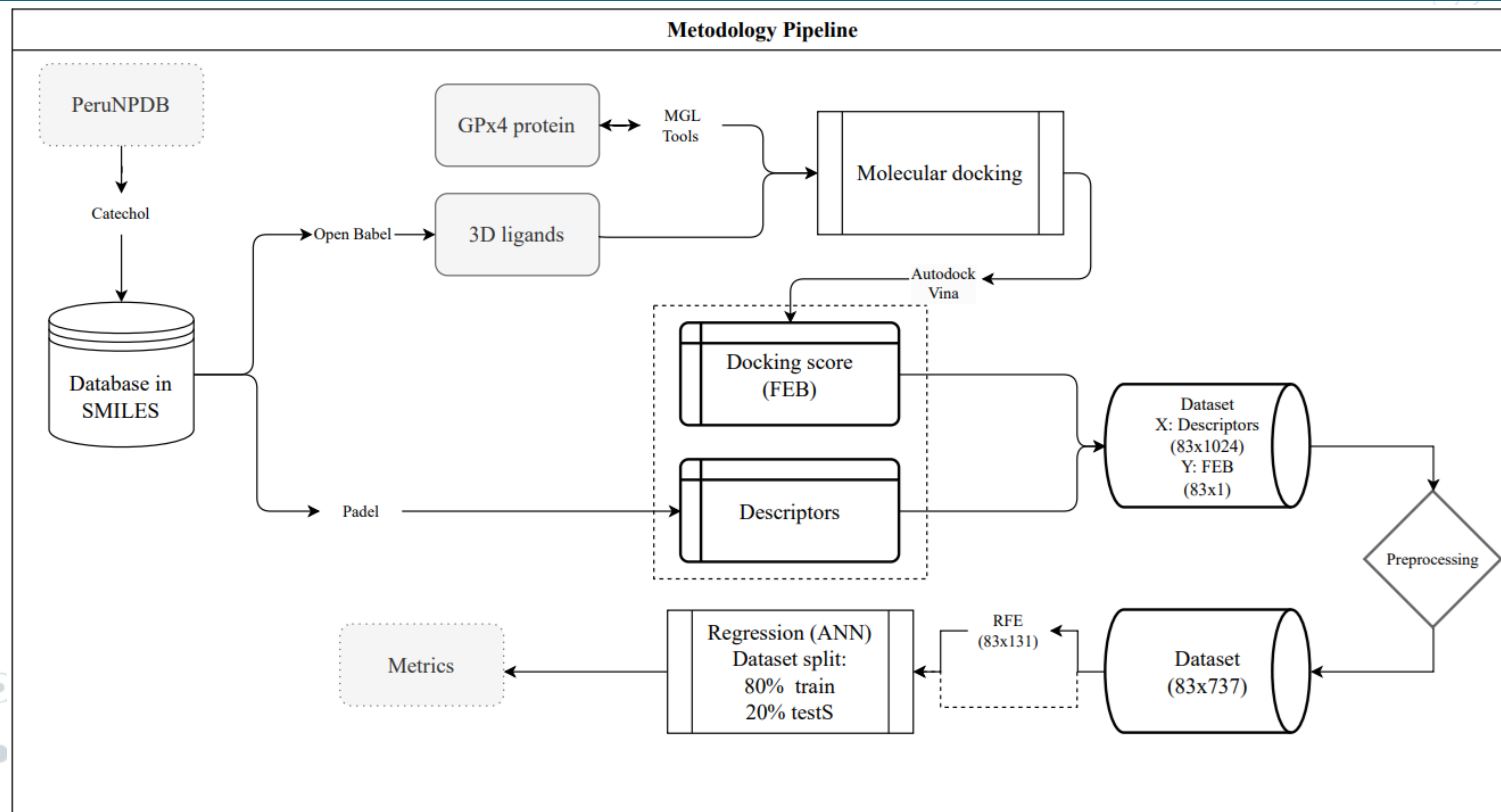


Validation

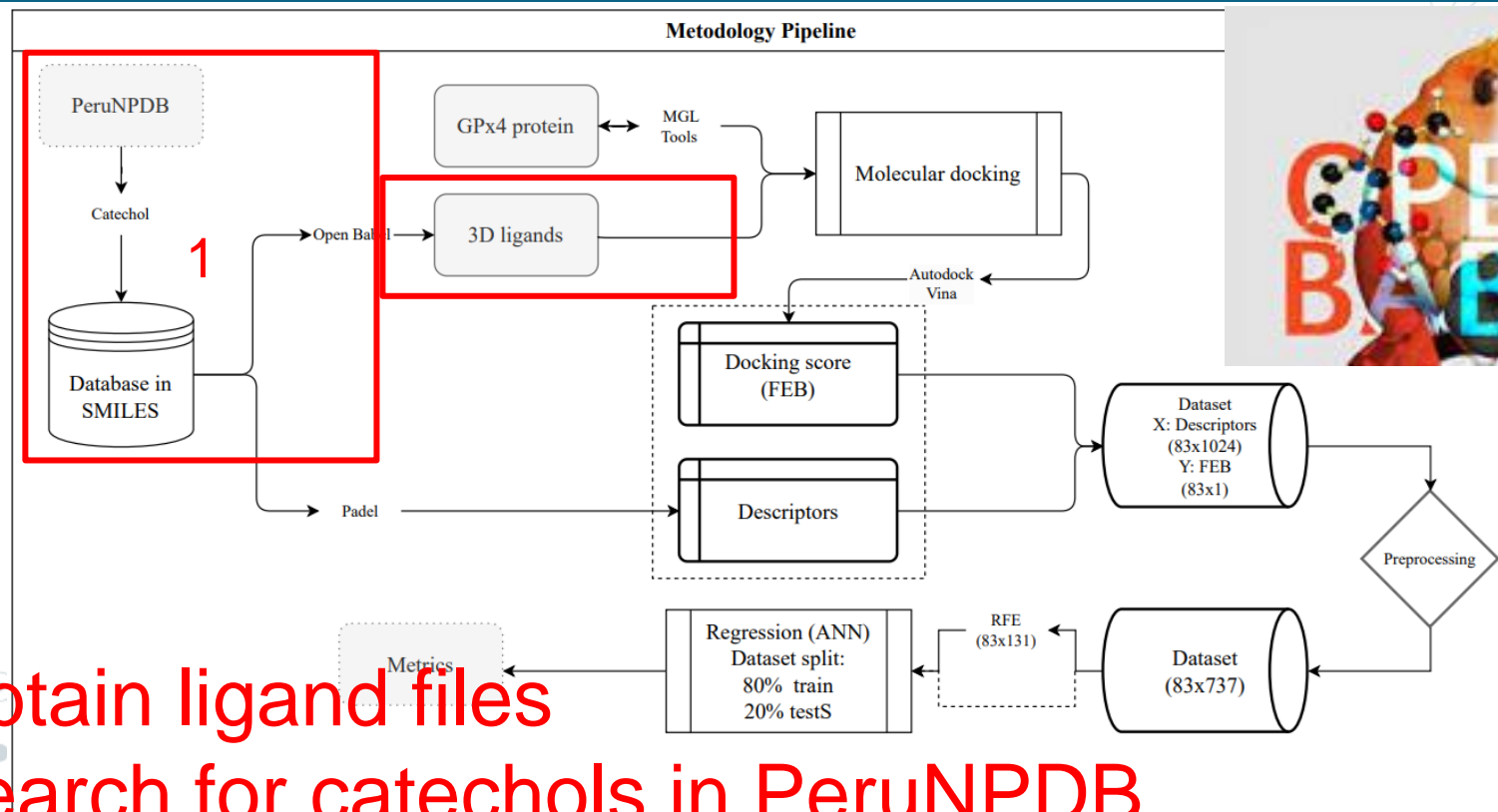
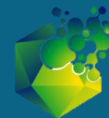
R2, RMSE, MSE

Available in: <https://github.com/inefable12/ExpInSilico24>

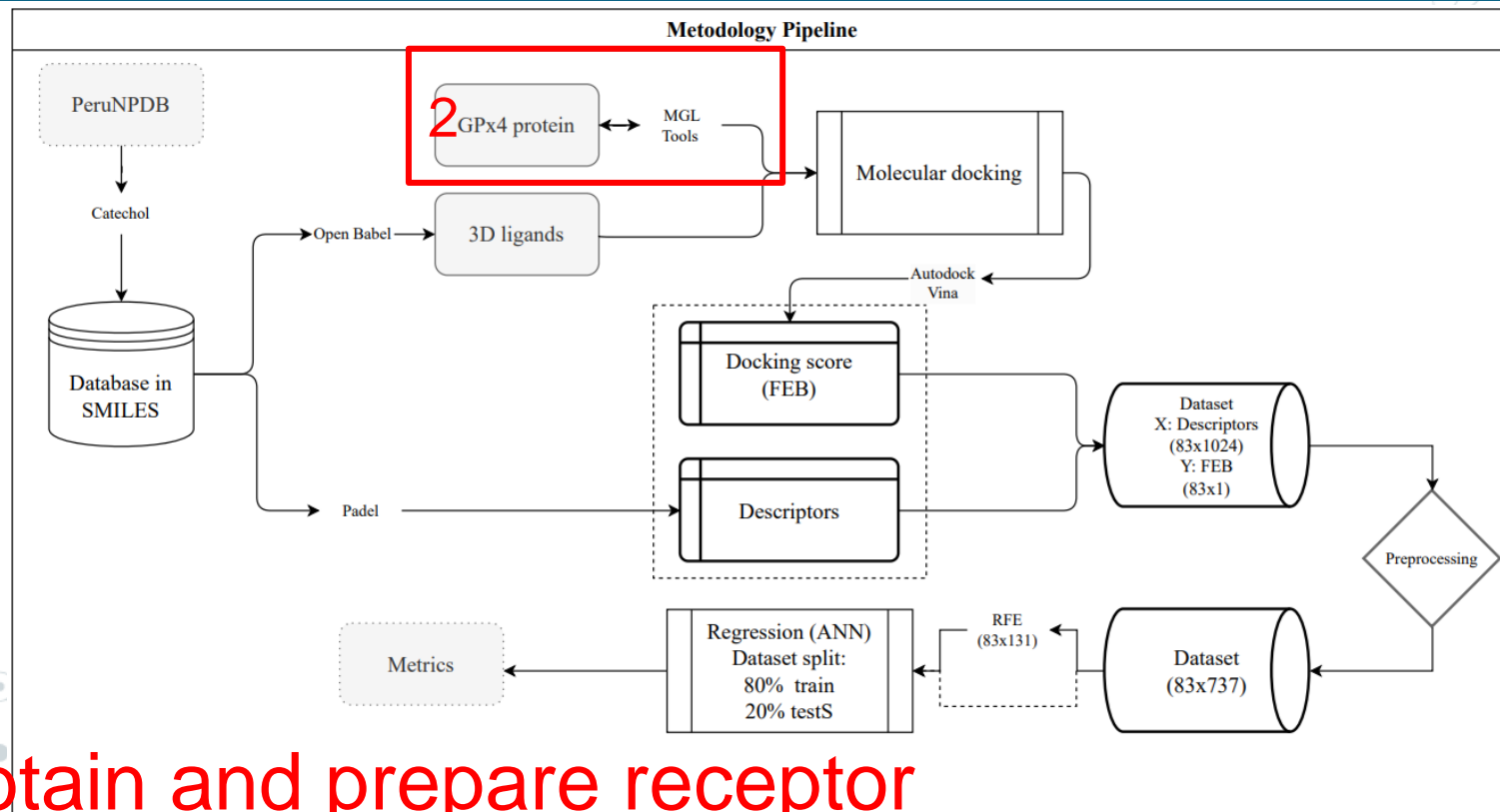
# Methodology



# Methodology

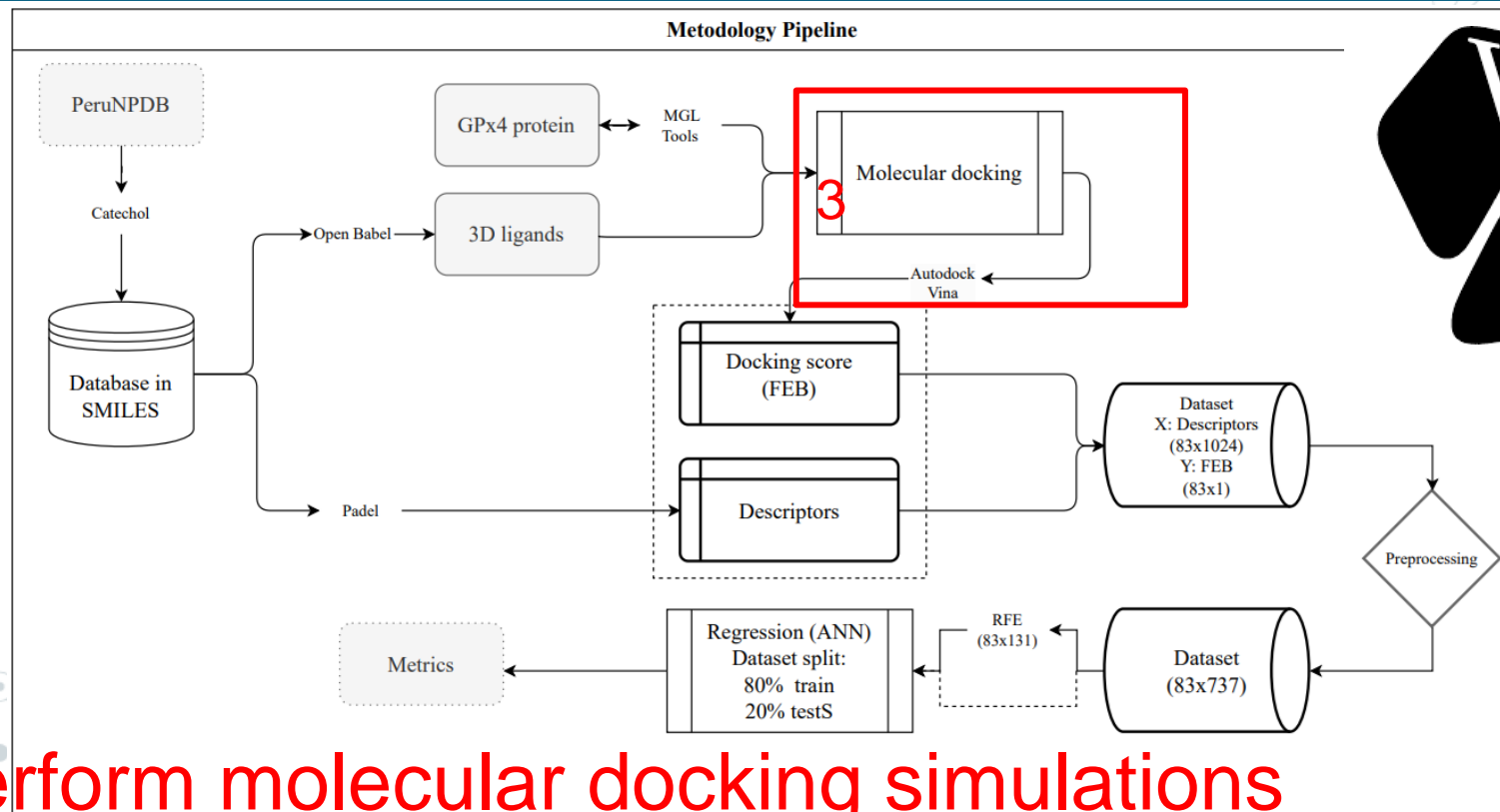
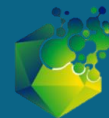


# Methodology

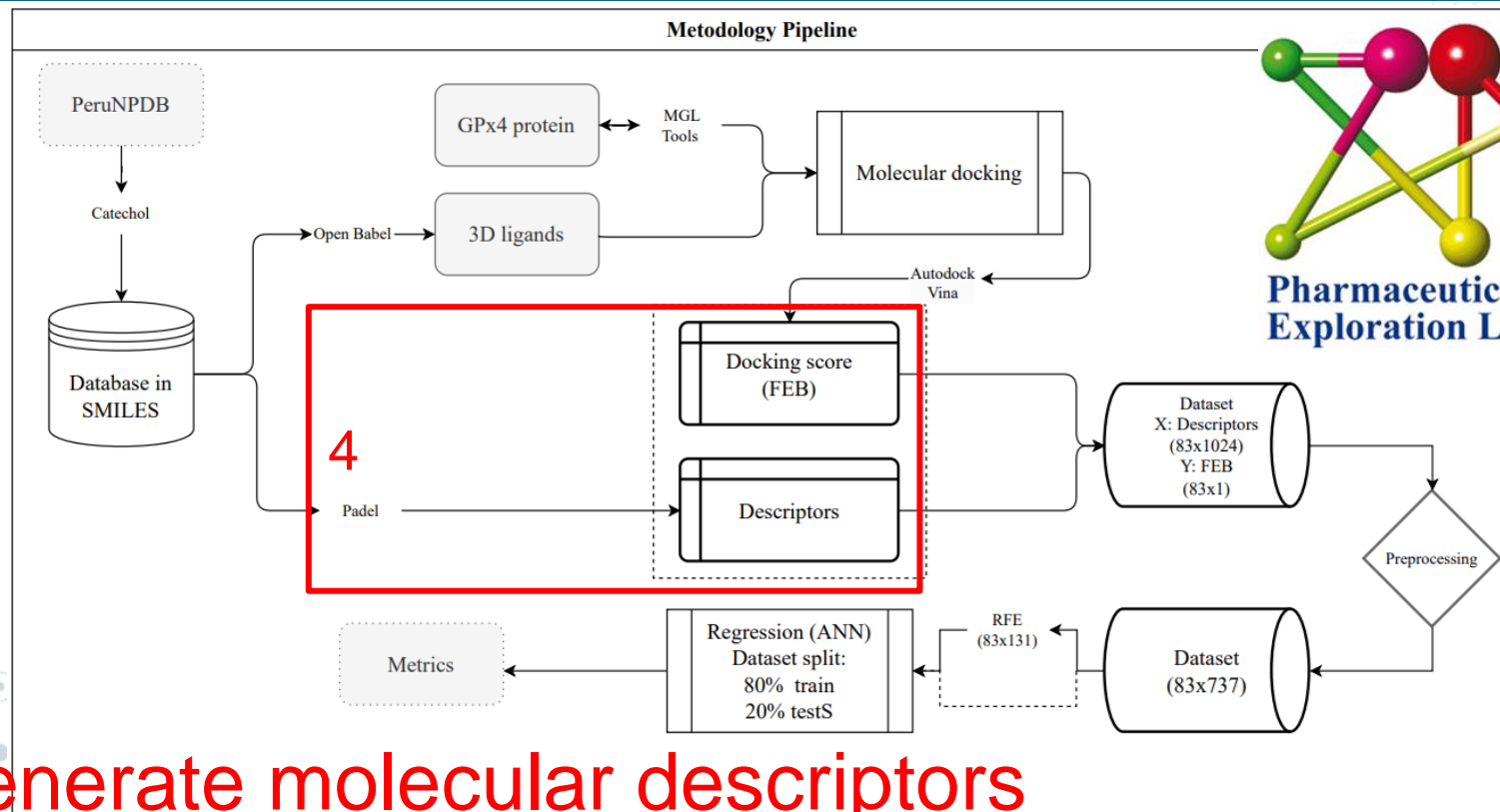
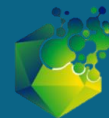


## 2. Obtain and prepare receptor

# Methodology



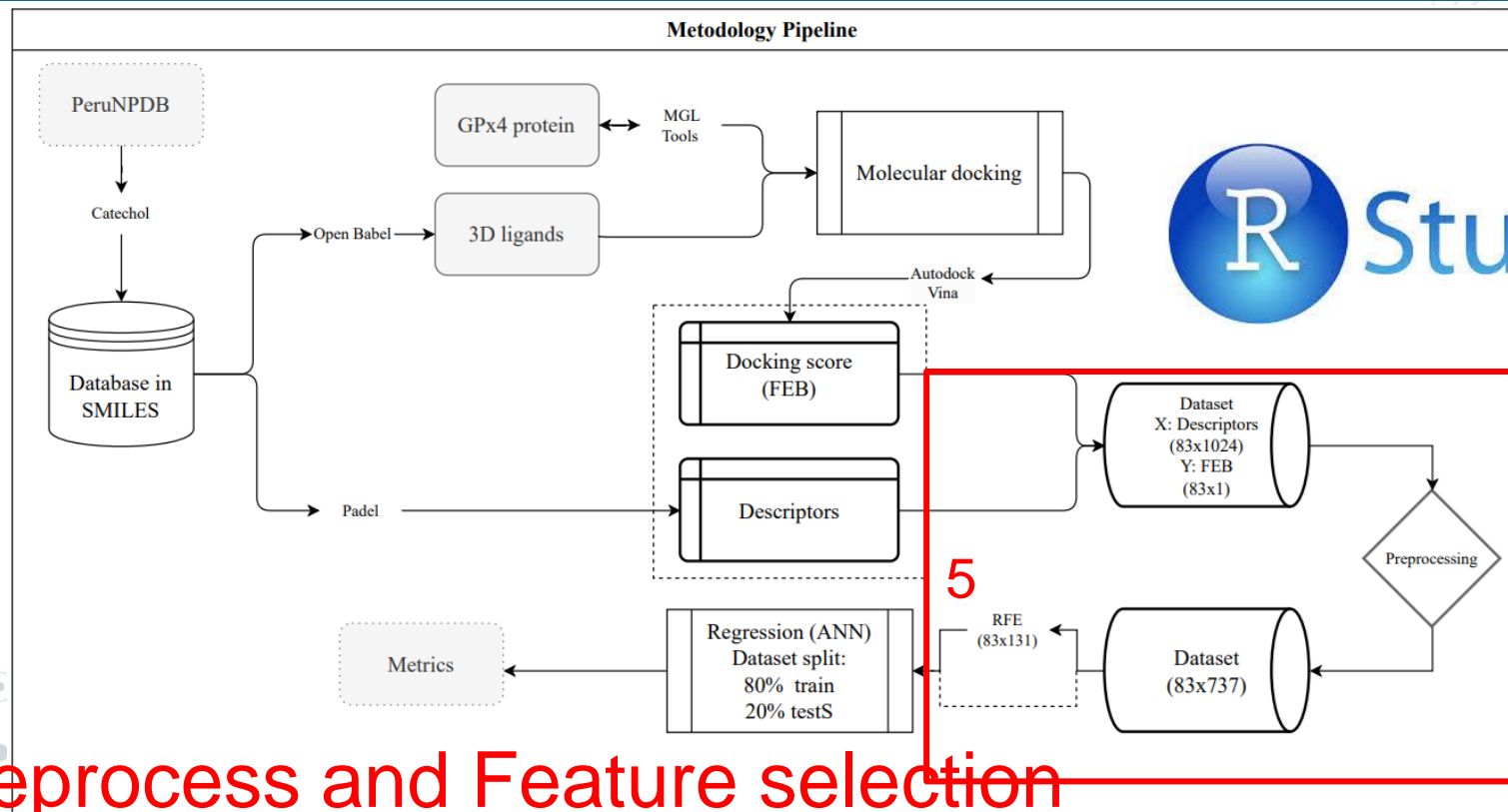
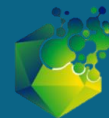
# Methodology



## 4. Generate molecular descriptors

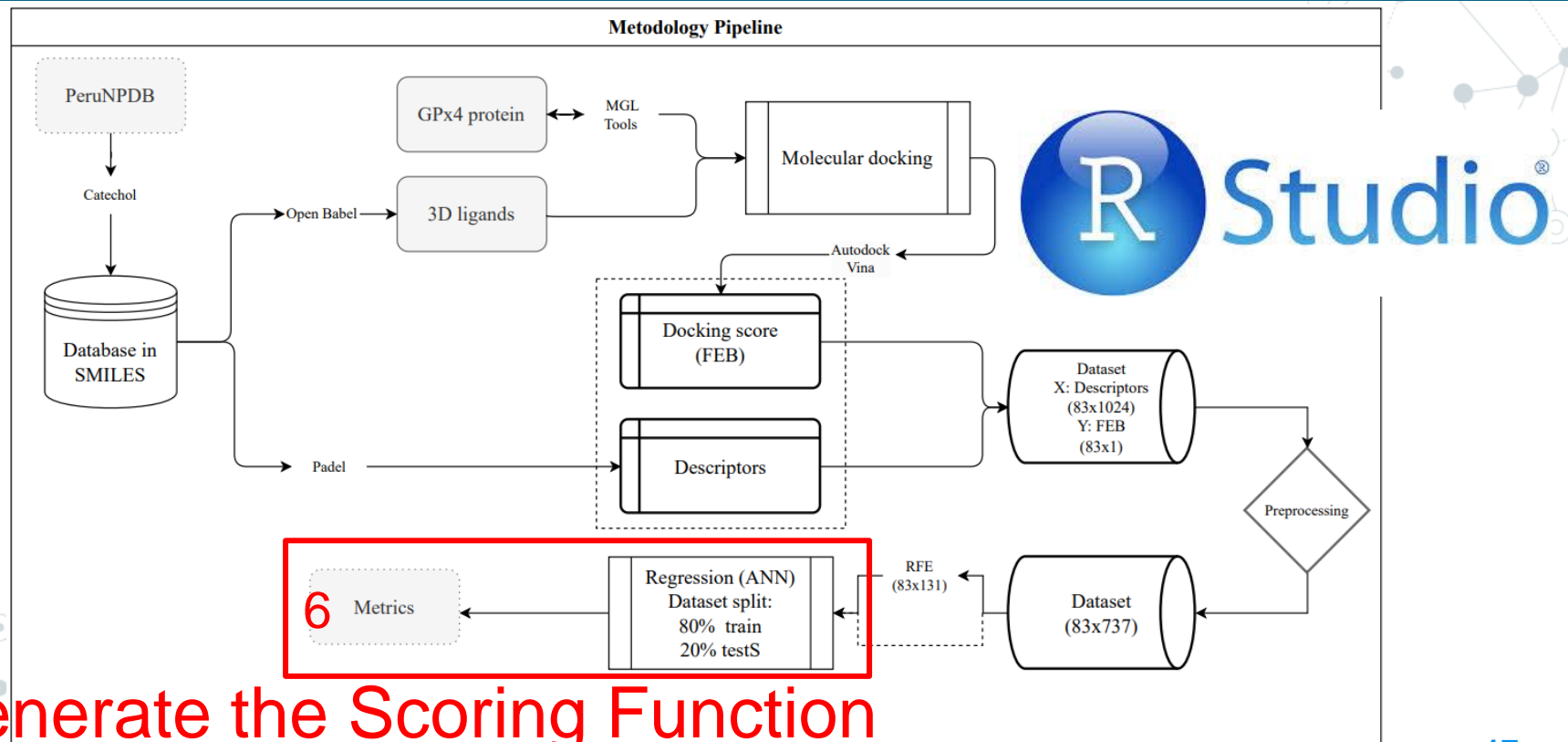


# Methodology



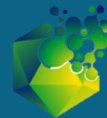
## 5. Preprocess and Feature selection

# Methodology



## 6. Generate the Scoring Function

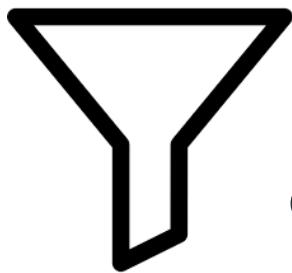
## Results | Molecules



# PERUNPDB

Peruvian Natural Products Database

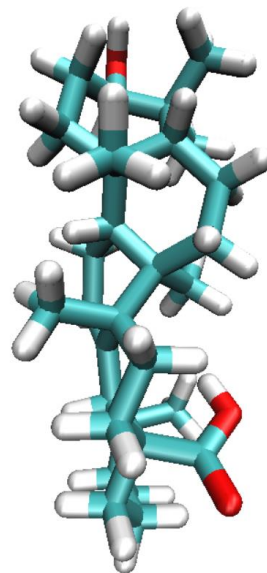
280 Natural  
Products



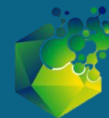
Functional group  
catechol

83 molecules (SMILES)

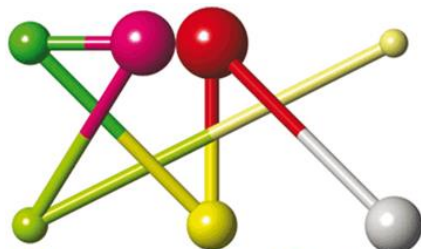
CC1CCC2(CCC3(C=CCC4C3(CCC5C4(CCC(C5(C)C)O)C)C)C2C1C)C)C(=O)O



Molecules minimized and  
protonated



# Results $\Rightarrow$ Dataset Descriptors $\rightarrow$ 1,024

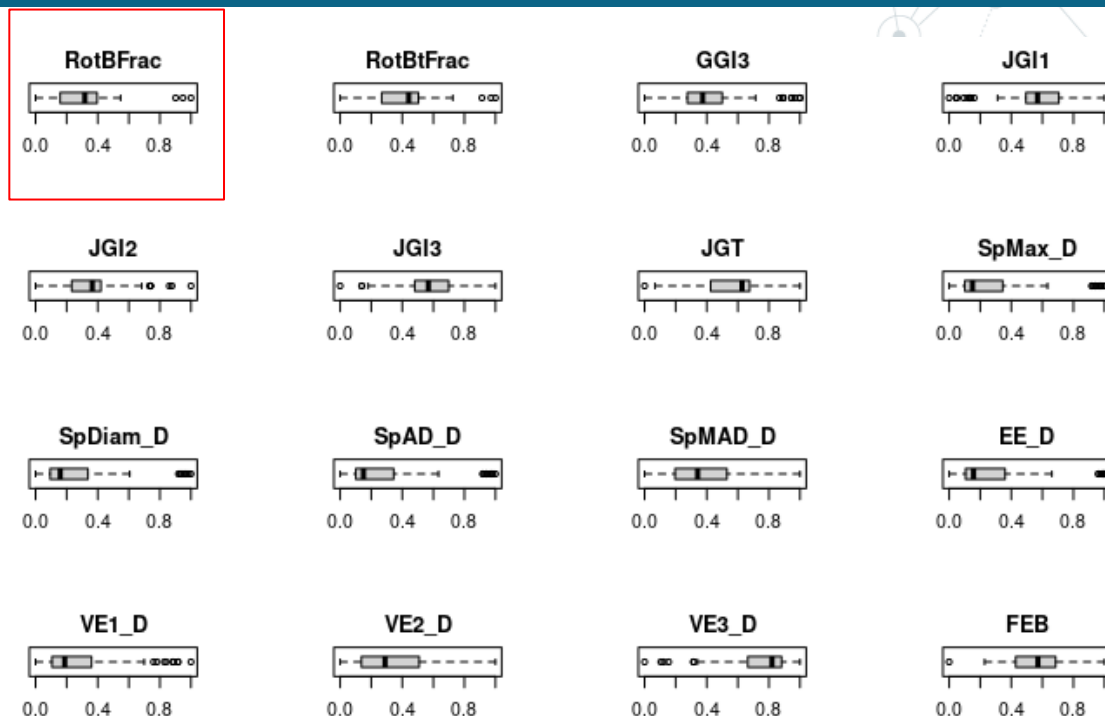


Pharmaceutical Data  
Exploration Laboratory

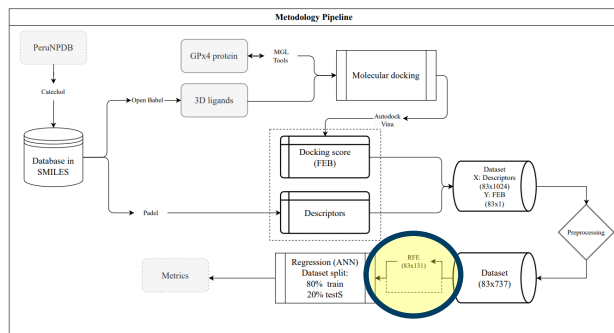
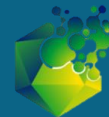
1,024 descriptors

Preprocessing

737 descriptors

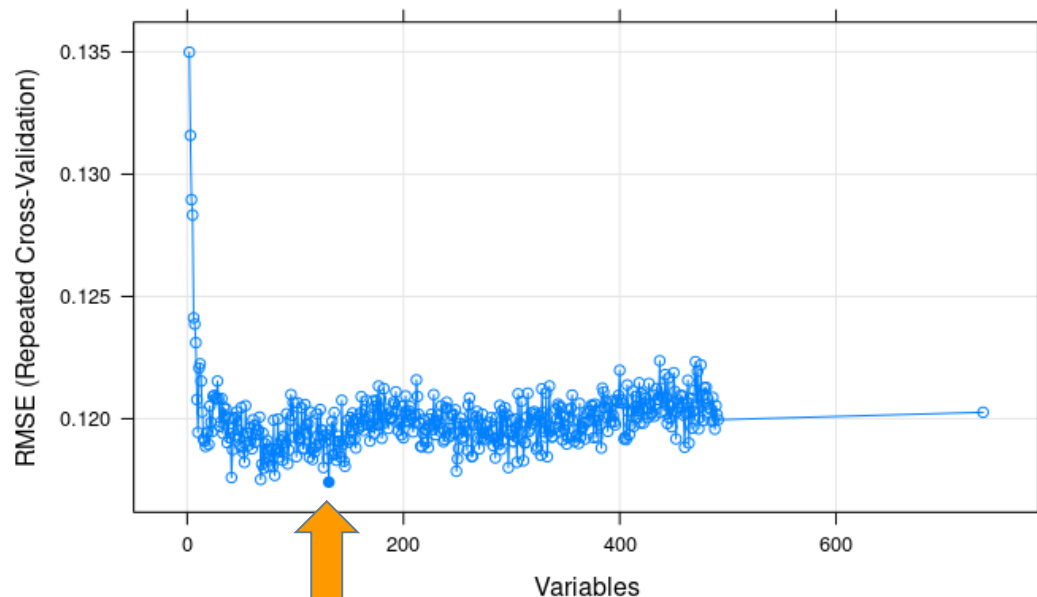


# Results $\Rightarrow$ Feature selection

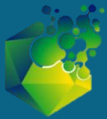


## Algorithm 1: Recursive feature elimination

- 1.1 Tune/train the model on the training set using all predictors
- 1.2 Calculate model performance
- 1.3 Calculate variable importance or rankings
- 1.4 **for** Each subset size  $S_i$ ,  $i = 1 \dots S$  **do**
- 1.5   Keep the  $S_i$  most important variables
- 1.6   [Optional] Pre-process the data
- 1.7   Tune/train the model on the training set using  $S_i$  predictors
- 1.8   Calculate model performance
- 1.9   [Optional] Recalculate the rankings for each predictor
- 1.10 **end**
- 1.11 Calculate the performance profile over the  $S_i$
- 1.12 Determine the appropriate number of predictors
- 1.13 Use the model corresponding to the optimal  $S_i$



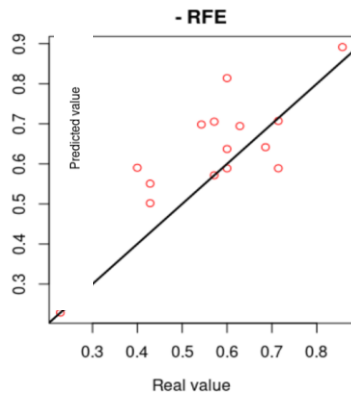
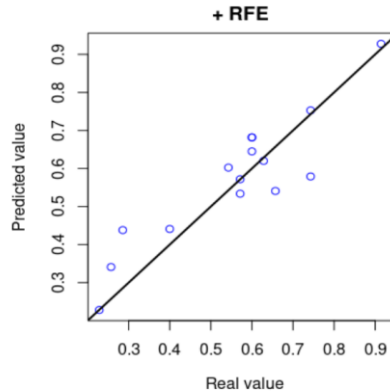
Minimum RMSE 131 descriptors 20



# Results $\Rightarrow$ Metrics of the proposed scoring function

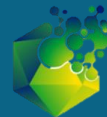
Input dataset: 83 (instances) X 131 descriptors + target (FEB)

Artificial Neural Network (ANN) algorithm



	R2	RMSE	MSE	MAE
Train	0.9894	0.0186	0.0003	0.0042
Test	0.6292	0.1062	0.0112	0.0809
Train + RFE	0.9881	0.0189	0.0003	0.0057
Test + RFE	0.8267	0.0787	0.0061	0.0596

# Conclusion



- ★ Chelation therapy, particularly in relation to ferroptosis and the inhibition of Glutathione peroxidase 4 (GPx4), has emerged as a significant area of investigation
- ★ The proposed methodology and results can serve as a starting point for the search for catechols on others natural products databases as well as search for new inhibitors for GPx4

Future Work: Include more molecules in the input dataset (consider other databases); evaluate more ML algorithms; train new target-specific functions for other target proteins.

Available in: <https://github.com/inefable12/ExplnSilico24>



# Acknowledgments

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IEEE CIBCB  
2024



**FURG**  
UNIVERSIDADE FEDERAL  
DO RIO GRANDE

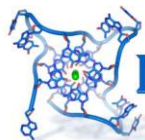


**FONDECYT**

Becas y financiamiento del Concytec



**CAPES**



**LIBIPMET**



**FAPERGS**



**CNPq**  
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Científico e Tecnológico



# Thanks!

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