

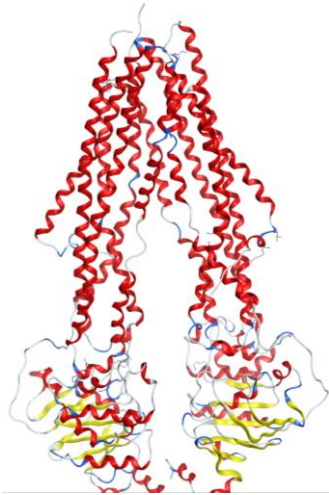


1st International Conference on Chemical Science

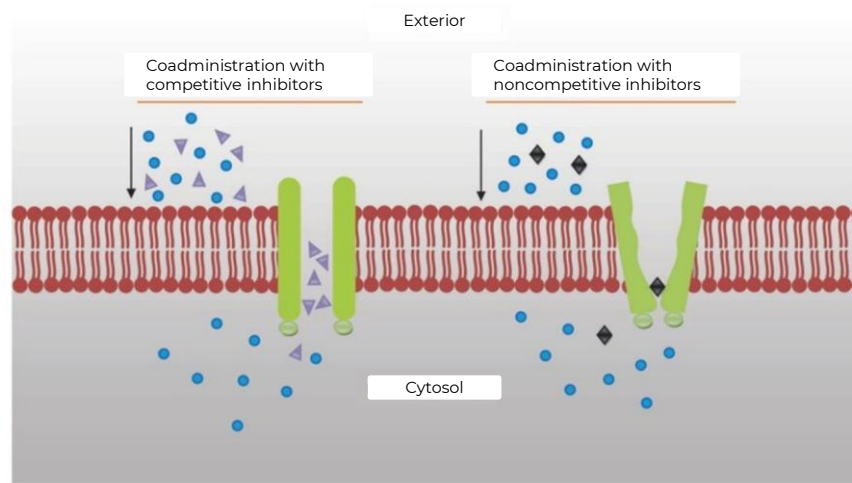
DEEP-LEARNING CLASSIFICATION MODEL ON SCREENING P-GLYCOPROTEIN INHIBITORS

Presenting author: **Vo Thanh Phuong**

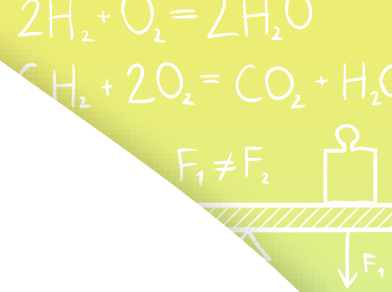
Multidrug resistance and P-glycoprotein



P-glycoprotein
(PDB code: 7A69)



P-glycoprotein inhibitors



P-glycoprotein inhibitors

1st generation

- Substances with clinical pharmacological effects
- High serum concentration
- High toxicity
- Nonspecific

2nd generation

- Structural transformation from 1st generation.
- Neutralizes the original pharmacological effect
- Reduce toxicity
- Nonspecific

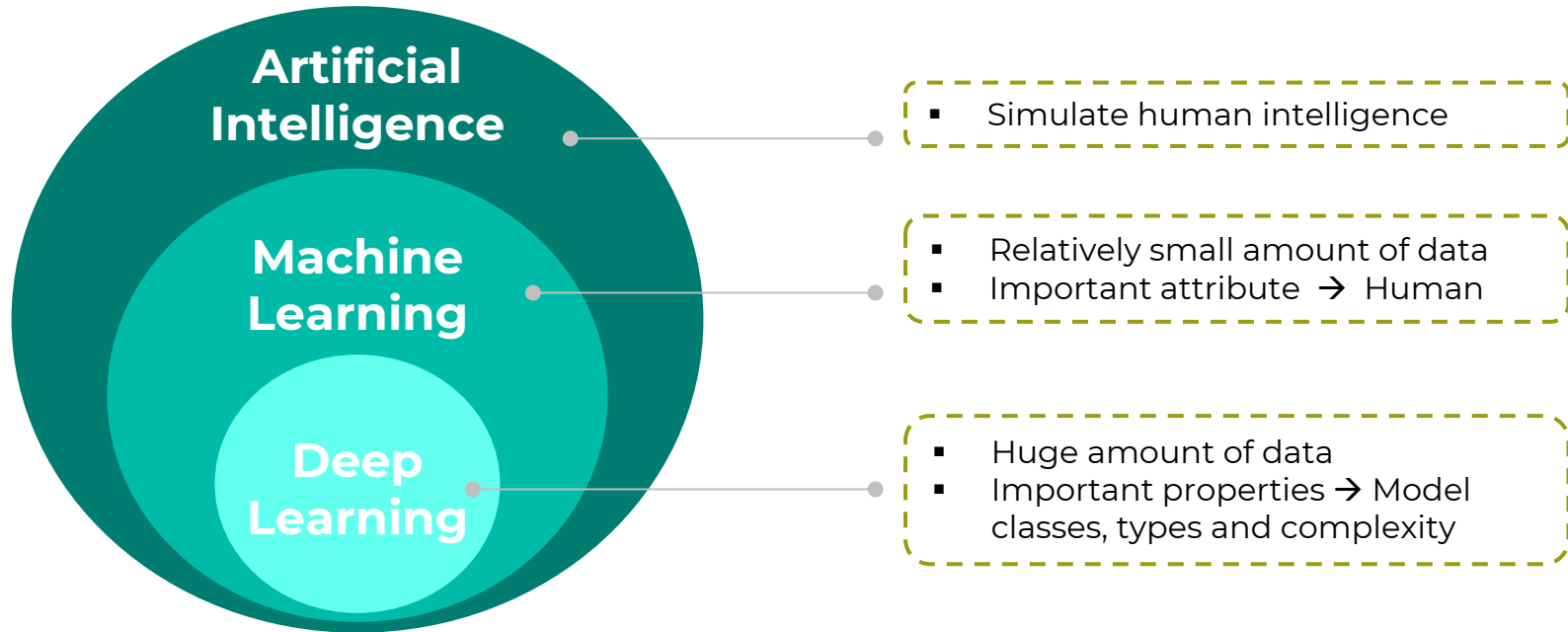
3rd generation

- Low serum concentration
 - Low toxicity
 - Higher specific to P-gp
- Ex: elacridar, zosuquidar, taxquidar

4th generation

- Natural compounds
- Low toxicity
- More efficient.
- Higher specific to target.

Artificial Intelligence (AI)



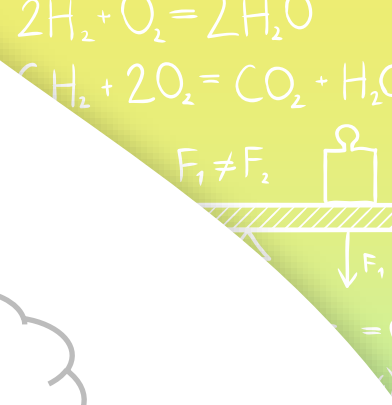
The study questions

Inhibitors

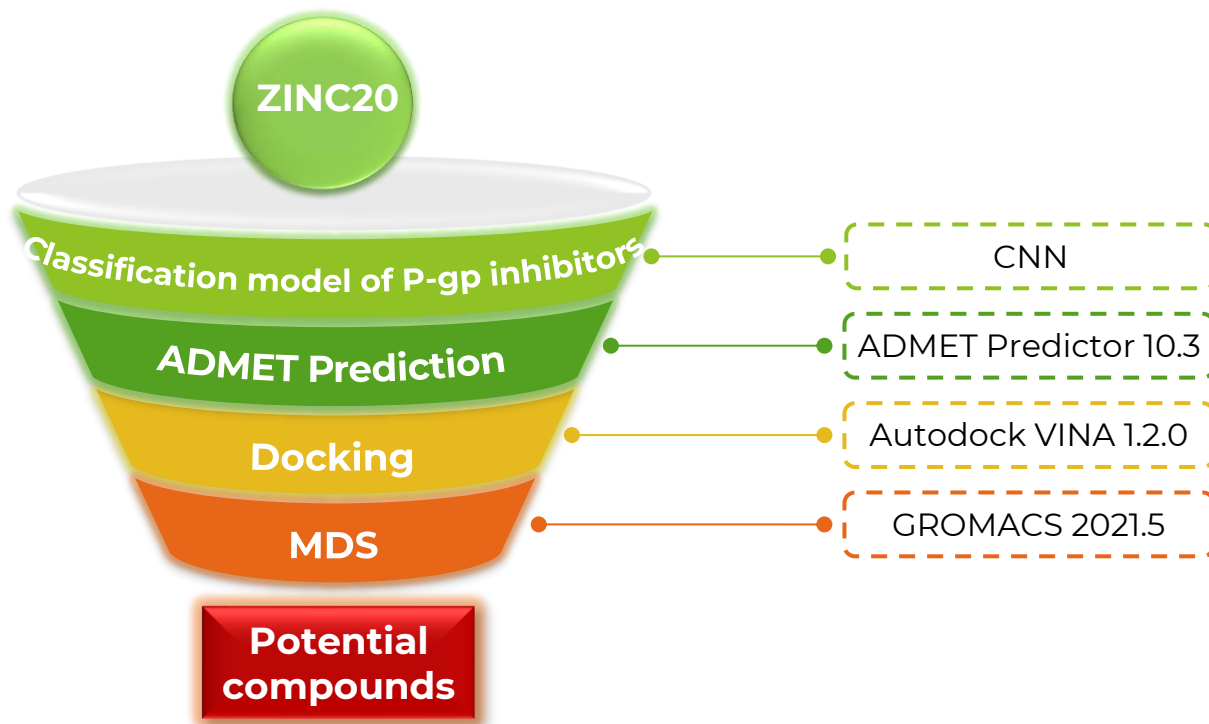


Non-inhibitors

P-GLYCOPROTEIN



Methodology Flowchart

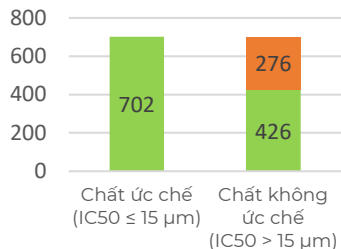


Classification models were published

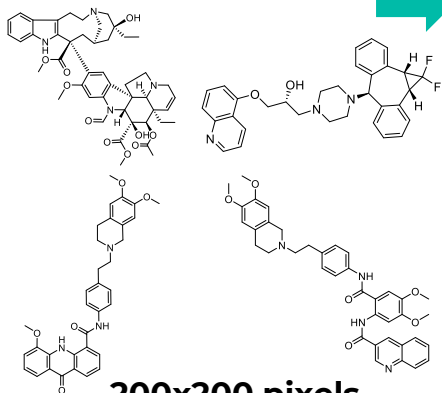
Research	Year	Methods	Databases	Accuracy	Research	Year	Methods	Databases	Accuracy
H.Sun et al	2005	NB	609 compounds	82.2%	S.Éric et al	2014	ANN, SVM, combine	135 compounds	89% 
YH.Wang et al	2005	Kohonen	206 compounds	82.3%	Khac-Minh Thai et al	2015	Backpropagation neural network	133 compounds	82%
		BPNN	174 compounds	29%	V.Prachayasittikul et al	2015	DT, SVM, ANN	2477 compounds	87,4% (ANN)
P.Crivori et al	2006	PLSD	148 compounds	82%	M.Yang et al	2015	18 models machine learning	2428 compounds	77.4-79.9%
F.Broccatelli et al	2011	MIF	1195 compounds	86%	Khac-Minh Thai et al	2016	BPNN, C5.0, C&R Tree, QUEST, CHAID, Logistic Regression, Bayesian Network, Discriminant Analysis, SVM, combine	2131 compounds	92% (validation set) 100% (test set)
L.Chen et al	2011	DT, RF, NB	1273 compounds	81.2%					
S.Rapposelli et al	2012	RF, C4.5, consensus	59 compounds	75% (RF)					
V.Poongavana m et al	2012	RF, kNN, SVM	1935 compounds	75% (RF)	VK.Hinge et al	2019	GBM, GLM, SVM, kNN	1274 compounds	87.1-96.9% (SVM)
F.Klepsch et al	2014	kNN, SVM, RF, DT, Binary QSAR	1954 compounds	73% (RF)	This research	2022	CNN	1404 compounds	-

Classification model of P-gp inhibitors

Databases
1404 compounds

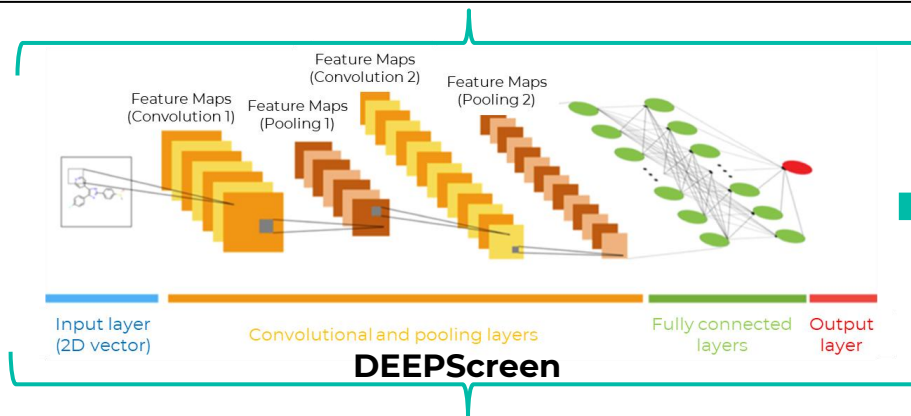


■ ChEMBL ■ PubChem



Optimization algorithm and hyperparameters

Optimization algorithm	Learning rate	Epoch	Fully connecte d layer	Drop out rate
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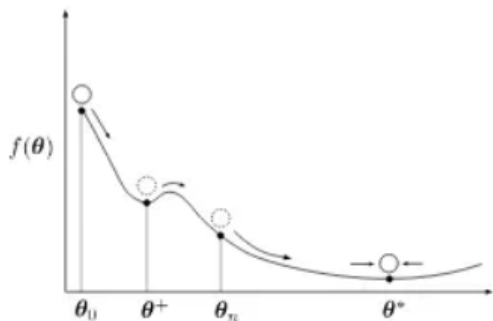
Evaluated parameters

Precision	Accuracy	Recall	F1score	MCC	AUC
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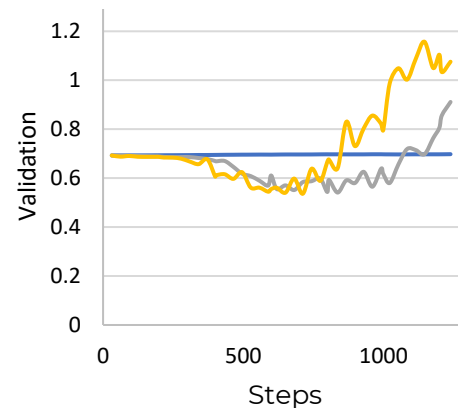
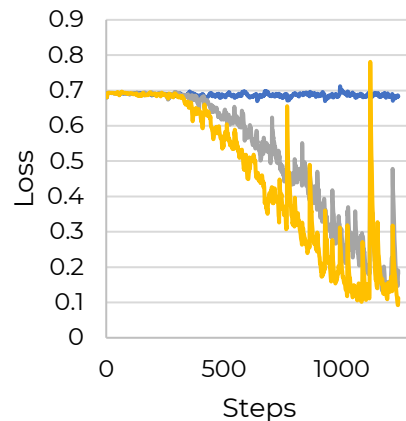
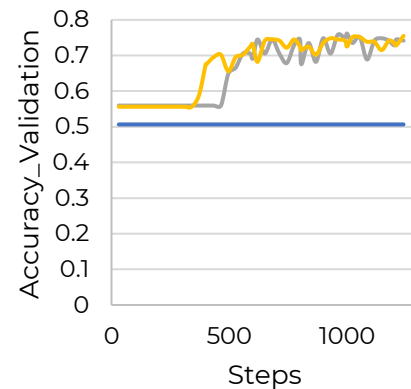
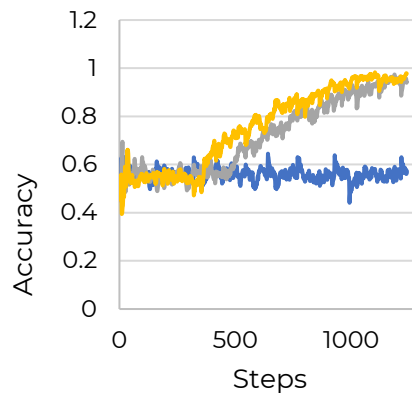
Evaluating optimization algorithm and hyper-parameters

Parameters	Optimization algorithm	Learning rate	Epoch	Fully connected layer	Drop out rate
Optimization algorithm	-	0.0005	40	16	0.6
Learning rate	adam	-	40	16	0.6
Epoch	adam	0.0005	-	16	0.6
Fully connected layer	adam	0.0005	40	-	0.6
Drop out rate	adam	0.0005	40	16	-

Optimization algorithm

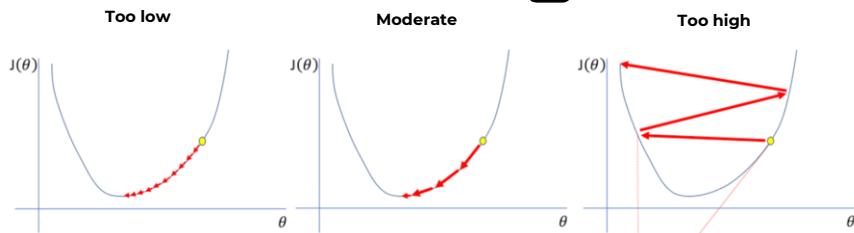


Parameters	Precision	Accuracy	Recall	F1score	MCC	AUC
Momentum	0.52	0.0	0.0	0.0	0.0	0.52
	0.49	0.0	0.0	0.0	0.0	0.53
	0.42	0.0	0.0	0.0	0.0	0.49
RMSprop	0.72	0.71	0.85	0.77	0.43	0.83
	0.74	0.73	0.82	0.77	0.47	0.80
	0.74	<u>0.82</u>	0.70	0.76	0.49	0.82
Adam	0.76	0.78	0.80	0.79	0.50	<u>0.86</u>
	<u>0.77</u>	0.75	<u>0.88</u>	<u>0.81</u>	<u>0.53</u>	0.85
	0.76	0.77	0.85	<u>0.81</u>	0.51	0.81

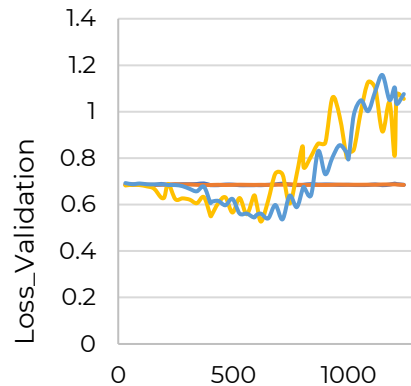
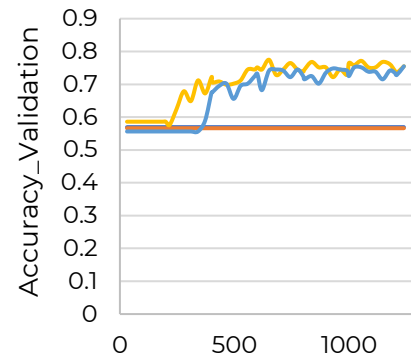
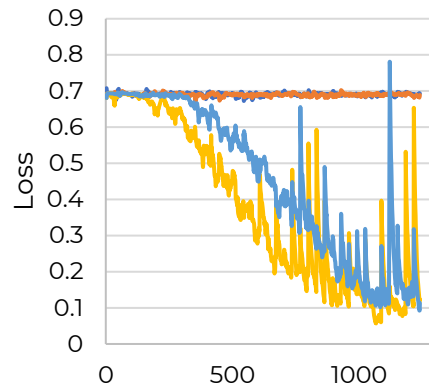
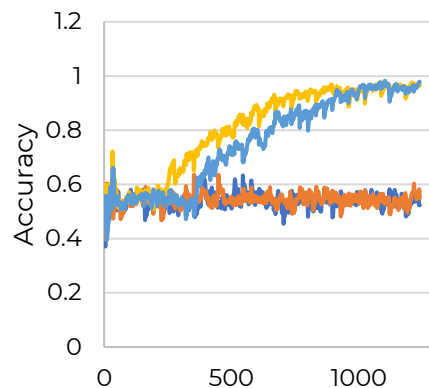


— momentum — RMSprop — adam

Learning rate



Learning rate	Precision	Accuracy	Recall	F1score	MCC	AUC
0.01	0.45	0.0	0.0	0.0	0.0	0.50
	0.46	0.0	0.0	0.0	0.0	0.50
	0.48	0.0	0.0	0.0	0.0	0.50
0.005	0.45	0.0	0.0	0.0	0.0	0.50
	0.42	0.0	0.0	0.0	0.0	0.50
	0.46	0.0	0.0	0.0	0.0	0.50
0.001	0.73	0.75	0.73	0.74	0.46	0.81
	0.74	0.71	0.84	0.77	0.47	0.81
	0.72	0.68	<u>0.88</u>	0.77	0.45	0.84
0.0005	0.76	<u>0.78</u>	0.80	0.79	0.50	<u>0.86</u>
	<u>0.77</u>	0.75	<u>0.88</u>	<u>0.81</u>	<u>0.53</u>	0.85
	0.76	0.77	0.85	<u>0.81</u>	0.51	0.81

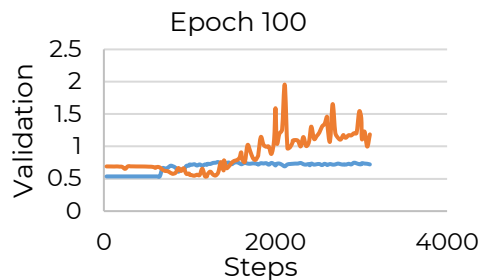
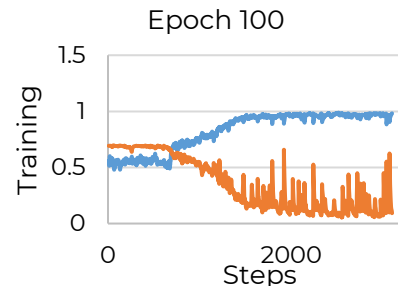
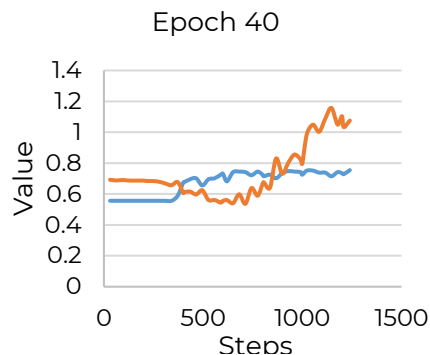
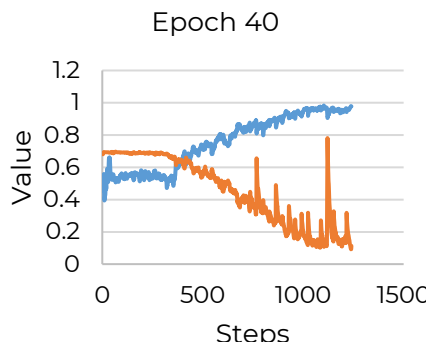
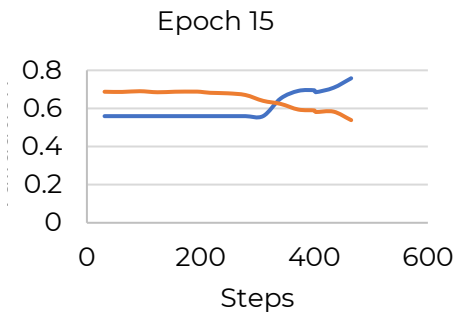
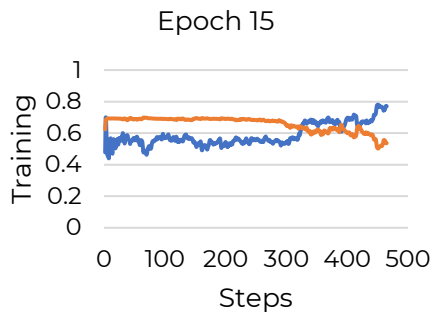


Steps

— 0,01 — 0,005 — 0,001 — 0,0005

Epoch

Epoch	Precision	Accuracy	Recall	F1score	MCC	AUC
5	0.48	1.00	0.02	0.04	0.09	0.73
	0.47	0.00	0.00	0.00	0.00	0.69
	0.45	0.00	0.00	0.00	0.00	0.72
15	0.69	0.69	0.77	0.73	0.37	0.77
	0.71	0.75	0.76	0.75	0.41	0.79
	0.63	0.58	<u>0.95</u>	0.72	0.35	0.78
30	0.73	0.73	0.87	0.79	0.41	0.79
	0.74	<u>0.79</u>	0.70	0.74	0.48	0.81
	0.74	0.77	0.78	0.77	0.47	0.84
40	0.76	0.78	0.80	0.79	0.50	0.86
	<u>0.77</u>	0.75	0.88	<u>0.81</u>	<u>0.53</u>	0.85
	0.76	0.77	0.85	0.81	0.51	0.81
100	0.73	0.74	0.82	0.78	0.44	<u>0.88</u>
	0.75	0.78	0.79	0.79	0.48	0.81
	0.73	0.73	0.79	0.76	0.46	0.83

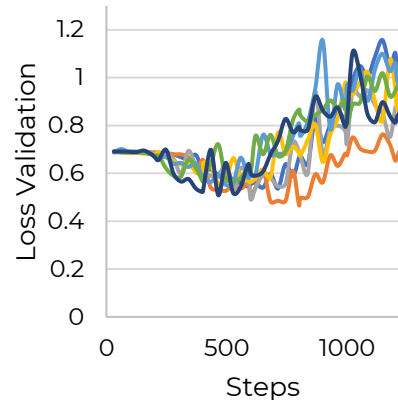
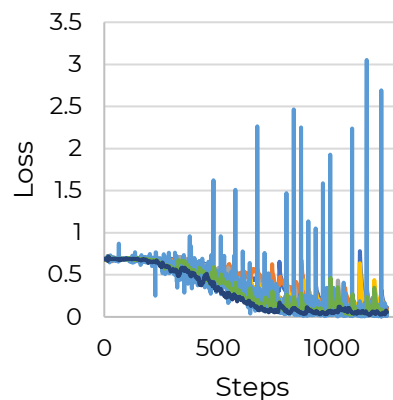
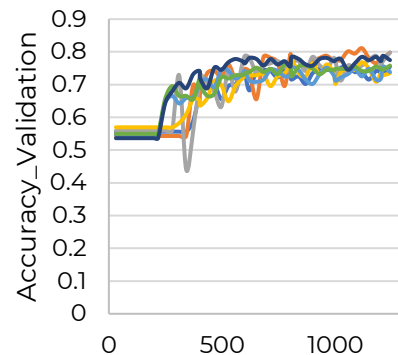
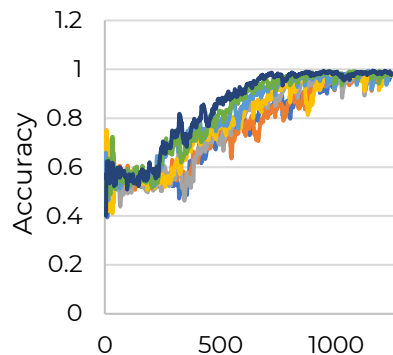


— Accuracy — Loss

— Accuracy Validation — Loss Validation

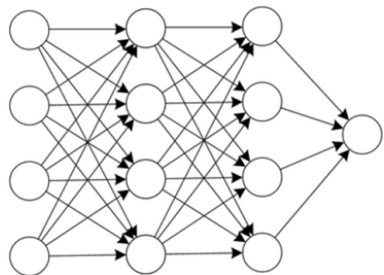
Fully connected layer

Fully connected layer	Precision	Accuracy	Recall	F1score	MCC	AUC
16	0.76	0.78	0.80	0.79	0.50	0.86
	0.77	0.75	0.88	0.81	0.53	0.85
	0.76	0.77	0.85	0.81	0.51	0.81
32	0.73	0.72	0.82	0.77	0.45	0.82
	0.78	0.77	0.83	0.8	0.56	0.84
	0.75	<u>0.82</u>	0.69	0.75	0.52	0.86
64	0.73	0.74	0.76	0.75	0.46	0.85
	0.75	0.74	0.88	0.8	0.46	0.85
	0.75	0.75	0.8	0.78	0.51	0.82
128	0.75	0.75	0.78	0.76	0.5	0.82
	0.73	0.73	0.76	0.75	0.45	0.81
	0.71	0.74	0.72	0.73	0.42	0.80
256	0.74	0.78	0.75	0.76	0.48	0.84
	0.73	0.78	0.75	0.76	0.45	0.84
	0.74	0.77	0.75	0.76	0.48	0.82
512	0.75	0.75	0.81	0.78	0.5	0.85
	0.73	0.68	0.91	0.78	0.46	0.82
	0.75	0.8	0.78	0.79	0.5	0.84

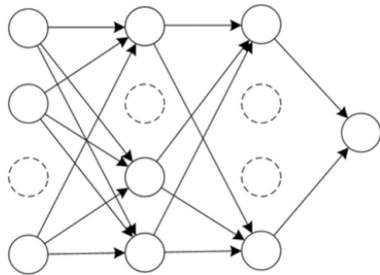


— 16 — 32 — 64 — 128
 — 256 — 512 — 1024

Drop out rate

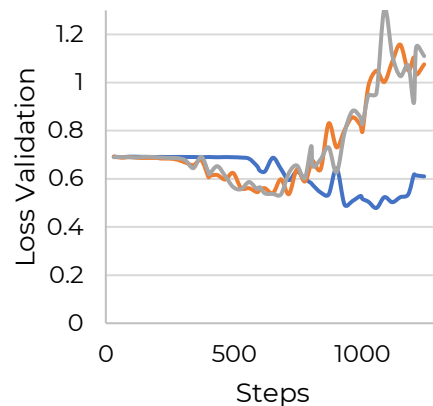
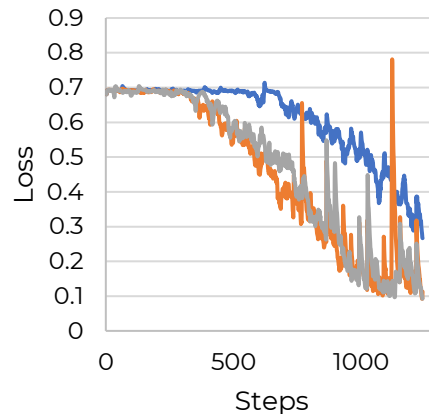
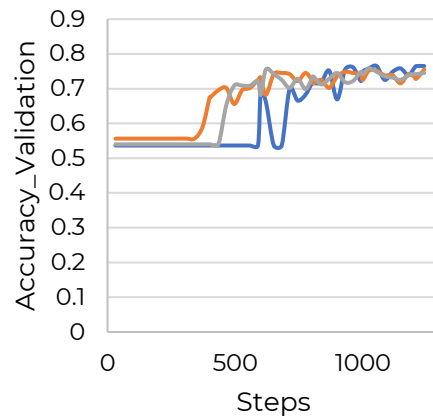
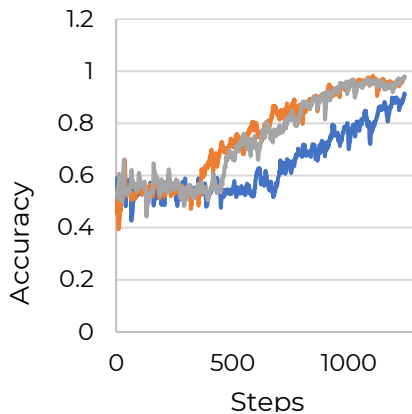


Normal neural network



Neural network with drop out rate

Parameters	Precision	Accuracy	Recall	F1score	MCC	AUC
0.4	0.70	<u>0.88</u>	0.57	0.69	0.47	0.79
	0.74	0.69	0.86	0.77	0.49	0.83
	0.73	0.75	0.76	0.75	0.45	0.83
0.6	0.76	0.78	0.80	0.79	0.50	<u>0.86</u>
	<u>0.77</u>	0.75	<u>0.88</u>	<u>0.81</u>	0.53	0.85
	0.76	0.77	0.85	<u>0.81</u>	0.51	0.81
0.8	<u>0.77</u>	0.79	0.79	0.79	<u>0.55</u>	0.81
	0.69	0.71	0.71	0.71	0.38	0.83
	0.74	0.74	0.81	0.77	0.47	0.82

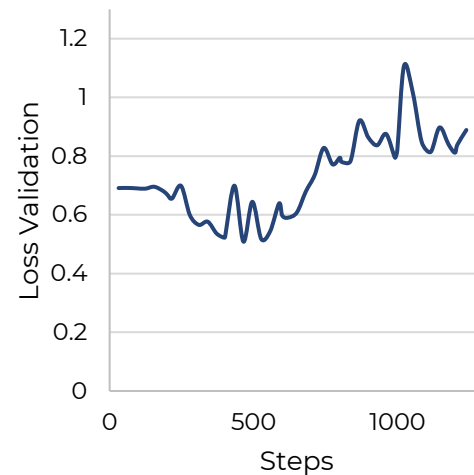
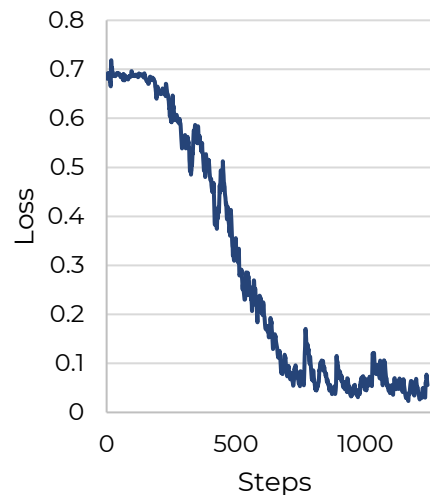
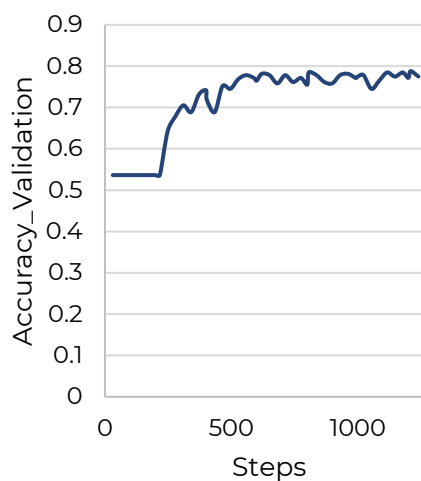
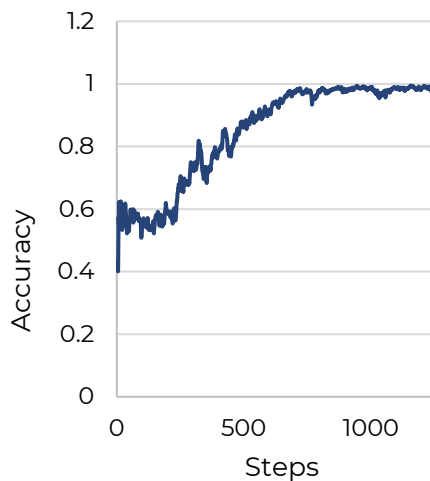


Selected model

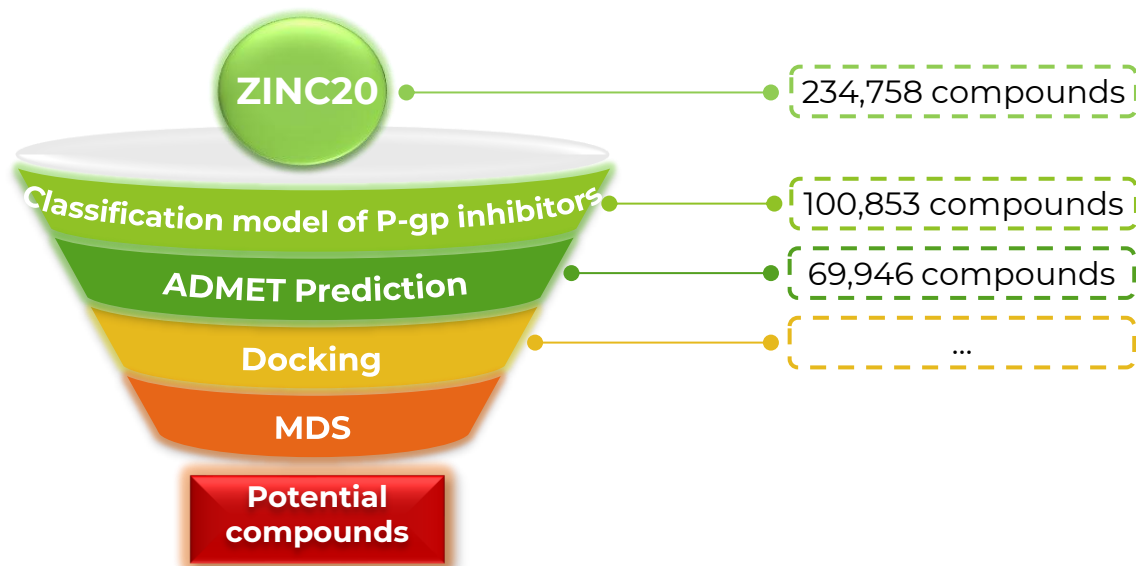
Optimization algorithm and hyperparameters

Evaluated parameters

Optimization algorithm	Learning rate	Epoch	Fully connected layer	Drop out rate	Precision	Accuracy	Recall	F1score	MCC	AUC
adam	0.0005	40	1024	0.6	0.79	0.75	0.91	0.82	0.58	0.86



Result of screening P-gp inhibitors

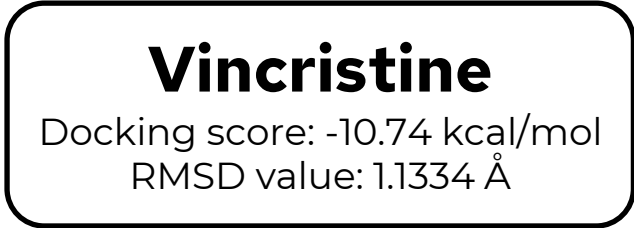


$2\text{H}_2 + \text{O}_2 = 2\text{H}_2\text{O}$

$\text{CH}_4 + 2\text{O}_2 = \text{CO}_2 + \text{H}_2\text{O}$

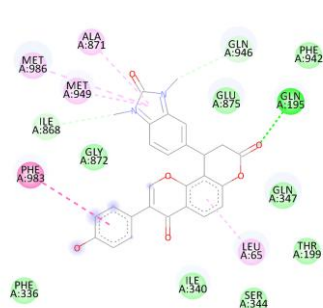
$F_1 \neq F_2$

Christine

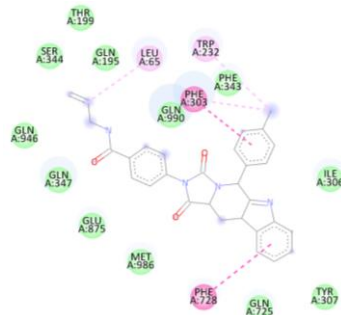


PDB code: 7A69
Resolution: 3.20 Å

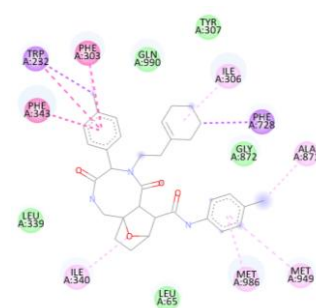
Docking



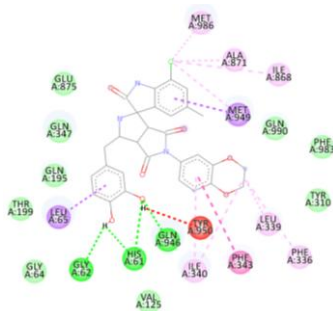
ZINC96221125 (A)
Docking score: -11.947 kcal/mol



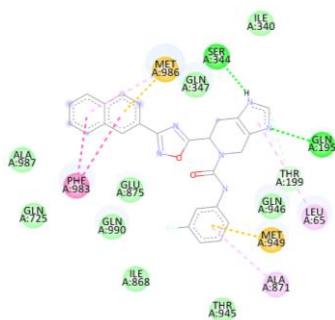
ZINC12882009 (B)
Docking score: -11.872 kcal/mol



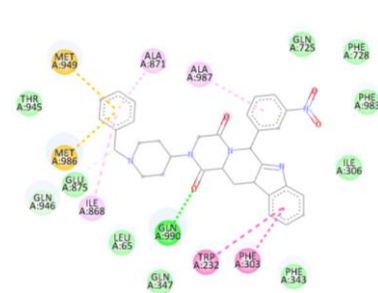
ZINC169771363 (C)
Docking score: -11.461 kcal/mol



ZINC70705366 (D)
Docking score: -11.313 kcal/mol



ZINC15675941 (E)
Docking score: -11.310 kcal/mol

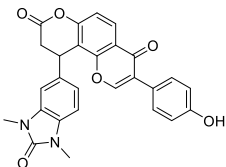


ZINC1877111 (F)
Docking score: -11.307 kcal/mol

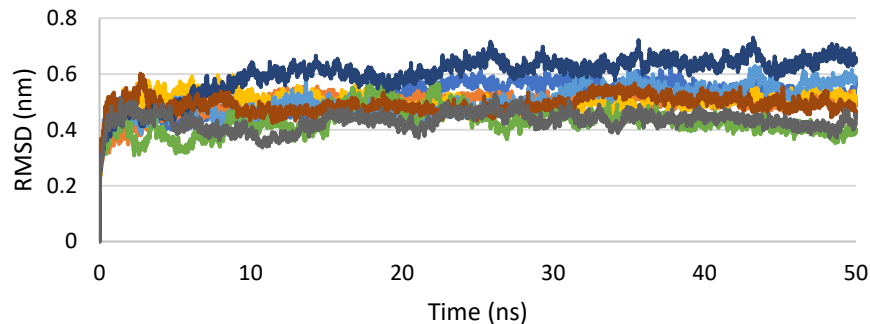
RMSD – Root Mean Square Deviation

ZINC96221125 (A)

Docking score: -11.947
kcal/mol

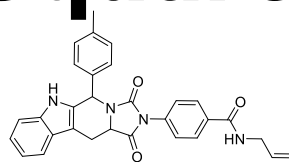


RMSD of protein

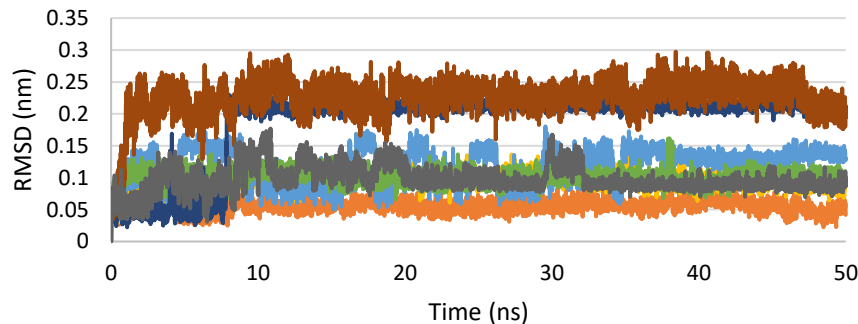


ZINC12882009 (B)

Docking score: -11.872
kcal/mol



RMSD of ligand

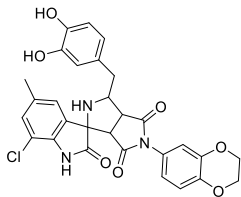


Protein tự do Vincristin ZINC96221125
ZINC12882009 ZINC169771363 ZINC70705366
ZINC15675941 ZINC1877111

Vincristin ZINC96221125 ZINC12882009
ZINC169771363 ZINC70705366 ZINC15675941
ZINC1877111

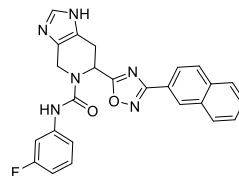
ZINC70705366 (D)

Docking score: -11.313
kcal/mol



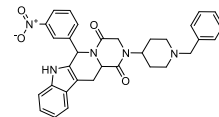
ZINC15675941 (E)

Docking score: -11.310
kcal/mol

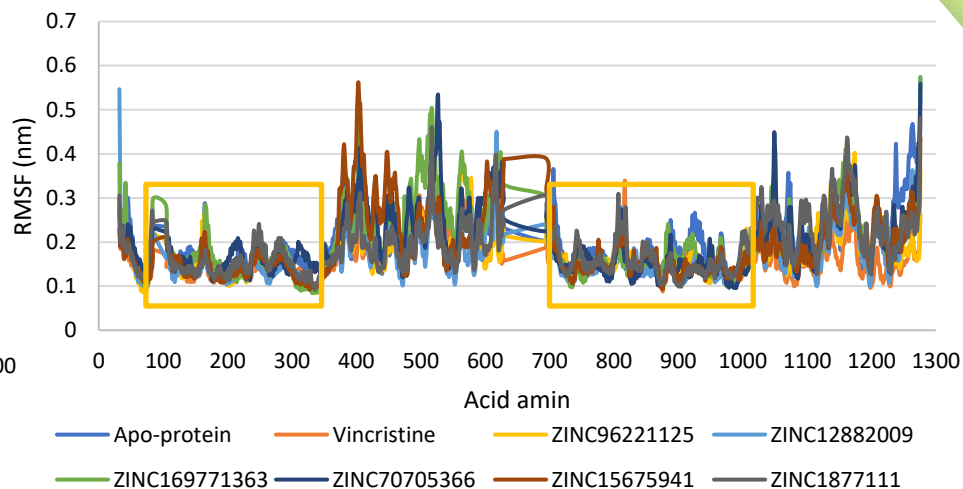
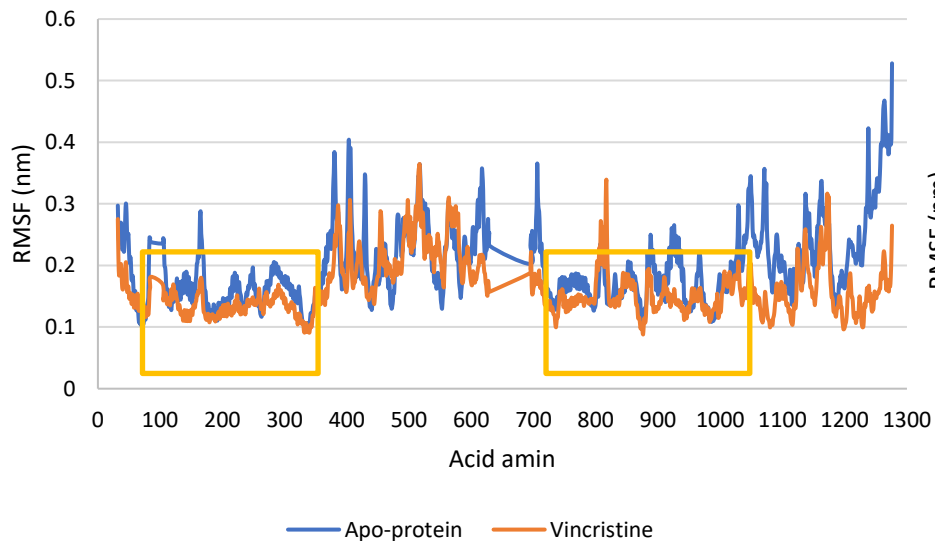
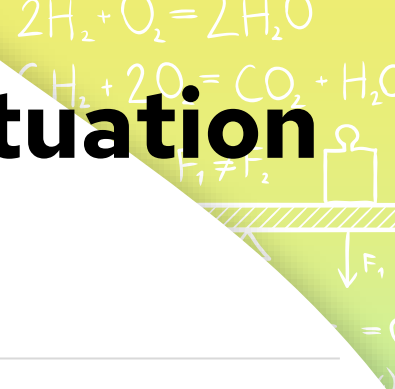


ZINC1877111 (F)

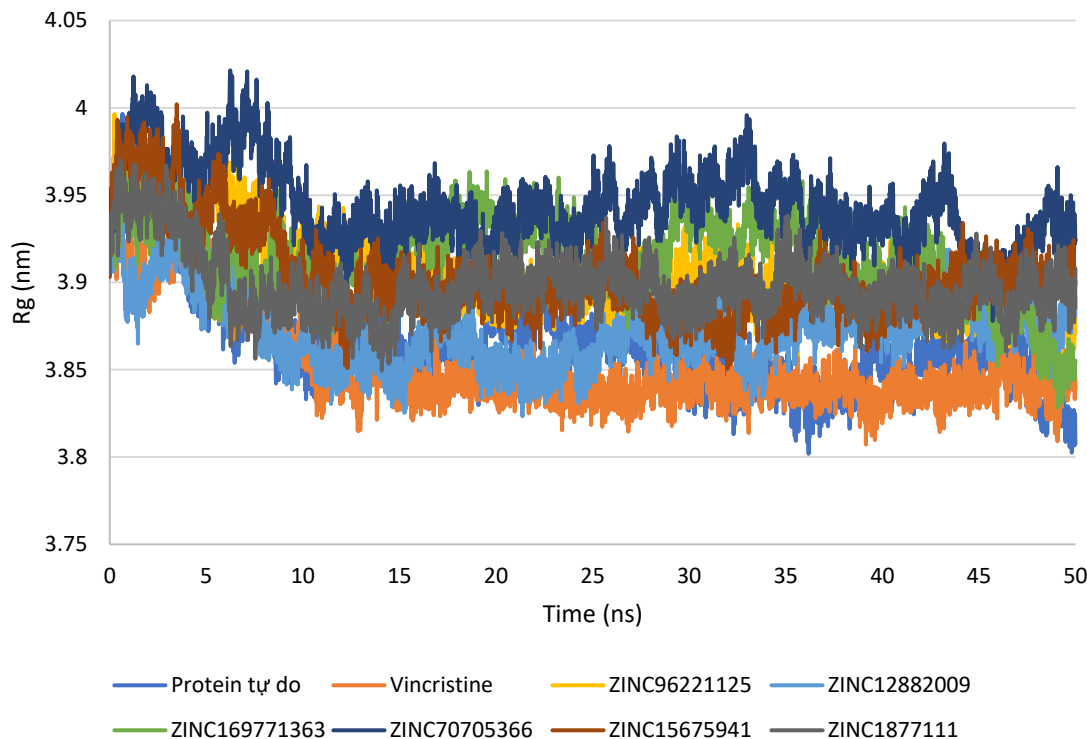
Docking score: -11.307
kcal/mol



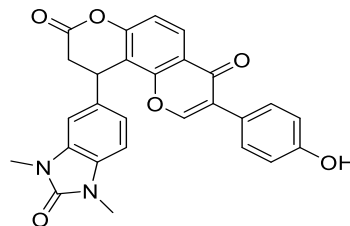
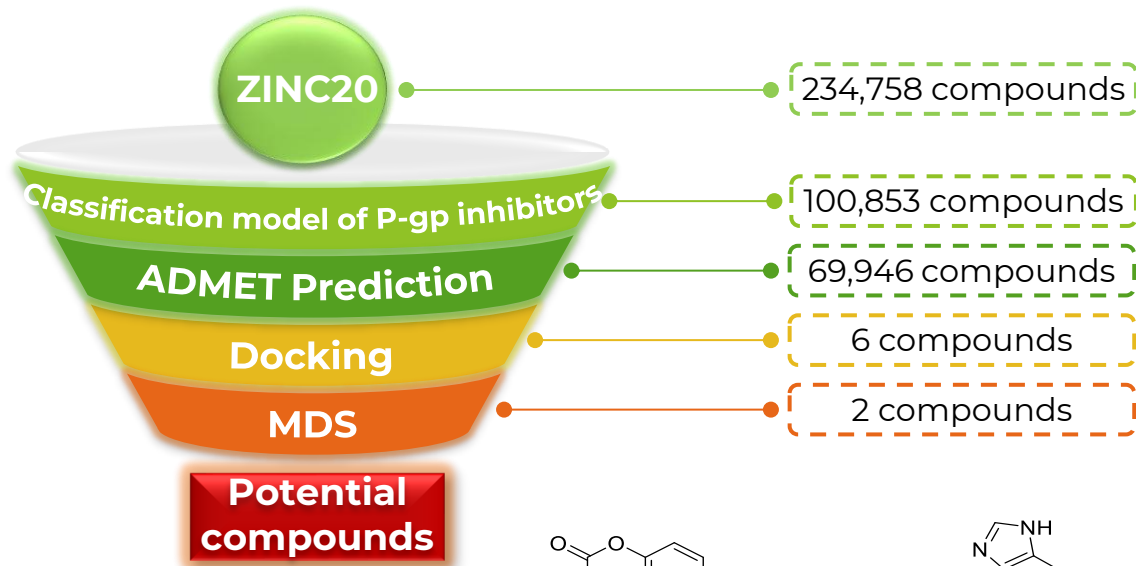
RMSF – Root Mean Square Fluctuation



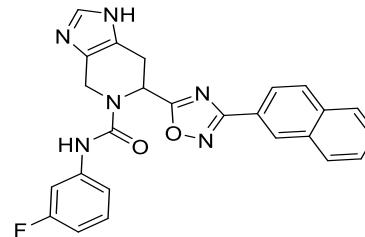
Rg – Radius of gyration



Result of screening P-gp inhibitors



ZINC96221125 (A)



ZINC15675941 (E)

Result of evaluating other datasets

Test sets	Classification threshold	TP	FP	TN	FN	Accuracy	Precision	Recall	F1-score	MCC
This research	Inhibitor: $IC_{50} \leq 15 \mu m$ Non-inhibitor: $IC_{50} > 15 \mu m$	147	49	91	15	0.79	0.75	0.91	0.82	0.58
ChEMBL (10%)	Inhibitor: $IC_{50} \leq 15 \mu m$ Non-inhibitor: $IC_{50} > 15 \mu m$	67	14	56	3	0.88	0.83	0.96	0.89	0.77
GF.Ecker et al	Inhibitor: $IC_{50} \leq 15 \mu m$ Non-inhibitor: $IC_{50} > 100 \mu m$	864	220	406	338	0.69	0.80	0.72	0.76	0.35
B.Zdrzil et al	Inhibitor: $IC_{50} \leq 15 \mu m$ Non-inhibitor: $IC_{50} > 100 \mu m$	66	59	57	9	0.64	0.53	0.88	0.66	0.38

Suggestion

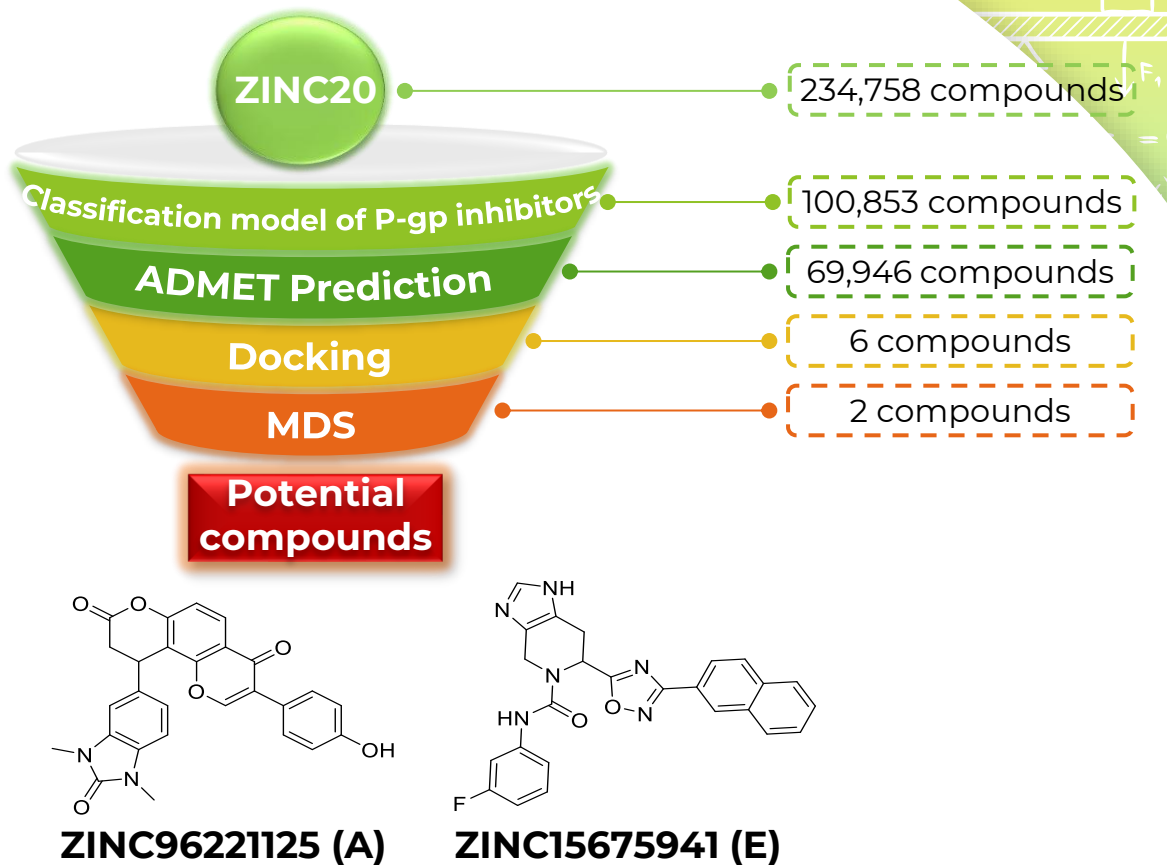
- Building model classification based on the ability of inhibitors: Strong - Weak - Non-inhibit.
- Using a standardized method to input data.

Classification models were published

Research	Year	Methods	Databases	Accuracy	Research	Year	Methods	Databases	Accuracy
H.Sun et al	2005	NB	609 compounds	82.2%	S.Eric et al	2014	ANN, SVM, combine	135 compounds	89% 
YH.Wang et al	2005	Kohonen	206 compounds	82.3%	Khac-Minh Thai et al	2015	Backpropagation neural network	133 compounds	82%
		BPNN	174 compounds	29%	V.Prachayasittikul et al	2015	DT, SVM, ANN	2477 compounds	87,4% (ANN)
P.Crivori et al	2006	PLSD	148 compounds	82%	M.Yang et al	2015	18 models machine learning	2428 compounds	77.4-79.9%
F.Broccatelli et al	2011	MIF	1195 compounds	86%	VK.Hinge et al	2019	GBM, GLM, SVM, kNN	1274 compounds	87.1-96.9% (SVM)
L.Chen et al	2011	DT, RF, NB	1273 compounds	81.2%	Khac-Minh Thai et al	2016	BPNN, C5.0, C&R Tree, QUEST, CHAID, Logistic Regression, Bayesian Network, Discriminant Analysis, SVM, combine	2131 compounds	92% (validation set) 100% (test set)
S.Rapposelli et al	2012	RF, C4.5, consensus	59 compounds	75% (RF)					
V.Poongavana m et al	2012	RF, kNN, SVM	1935 compounds	75% (RF)	This research	2022	CNN	1404 compounds	79%
F.Klepsch et al	2014	kNN, SVM, RF, DT, Binary QSAR	1954 compounds	73% (RF)					

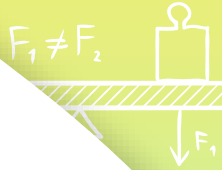
Conclusion

1. Building a deep learning model to classify P-gp inhibitors with good evaluation results
2. Predicted 100,853 natural compounds capable of inhibiting P-gp
3. Two potential substances to inhibit P-gp are
ZINC96221125 (A),
ZINC15675941 (E)



Suggestion

1. Extending simulation time to 100ns.
2. Testing *in vitro* and synthesizing (if necessary) potential compounds.
3. Building classification models for substrates and inhibitors.



Acknowledgement

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Phuong-Uyen Tran-Thi



Minh Quang Mai

Thank you for listening!

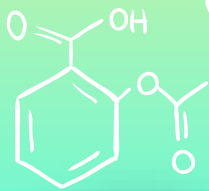
$$\begin{pmatrix} 1001 \\ 1110 \\ 1010 \\ 0001 \end{pmatrix}$$



$$(\pi k, 0); k \in \mathbb{Z}$$

$$ax^2 + bx + c = 0$$

$$\sin^2 \alpha + \cos^2 \alpha = 1$$



$$\phi(x) = \frac{1}{\sqrt{2\pi\sigma^2}}$$

$$y = |-2x|$$



$$F = m \cdot a$$



$$s = ut + \frac{1}{2}at^2$$
$$v = u + at$$
$$w = F \cdot s$$

