



## QSAR model to develop newer generation GSK-3 $\beta$ inhibitors targeting Alzheimer

Supriyo Saha<sup>1\*</sup>, Prinsa<sup>2</sup>, Vikash Jakhmola<sup>1</sup>, Arun Kumar Mahato<sup>3</sup>,  
Praveen Kumar Ashok<sup>4</sup>, Vishal Warikoo<sup>3</sup>, Sayantan Mukhopadhyay<sup>5</sup>

<sup>1</sup>Department of Pharmaceutical Chemistry, Uttaranchal Institute of Pharmaceutical Sciences, Uttaranchal University, Premnagar, Dehradun, Uttarakhand- 248007, INDIA.

<sup>2</sup>Siddhartha Institute of Pharmacy, Saharasthara Road Near IT-Park Dehradun 248001, Uttarakhand India.

<sup>3</sup>Sardar Bhagwan Singh University, Balawala, Dehradun 248001, Uttarakhand India.

<sup>4</sup>Gyani Inder Singh Institute of Professional Studies, Dehradun 248001, Uttarakhand India.

<sup>5</sup>College of Pharmacy, Shivalik Campus, Dehradun-248001. Uttarakhand India.

\*Corresponding author, Email address: [supriyo9@gmail.com](mailto:supriyo9@gmail.com); Orchid id: <https://orcid.org/0000-0003-1365-4698>

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**Abstract:** In the year 2022 most of the patients affected by the disease was around 65 year age. Among total number of patients, 73% were near 75 year or older age. It was also stated that maximum numbers of patients were women. Black Americans were more affected by Alzheimer than white Americans. GSK-3 has also been linked to the hyperphosphorylation of tau protein, the development of amyloid-beta plaques, other inflammatory responses, activation of microglial cells, the production of neurotoxic inflammatory factors, and a decrease in the level of acetylcholine, all of which together lead to Alzheimer's disease. GSK-3 controlled the inflammatory stress brought on by anomalies in the mitochondria and endoplasmic reticulum. However, none of the compounds utilised in the treatment were particularly helpful in curing the patient completely. The development of newer generation anti-Alzheimer therapeutic compounds was therefore hampered by this curse, and computational approaches were crucial in breaking it. The most effective QSAR model was  $pIC_{50} = -5.47052 + 2.60572 IC_1 + 1.64642 GATS_2e + 2.088 mindssC - 0.01441 ATSC_7s - 13.5191 AVP_0 + 0.16712 minssNH - 0.15369 minaaN + 0.01777 VR_2Dt + 1.52684 MATS_8s + 0.04725 nAtomP$  with all necessary acceptance criteria  $Q^2: 0.60111$ ,  $r^2: 0.65711$ ,  $|r^2 - r^2_0|: 0.07866$ ,  $k: 0.99121$   $[(r^2 - r^2_0)/r^2]$   $0.00543$  or  $k': 0.92437$   $[(r^2 - r^2_0)/r^2]$   $0.12513$ . It is clear that our QSAR model will be a blessing for humanity if we wish to produce a chemical that works as a GSK-3 inhibitor to treat Alzheimer's disease in the near future.

**Keywords:** GSK-3 $\beta$ ; Alzheimer Disease; Modelability Index; KS Method; GT acceptable criteria; YR Test.

### 1. Introduction

According to recent statistics, more than 60 lakh Americans had Alzheimer's disease. Most patients with the condition in 2022 were around 65 years old (Tang *et al.*, 2014; Limor & Eldar-Finkelman 2013; El khatabi *et al.*, 2021). A total of 73% of the patients were 75 years of age or older. Additionally, it was noted that women made up the majority of the patients. According to the

Alzheimer's Facts and Figures Report Alzheimer's Association, black Americans were more likely to develop Alzheimer's disease than white Americans. Rivastigmine, Donepezil, galantamine, memantine are some commercially available anti Alzheimer drugs. GSK-3, or glycogen synthase kinase 3, originally attracted attention in year 1980. According to (Pal & Saha 2019; Ling *et al.*, 2013), the enzyme was primarily used to facilitate the production of glycogen from glucose using uridine diphosphate glucose molecules. GSK was a cell-specific enzyme with a serine/threonine amino acid basis (Akihiko 2006; Toral-Rios *et al.*, 2020). The enzyme comes in two varieties, GSK-3 and GSK-3. Through the phosphorylation of serine21 for alpha and serine9 for beta, this enzyme primarily initiated the downregulation process of neurons (Angela *et al.*, 2021). According to (Griebel *et al.*, 2019), GSK-3 controlled the development of beta-amyloid plaques via the Wingless and Int-1/phosphatidylinositol-3 pathway. According to (Kim *et al.*, 2006), GSK-3 has also been linked to the hyperphosphorylation of tau protein (Kareti & Subash 2020; Chtita *et al.*, 2016), the development of amyloid-beta plaques, other inflammatory responses, activation of microglial cells, the production of neurotoxic inflammatory factors, and a decrease in the level of acetylcholine, all of which contribute to the development of Alzheimer's disease (El Alaouy *et al.*, 2021; El-Mernissi *et al.*, 2023). According to Hooper *et al.*, 2008, GSK-3 controlled the inflammatory stress caused by anomalies in the endoplasmic reticulum and the mitochondria (El Alaouy *et al.*, 2023). These pathways have been collectively linked to numerous neurological conditions like Parkinson's, Alzheimer's, mood swings, and other illnesses connected to cognition and behaviour (Ma, 2014; De Strooper & Karran 2016). To anticipate the bioactivity of newer generation GSK-3 inhibitors effective against Alzheimer's disease, we created a QSAR model in this context.

## 2. Materials and Methodology

### 2.1. Dataset and Descriptor Calculation

A dataset of 124 GSK-3 inhibitors for Alzheimer's disease was obtained from the database (Thomas *et al.*, 2012). The ACD ChemSketch software was used to create each molecule, which was then saved in MDL Mol format. Then, using the PADEL descriptor, two-dimensional descriptors of the molecules were derived (Saha *et al.*, 2022a). The biological activities associated with each molecular descriptor were tabulated in CSV format, with IC50 values converted to pIC50 values.

### 2.2. Modelability Index

Modelability index is a method for estimating feasibility that is defined by the ratio between the total number of pairings and the nearest-neighbour pairs of compounds that belong to the same activity class (Saha *et al.*, 2022b; Alamari *et al.*, 2023). This idea was related to the wasteful efforts of a QSAR dataset involved in the creation of a QSAR model.

### 2.3. Descriptor Pretreatment

Then, by using a variance cut off and correlation coefficient values of 0.0001 and 0.99, respectively, closely related descriptors found in the dataset were eliminated (Saha *et al.*, 2022).

### 2.4. Dataset Division

The Kennard Stone (KS), Random Faster, and Euclidean Distance methods were typically used to partition the dataset into training and test sets. We chose the KS approach to partition the dataset of 124 molecules into a training set and a test set in this instance. Following dataset partition, the training set contained 86 molecules, whereas the test set contained 38 molecules (de Moura *et al.*, 2021).

### 2.5. Suitable Descriptor Selection

Using Stepwise MLR software, a set of appropriate descriptors was chosen with F values ranging from 3.9 to 4.0. Then, the R<sup>2</sup> cut off value of 0.6 was shown to be the optimum subset combination (Kumar *et al.*, 2023).

### 2.6. Stepwise regression

The construction of a stepwise multiple linear regression equation involved three independent processes, including the discovery of an initial model, repeating the previous step to improve the F and R<sup>2</sup> value, and calibrating the model. Statistical SPSS software was used to create the stepwise regression equation, which was evaluated using the parameters of explained variance (R<sup>2</sup><sub>a</sub>), correlation coefficient (R), standard error of estimate (s), and variance ratio (F) with a given DF. Finally, using cross validation R<sup>2</sup> (Q<sup>2</sup>), SPRESS, and SDEP parameters, the LOO approach was used to validate the model (Hassan *et al.*, 2022).

### 2.7. QSAR Equation Development

According to the accuracy of the predictions, the final QSAR model was created by Multiple Linear Regression Plus valid software (Hanieh *et al.*, 2022).

### 2.8. QSAR Equation Validation

The acceptable model criteria of Golbraikh and Tropsha (GT acceptable criteria) were used to validate the constructed QSAR model. The following were the requirements for an acceptable model (Ambure & Roy 2016).

1.  $Q^2 > 0.5$ .
2.  $R^2 > 0.6$ .
3.  $|r^2 - r'^2| < 0.3$ .
4.  $[0.85 < k < 1.15 \text{ and } ((r^2 - r'^2)/r^2) < 0.1 \text{ or } [0.85 < k' < 1.15 \text{ and } ((r'^2 - r^2)/r'^2) < 0.1]$ .

### 2.9. QSAR Equation Validation

The LOO procedure was used to cross-validate the QSAR model. By using mahalanobis distance and euclidean distance approaches, the model's applicability domain was examined. A specified application domain threshold value was compared to the distance between a test set and its closest neighbour in the training set (Yap 2011).

### 2.10. MLR YRandomization (YR) test

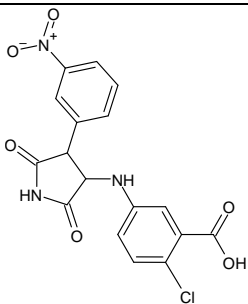
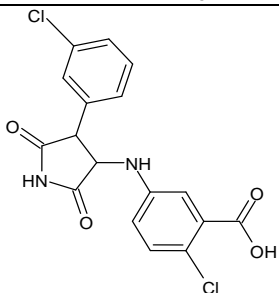
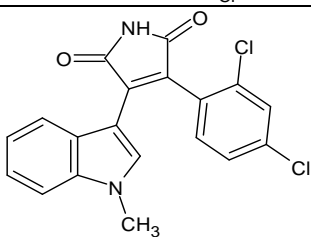
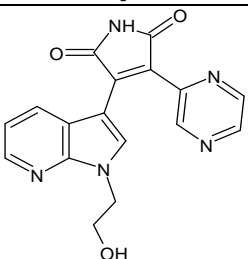
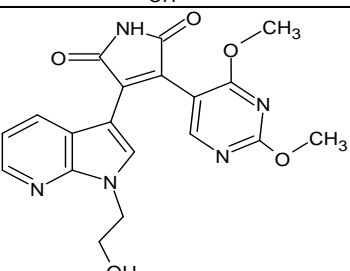
In the YR test, a quicker random technique was used to create a random multiple linear regression model by changing the dependent variable while keeping the independent variable constant. After multiple trials, the model with considerably better R<sup>2</sup> and Q<sup>2</sup> values demonstrated that the proposed model was reliable and repeatable. In order to pass this test, another parameter, cRp<sup>2</sup>, which must be more than 0.5, was also calculated (Golbraikh *et al.*, 2014).

## 3. Results and Discussion

When the modelability index value of the entire dataset was first verified, it was found to be 0.55, with 41 molecules having a high total active/lower activity and 83 molecules having a low total active/toxic activity, with a threshold value of 0.65. Therefore, the model's modelability index score was 0.5926, indicating that the dataset was near to what was needed to create a good QSAR

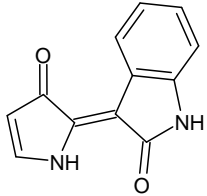
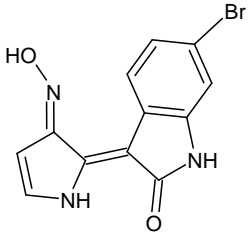
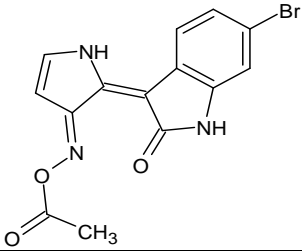
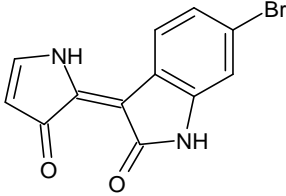
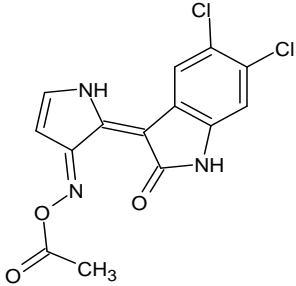
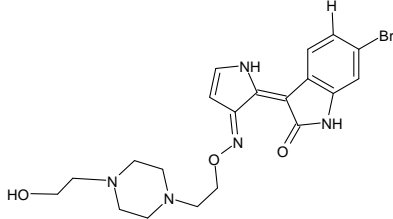
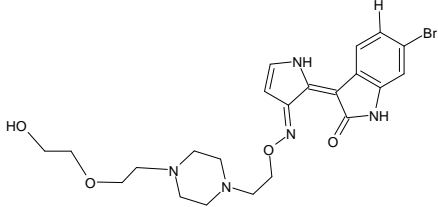
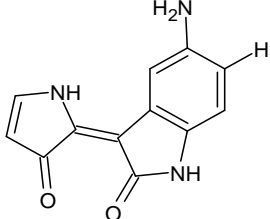
(Quantitative Structure Activity Relationship) model. The Kennard-Stone approach was then used to split the entire dataset into training and test set. In the training and test sets, there were, respectively, 86 and 38 molecules present. The most likely group of descriptors to employ in a successful QSAR model were found using stepwise multiple linear regression analysis. Then, using the best set of descriptors available, the best subset selection process was carried out using an R2 cut-off value of 0.6 and an R2 cut-off value of 0.5 for inter-correlation between descriptors (Ballabio *et al.*, 2014). Following the multiple linear regression analysis, we created five distinct QSAR models (Table 1 and Table 2), ranging from the fewest to the most descriptors.

**Table 1.** Actual pIC50, and Predicted pIC50 Values of Training Set Molecules of the best QSAR Model.

SN	Structure of the compounds	Actual pIC50	Predicted pIC50
1		-1.41497	-2.22094
2		-2.89542	-2.73921
3		-1.53148	-2.18685
4		-1.39794	-0.72689
5		-0.77815	-0.40648

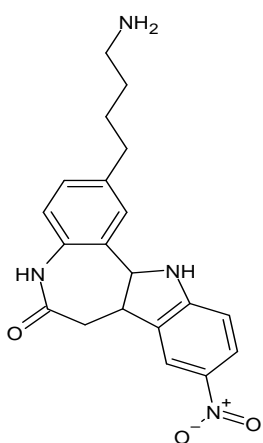
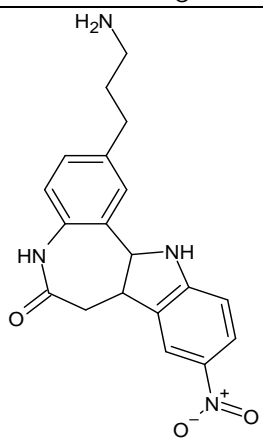
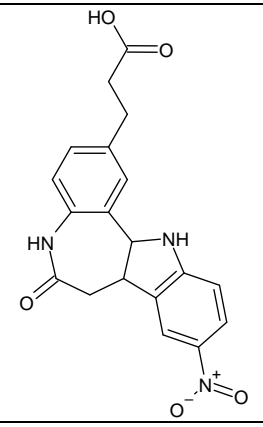
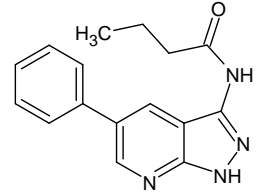
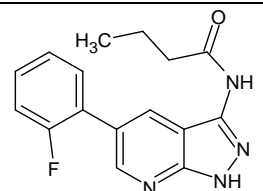
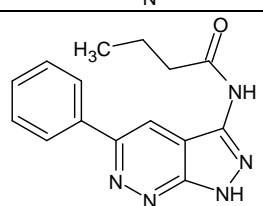
6		-0.60206	-0.58177
7		-1.41497	-1.62494
8		-2.14613	-1.1836
9		0.221849	-0.35942
10		-2.94939	-0.99586
11		-3.65031	-1.34828
12		-0.44716	0.589746

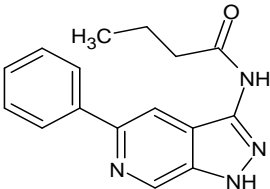
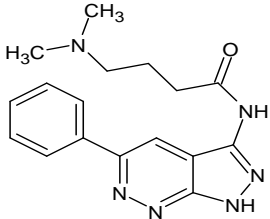
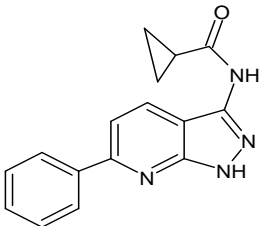
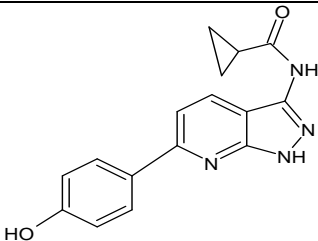
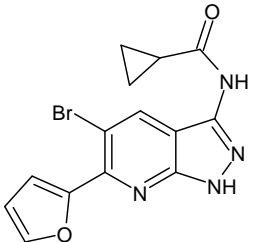
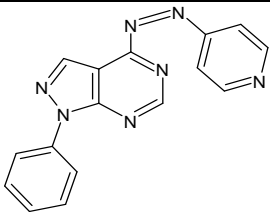
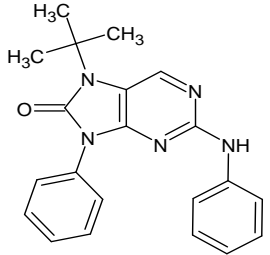
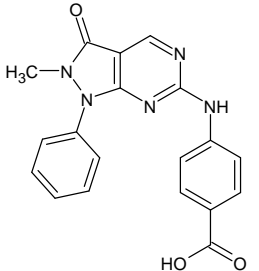
13		-0.8451	-0.54697
14		-0.73239	-0.51165
15		-2.48287	-2.19145
16		-1.96379	-2.13535
17		-2.43136	0.083766
18		-1.17609	-1.86128
19		-1.34242	-1.27194

20		-2.77815	-0.62703
21		-0.69897	-0.12701
22		-1	-0.78529
23		-1.65321	-0.87523
24		-0.60206	-0.93966
25		-0.69897	-1.00089
26		-1.14613	-1.03339
27		-1.90309	-0.72496

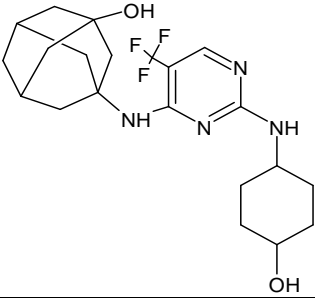
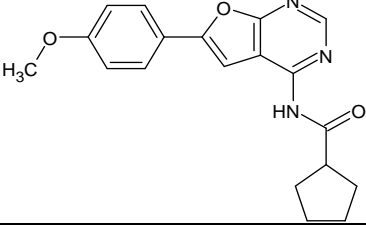
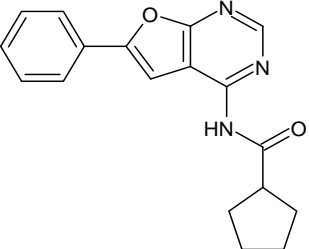
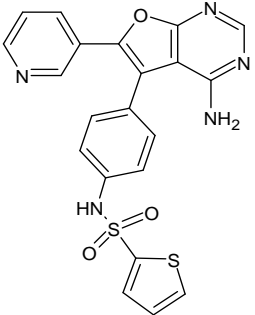
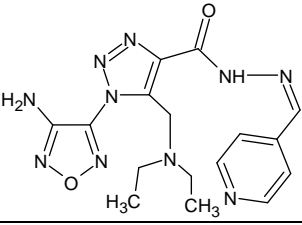
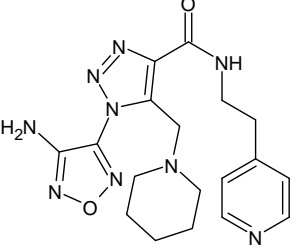
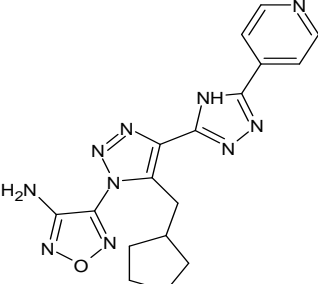
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29		-1.60206	-2.3758
30		-0.32222	-1.52093
31		-1.36173	-1.96416
32		-0.60206	-0.68383
33		-1.47712	-0.39746
34		-1.60206	-1.70237



35		-0.77815	-1.90844
36		-0.39794	-1.97428
37		-0.81291	-1.35609
38		-1.74819	-1.75919
39		-1.25527	-1.4052
40		-0.60206	-1.51684

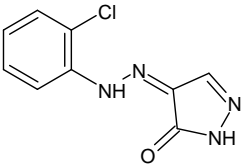
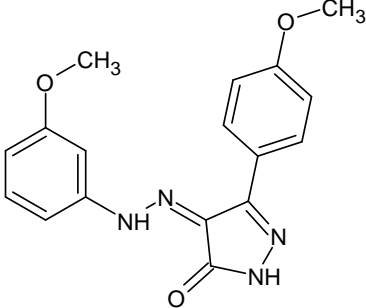
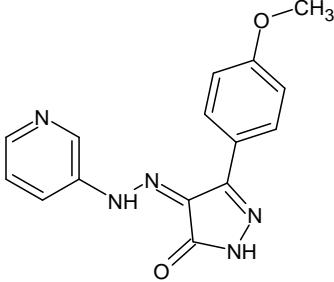
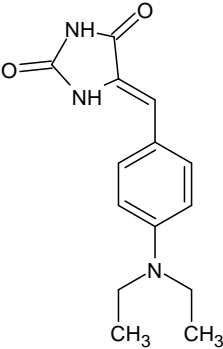
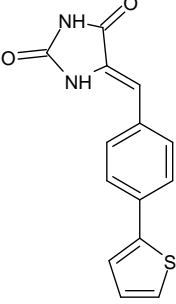
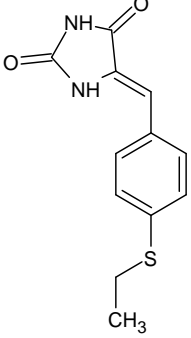
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42		-1.34242	-0.69354
43		-2.62839	-0.8534
44		-0.90309	-1.86433
45		-0.8451	-0.59118
46		-2	-0.80109
47		-3.38021	-2.50705
48		-2.98227	-0.54668

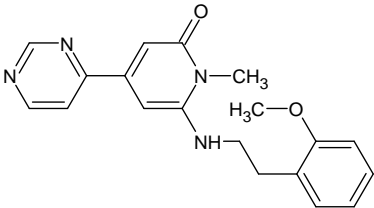
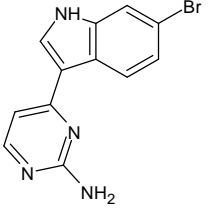
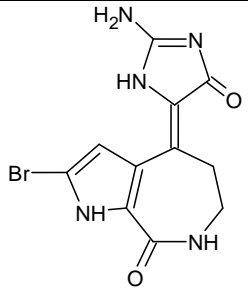
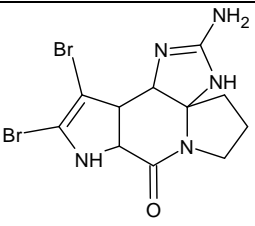
49		-2.88081	-2.81112
50		-2.25527	-2.13329
51		-3.54407	-2.17863
52		-2.17609	-1.89979
53		-2.6902	-2.88638
54		-1.11394	-1.97767

55		-1.61278	-1.49188
56		-1.50515	-0.97557
57		-1.36173	-1.86114
58		-1.36173	-1.27403
59		-2.61278	-1.54548
60		-3.06446	-1.26618
61		-2.44716	-1.51465

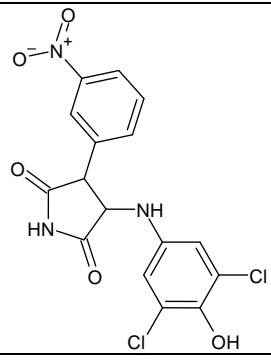
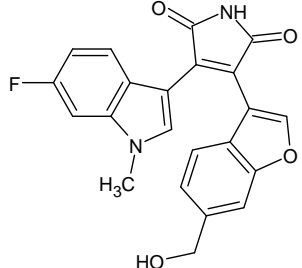
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63		-2.38021	-2.60846
64		-2.4624	-2.53969
65		-0.54407	-1.49584
66		-0.36173	-1.76997
67		-2.14613	-2.36521
68		-2.27875	-1.50115

69		-1.23045	-0.76386
70		-0.8451	-1.10673
71		-2.54407	-2.92428
72		-2.83885	-2.337
73		-2.11394	-2.5921
74		-2.74819	-2.86505
75		-2.01703	-2.19594
76		-1.17609	-1.9819

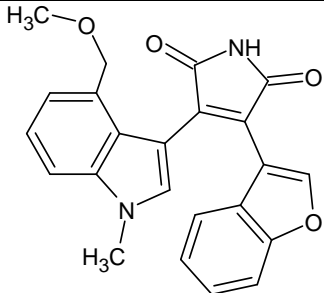
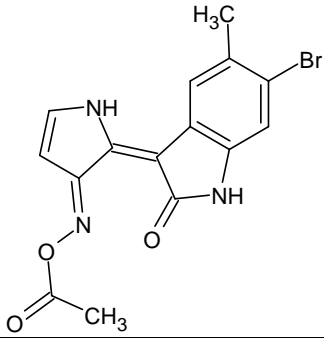
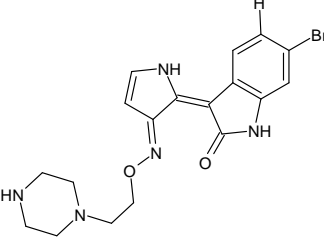
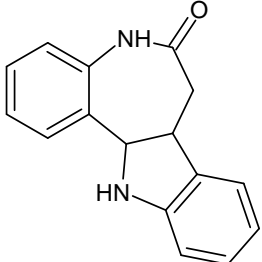
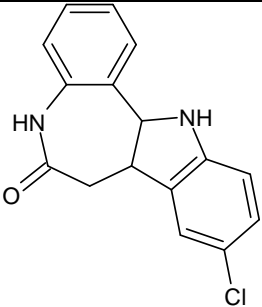
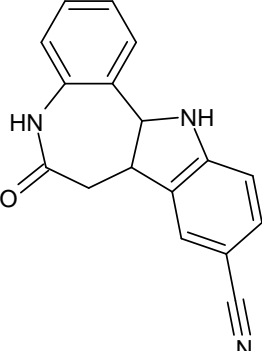
77		-3.17319	-1.66181
78		0.09691	-3.19567
79		-0.30103	-2.73399
80		-3.62325	-0.74004
81		-3.80618	-1.02228
82		-3.89209	-1.48276

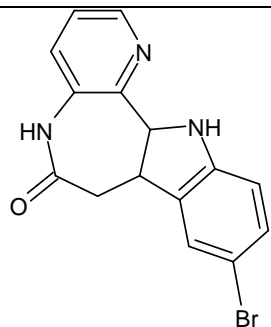
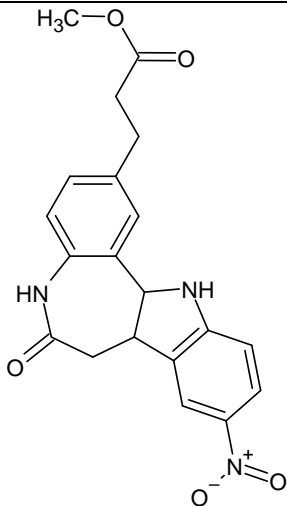
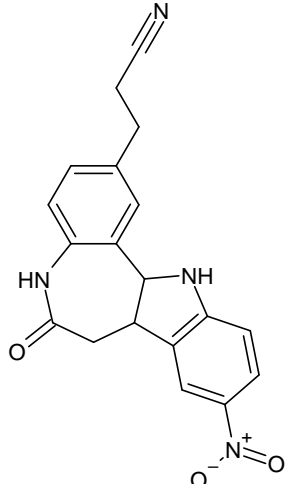
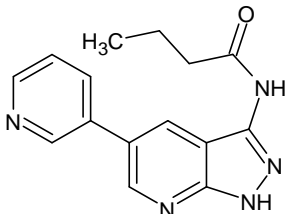
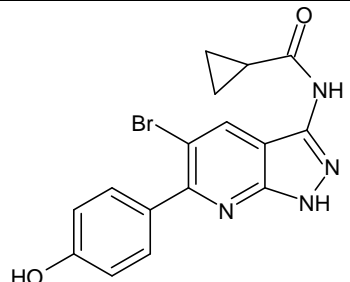
83		-1.24055	-3.39249
84		-3.39794	-3.80155
85		-1	-1.0735
86		-3.47712	-2.29833

**Table 2.** Actual pIC<sub>50</sub>, and Predicted pIC<sub>50</sub> Values of Test Set Molecules of the best QSAR Model.

SN	Structure of the compounds	Actual pIC <sub>50</sub>	Predicted pIC <sub>50</sub>
1		-1.30103	-1.27507
2		0.455932	-2.94906

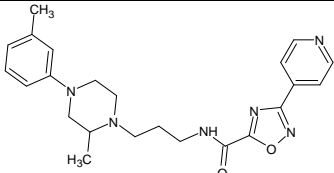
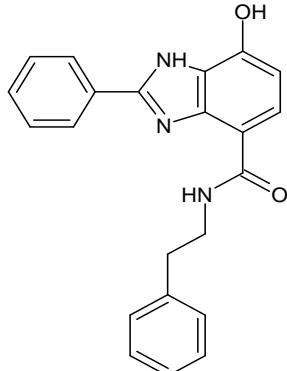
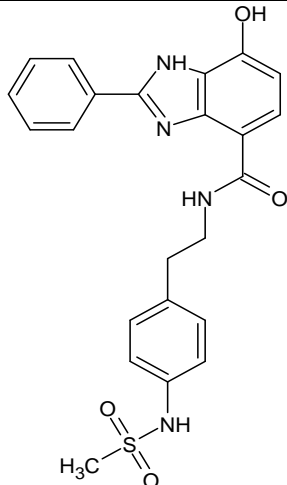
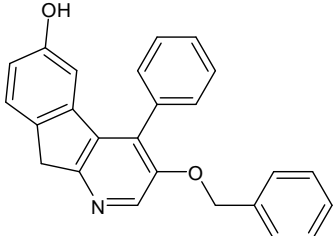
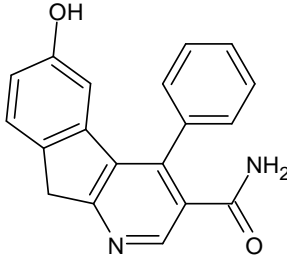
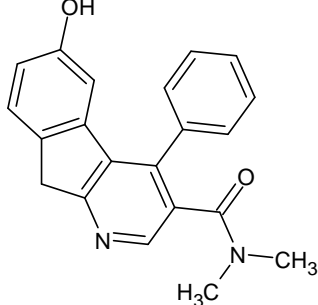


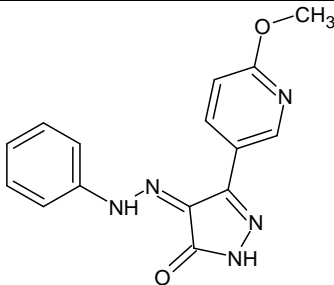
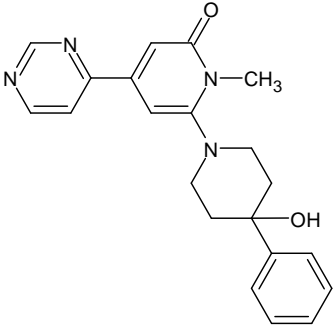
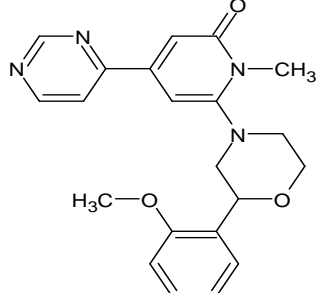
3		0.638272	-2.59976
4		-0.8451	-2.57599
5		-0.51851	-1.04211
6		-2.79239	-1.98943
7		-1.38021	-1.9894
8		-1	-1.7943

9		-1.25527	-2.29929
10		-1.53148	-0.10967
11		0.09691	0.108851
12		-1.04139	-1.35735
13		0.09691	-0.66613

14		-1.87506	-0.14005
15		-0.39794	-2.33035
16		-0.60206	-2.47494
17		-3.23045	-3.2014
18		-2.79796	-2.8862
19		-1.96379	-2.2231
20		-0.69897	-1.86114

21		-0.69897	-1.23586
22		-1.47712	-0.77889
23		-2	-1.98689
24		-1.81291	-1.39531
25		-1.64345	-1.59345
26		-0.49136	-1.03709
27		-1.72428	-2.42491
28		-1.25527	-1.79302
29		-2.61278	-2.72557

30		-3.05308	-2.05047
31		-2.76343	-2.62762
32		-1.39794	-3.01513
33		-3.76343	-2.46821
34		-3.61278	-3.70334
35		-3.17609	-0.90886

36		-0.65321	-1.0735
37		-0.92942	-3.74375
38		-1.20683	-1.47041

### 3.1. Model 1 (with 10 descriptors)

$pIC_{50} = -5.47052 + 2.60572 IC_1 + 1.64642 GATS2e + 2.088 mindssC - 0.01441 ATSC7s - 13.5191 AVP-0 + 0.16712 minssNH - 0.15369 minaaN + 0.01777 VR2\_Dt + 1.52684 MATS8s + 0.04725 nAtomP.$

[Internal Validation Parameters (IVP): SEE :0.58767,  $r^2$  :0.70183,  $r^2$  adjusted :0.66207, PRESS :25.90197, F :17.6534 (DF (Degree of Freedom) :10, 75); Leave-One-Out(LOO) Result: Q2 :0.60111, Average  $rm^2$ (LOO) :0.47316, Delta  $rm^2$ (LOO) :0.19941; External Validation Parameters (EVP)(Without Scaling)::  $r^2$  :0.65711,  $r_0^2$  :0.65354, reverse  $r_0^2$ :0.57488, RMSEP (Root Mean Square Error of Prediction) :0.63121, Q2f1/ $R^2$ (Pred) :0.68626, Q2f2 :0.65324; EVP (After Scaling): Average  $rm^2$ (test) :0.54109, Delta  $rm^2$ (test) :0.1653]

{GT acceptable criteria :  $Q^2$ : 0.60111 Passed ( $Q^2 > 0.5$ ),  $r^2$ : 0.65711 Passed ( $r^2 > 0.6$ ),  $|r_0^2 - r'^0^2|$ : 0.07866 Passed ( $|r_0^2 - r'^0^2| < 0.3$ ), k: 0.99121 [ $(r^2 - r_0^2)/r^2$ ] 0.00543 or k': 0.92437 [ $(r^2 - r'^0^2)/r^2$ ] 0.12513 Passed}

### 3.2. Model 2 (with 11 descriptors)(Roy and Mitra 2011)

$pIC_{50} = -6.19416 + 2.64534 IC_1 + 1.80112 GATS2e + 2.20934 mindssC - 0.01408 ATSC7s - 12.84456 AVP-0 + 0.19708 minssNH - 0.1799 minaaN + 0.02228 VR2\_Dt + 1.61577 MATS8s + 0.05144 nAtomP - 0.25802 nF12Ring.$

[IVP:: SEE :0.55403,  $r^2$  :0.73853,  $r^2$  adjusted :0.69966, PRESS :22.71409, F :19.00109 (DF :11, 74); Leave-One-Out(LOO) Result :: Q2 :0.59013, Average  $rm^2$ (LOO) :0.47465, Delta  $rm^2$ (LOO) :0.12766; EVP(Without Scaling)::  $r^2$  :0.66916,  $r_0^2$  :0.6592, reverse  $r_0^2$ :0.61934, RMSEP:0.62738, Q2f1/ $R^2$ (Pred) :0.69006, Q2f2 :0.65743; EVP (After Scaling):: Average  $rm^2$ (test) :0.5594, Delta  $rm^2$ (test) :0.09565]

{GT acceptable criteria::  $Q^2$  : 0.59013 Passed,  $r^2$ : 0.66916 Passed,  $|r_0^2-r'^0^2|$ : 0.03986 Passed), k: 0.97891 [ $(r^2-r_0^2)/r^2$ ] 0.01489 or k': 0.93738 [ $(r^2-r_0^2)/r^2$ ] : 0.07445 Passed}

### 3.3. Model 3 (with 12 descriptors)

pIC50 = -7.11297 + 2.59644 IC1 -0.23252 minsssN +2.11949 GATS2e +2.03621 mindssC -0.01331 ATSC7s -10.98537 AVP-0 +0.24422 minssNH -0.16546 minaaN +0.02086 VR2\_Dt +1.21546 MATS8s +0.03775 nAtomP -0.2656 nF12Ring.

[IVP:: SEE :0.53557,  $r^2$  :0.75896,  $r^2$  adjusted :0.71933, PRESS :20.93933, F :19.15421 (DF :12, 73); Leave-One-Out(LOO) Result :: Q2 :0.64714, Average  $rm^2$ (LOO) :0.53284, Delta  $rm^2$ (LOO) :0.14785; EVP (Without Scaling)::  $r^2$  :0.72485,  $r_0^2$  :0.72259, reverse  $r_0^2$ :0.67595, RMSEP:0.56733, Q2f1/ $R^2$ (Pred) :0.74655, Q2f2 :0.71988; EVP (After Scaling):: Average  $rm^2$ (test) :0.62788, Delta  $rm^2$ (test) :0.09232]

{GT acceptable criteria::  $Q^2$  : 0.64714 Passed,  $r^2$ : 0.72485 Passed,  $|r_0^2-r'^0^2|$  : 0.04664 Passed, k: 0.97418 [ $(r^2-r_0^2)/r^2$ ] 0.00311 or k' : 0.95766 [ $(r^2-r_0^2)/r^2$ ] 0.06745 Passed}

### 3.4. Model 4 (with 13 descriptors)(Roy et al., 2014)

pIC50 = -6.022 +2.58977 IC1 -0.24611 minsssN +1.93576 GATS2e -1.28529 GATS7v +2.08453 mindssC -0.0132 ATSC7s -10.29187 AVP-0 +0.24584 minssNH -0.15455 minaaN +0.02051 VR2\_Dt +1.09995 MATS8s +0.03865 nAtomP -0.20946 nF12Ring.

[IVP::SEE :0.51741,  $r^2$  :0.77811,  $r^2$  adjusted :0.73804, PRESS :19.27568, F :19.42172 (DF :13, 72); Leave-One-Out(LOO) Result :: Q2 :0.69747, Average  $rm^2$ (LOO) :0.5901, Delta  $rm^2$ (LOO) :0.16211; EVP(Without Scaling)::  $r^2$  :0.72304,  $r_0^2$  :0.71848, reverse  $r_0^2$ :0.68331, RMSEP:0.57069, Q2f1/ $R^2$ (Pred) :0.74354, Q2f2 :0.71655; EVP(After Scaling):: Average  $rm^2$ (test) :0.62587, Delta  $rm^2$ (test) :0.08572]

{GT acceptable criteria :  $Q^2$  : 0.69747 Passed,  $r^2$ : 0.72304 Passed,  $|r_0^2-r'^0^2|$  : 0.03516 Passed, k: 0.97811 [ $(r^2-r_0^2)/r^2$ ] 0.00632 or k' : 0.9528 [ $(r^2-r_0^2)/r^2$ ]: 0.05495 Passed}

### 3.5. Model 5 (with 24 descriptors)(Dimitrov et al., 2002)

pIC50 = -5.31625 - 0.09091 ALogP +2.23424 IC1 -0.21727 minsssN +0.98009 GATS2e +1.21443 mindssC -0.0104 ATSC7s -8.07662 AVP-0 +0.56286 MATS8s +0.15643 minssNH -2.0612 GATS7v -0.17167 C1SP2 +0.03561 nAtomP +0.01557 VR2\_Dt -0.13713 minaaN -0.28466 nF12Ring +0.03612 AATSC4v -5.72469 VE1\_D +3.51384 VE1\_Dze +0.46693 ndsN +0.83305 SP-5 -0.11812 MDEC-22 -0.02118 MPC6 -0.17558 AATS4s -0.24231 nCl.

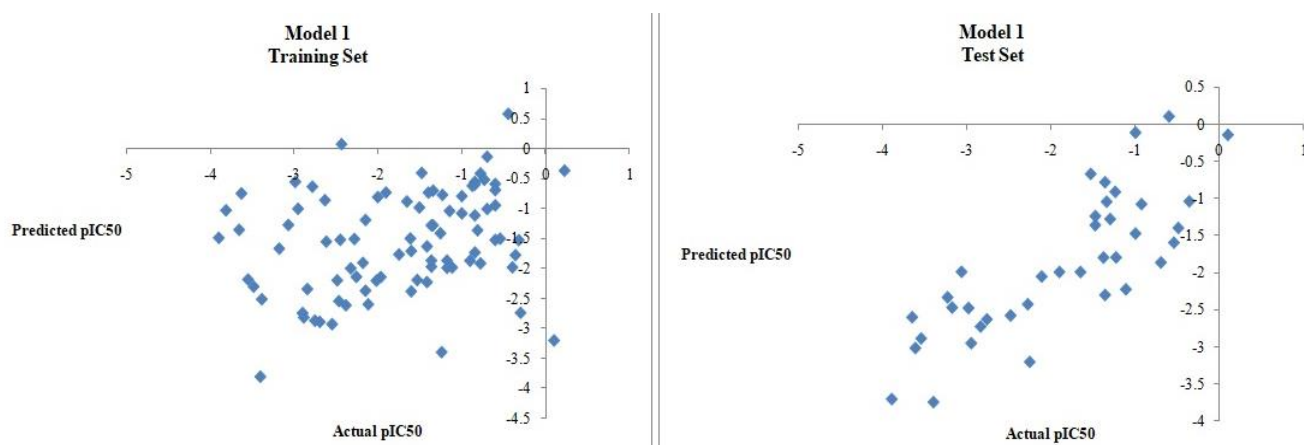
[IVP:: SEE :0.35722,  $r^2$  :0.91039,  $r^2$  adjusted :0.87514, PRESS :7.78406, F :25.82319 (DF :24, 61); Leave-One-Out(LOO) Result :: Q2 :0.80158, Average  $rm^2$ (LOO):0.73688, Delta  $rm^2$ (LOO):0.01789; EVP(Without Scaling)::  $r^2$  :0.88284,  $r_0^2$  :0.86732, reverse  $r_0^2$ :0.81182, RMSEP:0.39046, Q2f1/ $R^2$ (Pred) :0.87995, Q2f2 :0.86731; EVP (After Scaling):: Average  $rm^2$ (test) :0.75257, Delta  $rm^2$ (test) :0.11285]

{GT acceptable criteria:: Q<sup>2</sup>: 0.80158 Passed,  $r^2$ : 0.88284 Passed,  $|r_0^2-r_0'^2|$ : 0.0555 Passed, k : 1.00114 [ $(r^2-r_0'^2)/r^2$ ] 0.01758 or k' : 0.96682 [ $(r^2-r_0'^2)/r^2$ ] : 0.08045 Passed}.

The findings revealed that all models met the criteria for acceptance, however only Model 1 had the bare minimum of descriptors (Paola 2013). Model 5 showed the highest Q2 (0.80158) and R2 (0.88284) values. There were 24 descriptors in this model. More descriptors increase prediction noise. One description was assigned for every ten molecules according to a rule. In this case, Model 1 was regarded as the best model (Krstajic et al., 2014). In Model 1, the model was predicted using just 10 descriptors. In this model IC1 (Information Content index), GATS2e (Geary autocorrelation of lag 2 weighted by Sanderson electronegativity), mindssC (Minimum atom-type E-State =C), minssNH (Minimum atom-type E-State: -NH-), VR2\_Dt (normalised Randic-like eigenvector-based index from detour matrix), MATS8s (Moran autocorrelation of lag 8 weighted by I-state) and nAtomP (Number of atoms in the largest pi system) were positively contributed in the bioactivity (Zhang et al., 2006) The model meets every requirement for validation, according to the validation parameter. Figure 1's curve between the actual and projected pIC50 values in the training and test set demonstrated that the difference between the two values was within acceptable bounds. According on the applicability domain study, two compounds were found to be outliers (Rucker et al., 2007). The average R2, Q2 (LOO), and cRp2 values for the model are 0.15, -0.16, and 0.64, respectively, according to the YR test results (Table 3).

**Table 3.** Y Randomization (YR) Data of the best QSAR Model.

Avg $R^2$	Avg $Q^2$ (LOO)	cRp <sup>2</sup>
0.15	-0.16	0.64



**Figure 1** Graph between Actual and Predicted pIC50 values in Training Set and Test Set.



## Conclusion

Here, we draw the conclusion that the established QSAR model will function as a good predictor with any chemical scaffold and descriptor combination in order to develop newer generation GSK-3 inhibitors targeting Alzheimer's disease.

## List of Abbreviations

QSAR: Quantitative Structure Activity Relationship, DF: Degree of Freedom, SPRESS: Standard Deviation based on Predicted Residual Error Sum of Squares, SDEP: Standard Deviation of Error of Prediction, RMSEP: Root Mean Square Error of Prediction, LOO: Leave One Out, MLR: Multiple Linear Regression.

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**Author Contributions:** Data collection - Vikash Jakhmola, Arun Kumar Mahato, and Praveen Kumar Ashok; Data interpretation: Vishal Warikoo and Sayantan Mukhopadhyay; QSAR study: Prinsa; Supervision – Supriyo Saha.

**Funding:** The work is not funded by any organization.

**Availability of Data and Material:** All data used to support the findings of this study are included within the main text. Actual pIC<sub>50</sub>, Predicted pIC<sub>50</sub> values and Y-Randomization Data of other models (Model 2, 3, 4 and 5) are included in Supplementary files ([Table S1](#), [Table S2](#) and [Table S3](#)).

**Declaration:** This is an original work and no part is submitted to other Journal.

**Conflicts of Interest:** There is no conflict of interest to declare.

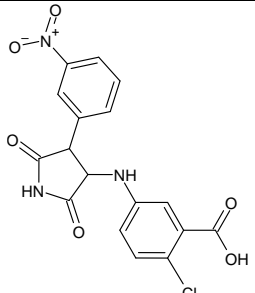
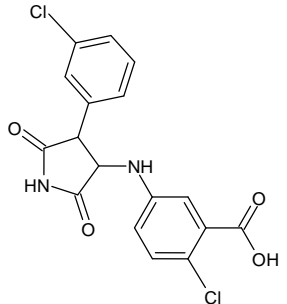
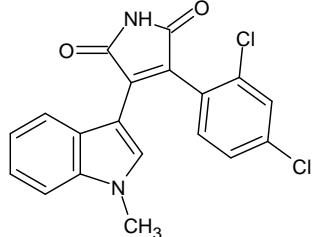
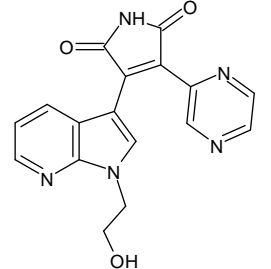
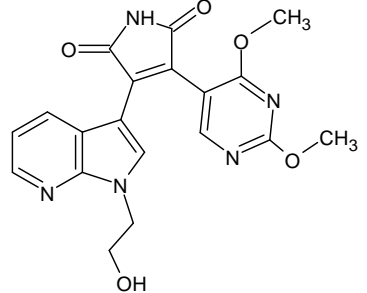
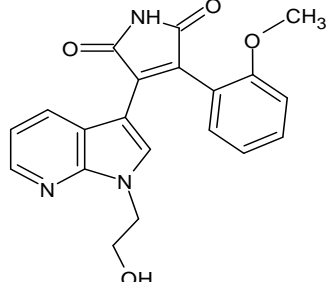
## References

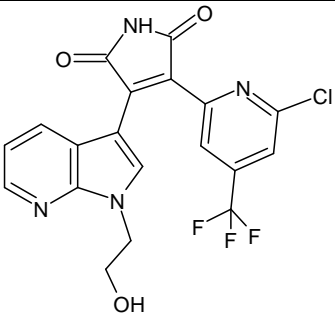
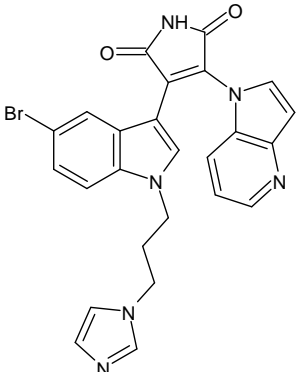
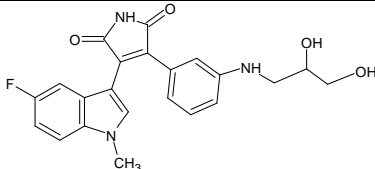
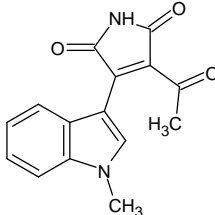
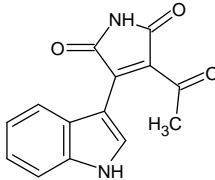
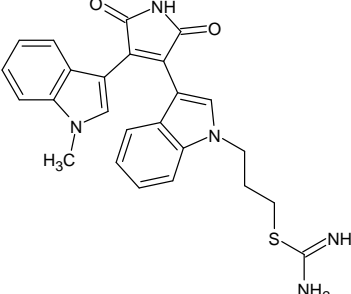
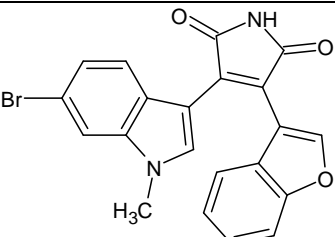
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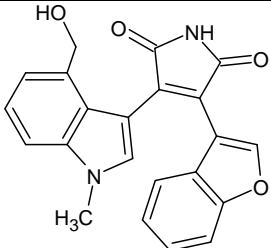
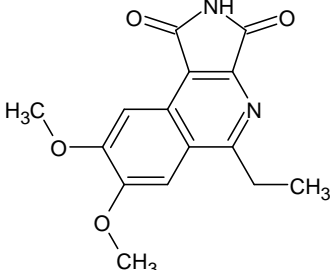
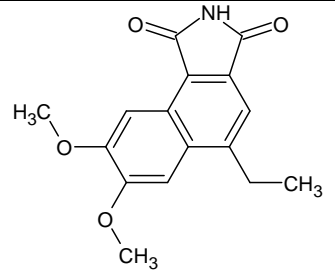
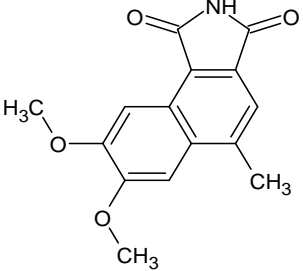
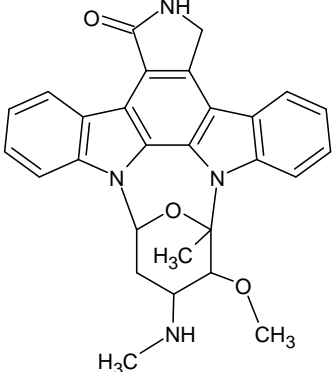
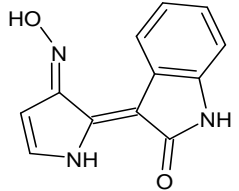
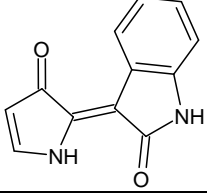
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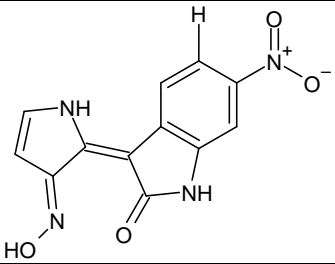
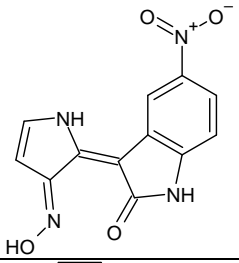
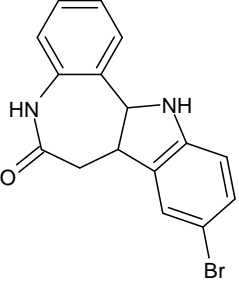
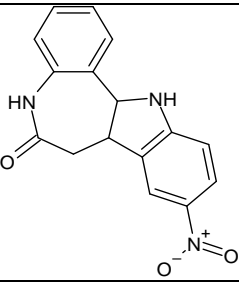
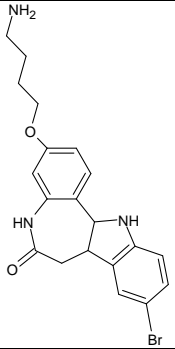
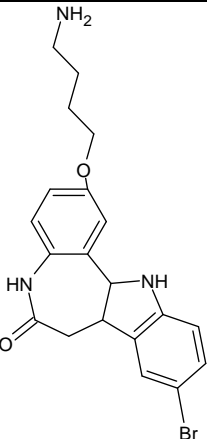
**Table S1.** Actual pIC<sub>50</sub>, and Predicted pIC<sub>50</sub> Values of Training Set Molecules of different QSAR Models.

SN	Structure of the compounds	Actual pIC <sub>50</sub>	Predicted pIC <sub>50</sub> (Model 2)	Predicted pIC <sub>50</sub> (Model 3)	Predicted pIC <sub>50</sub> (Model 4)	Predicted pIC <sub>50</sub> (Model 5)
1		-1.41497	-2.30004	-2.23258	-2.14573	-1.40867
2		-2.89542	-2.82135	-2.6834	-2.66375	-2.5139
3		-1.53148	-2.13956	-2.03201	-1.96968	-1.85593
4		-1.39794	-0.79598	-0.72437	-0.85654	-1.45258
5		-0.77815	-0.43003	-0.33837	-0.54359	-0.68705
6		-0.60206	-0.5895	-0.48583	-0.55114	-0.85404

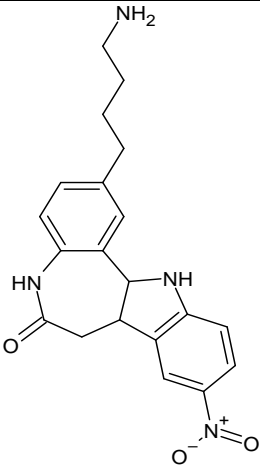
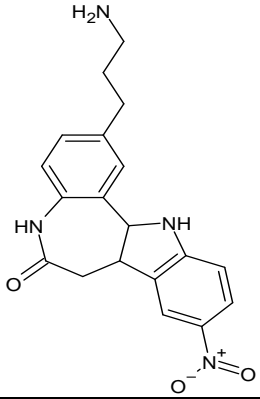
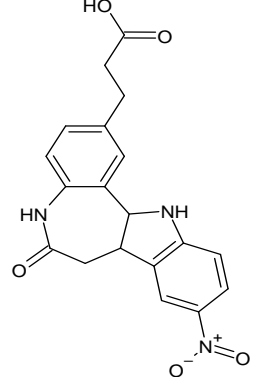
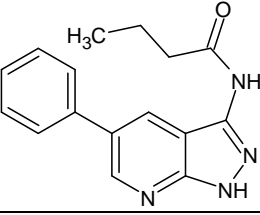
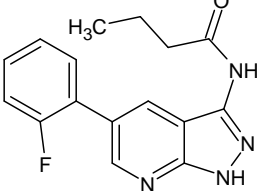
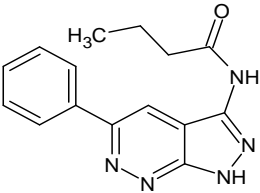
7		-1.41497	-1.72622	-1.73665	-1.77401	-1.22522
8		-2.14613	-1.15536	-0.99847	-0.93181	-1.75658
9		0.221849	-0.27469	-0.28134	-0.35449	0.109629
10		-2.94939	-0.91179	-0.86128	-0.73648	-0.72958
11		-3.65031	-1.1996	-1.08469	-1.00174	-0.5754
12		-0.44716	0.697029	0.59284	0.537598	0.654765
13		-0.8451	-0.47302	-0.4567	-0.43978	-0.34366

14		-0.73239	-0.40635	-0.29248	-0.33784	-0.19527
15		-2.48287	-2.04245	-1.81369	-1.8969	-2.36854
16		-1.96379	-2.01599	-1.83776	-1.94506	-2.3328
17		-2.43136	-1.44855	-1.36137	-1.18429	-1.09335
18		-1.17609	-1.86729	-1.86815	-2.13011	-2.45918
19		-1.34242	-1.20029	-1.07961	-1.13321	-0.92177
20		-2.77815	-0.51826	-0.58883	-0.60891	-0.84507

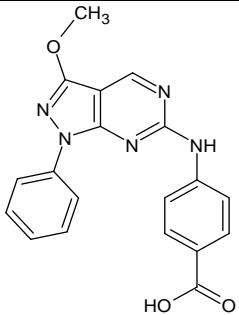
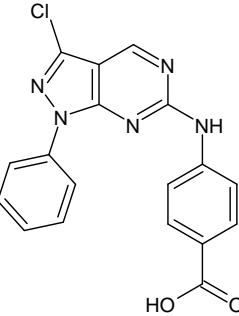
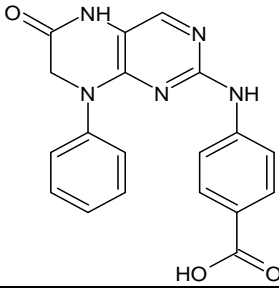
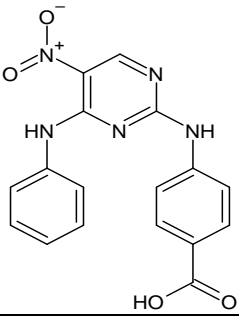
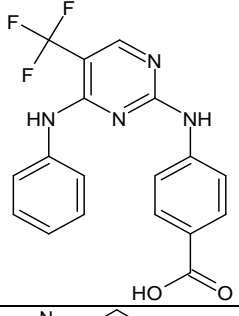
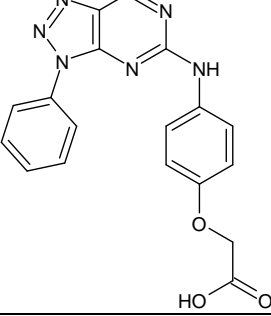
21		-0.69897	-0.02092	-0.11468	-0.17541	-0.83205
22		-1	-0.68463	-0.70411	-0.59629	-0.65531
23		-1.65321	-0.68596	-0.91526	-0.75859	-0.36744
24		-0.60206	-0.7294	-0.9344	-0.83984	-0.65749
25		-0.69897	-0.79755	-0.97665	-1.03631	-1.25777
26		-1.14613	-1.00397	-1.07686	-1.0799	-1.27856
27		-1.90309	-0.73288	-0.8216	-1.01674	-1.18456
28		-0.87506	-0.6296	-0.70327	-0.76289	-0.63109

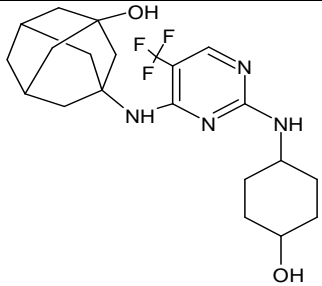
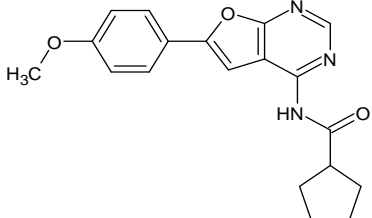
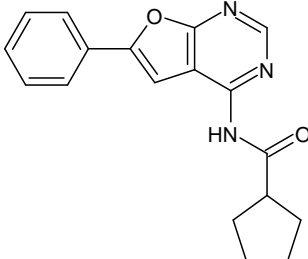
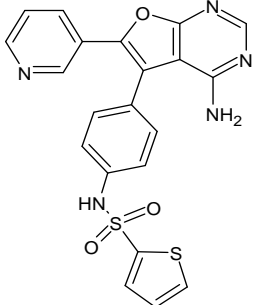
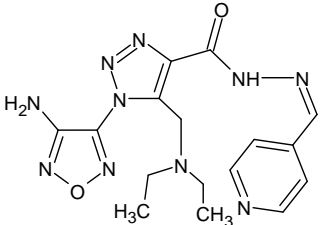
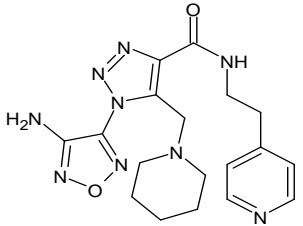
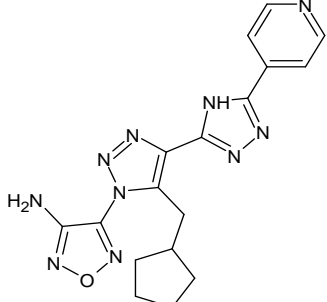
29		-1.60206	-2.32736	-2.17871	-2.16424	-2.3064
30		-0.32222	-1.36718	-1.04414	-0.95986	-1.68108
31		-1.36173	-1.89785	-1.59642	-1.38647	-1.28267
32		-0.60206	-0.63048	-0.70215	-0.70853	-0.89312
33		-1.47712	-0.32444	-0.42398	-0.40326	-0.28892
34		-1.60206	-1.78293	-1.77262	-1.76719	-1.21492

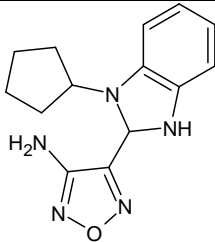
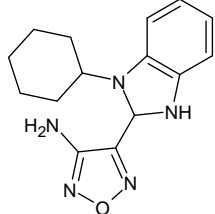
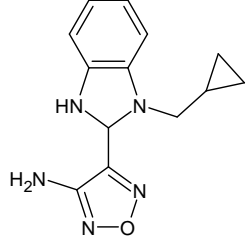
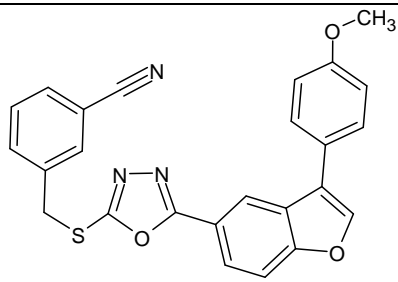
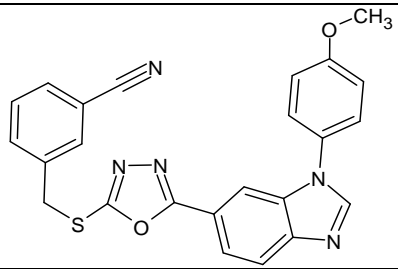
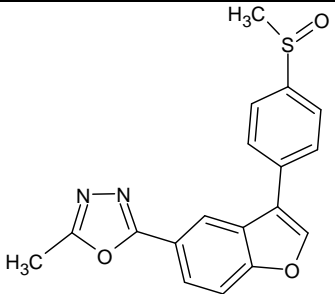
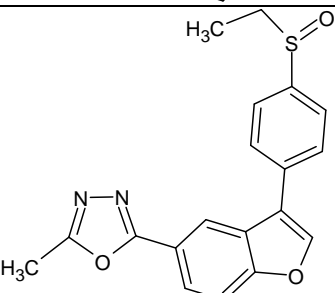


35		-0.77815	-1.85024	-1.78648	-1.70026	-1.66258
36		-0.39794	-1.99331	-1.88426	-1.78381	-1.54936
37		-0.81291	-1.28162	-1.20721	-1.11966	-1.19969
38		-1.74819	-1.70293	-1.66593	-1.64999	-1.16942
39		-1.25527	-1.32476	-1.27739	-1.29819	-1.20384
40		-0.60206	-1.50572	-1.8366	-1.79823	-1.26106

41		-0.8451	-1.73161	-1.72174	-1.83262	-2.13273
42		-1.34242	-0.6871	-0.72391	-0.84536	-0.91578
43		-2.62839	-0.7903	-0.72911	-0.72825	-0.17177
44		-0.90309	-1.81215	-1.70345	-1.77353	-1.40783
45		-0.8451	-0.51051	-0.34936	-0.43911	-0.64388
46		-2	-0.79856	-0.87639	-0.78181	-0.0336
47		-3.38021	-2.57317	-2.56155	-2.73292	-2.40363
48		-2.98227	-0.50783	-0.65366	-0.9334	-0.6203

49		-2.88081	-2.81615	-3.16829	-3.42202	-3.71252
50		-2.25527	-2.2175	-2.19284	-2.4026	-2.19672
51		-3.54407	-2.20601	-2.30905	-2.3306	-2.52371
52		-2.17609	-1.9437	-2.02975	-2.03443	-2.5492
53		-2.6902	-2.88344	-2.83131	-2.7947	-2.52929
54		-1.11394	-2.12724	-2.06828	-2.10328	-2.14187

55		-1.61278	-1.61625	-1.56539	-1.40164	-1.59834
56		-1.50515	-0.84986	-0.72522	-0.86441	-0.80867
57		-1.36173	-1.85979	-1.79061	-1.90179	-1.38761
58		-1.36173	-1.25793	-1.1872	-1.34339	-0.96918
59		-2.61278	-1.5973	-1.79574	-1.82646	-2.47975
60		-3.06446	-1.33031	-1.61328	-1.56254	-1.92922
61		-2.44716	-1.61252	-1.63734	-1.52088	-2.17555

62		-2.32222	-1.85875	-2.06846	-2.12803	-2.33823
63		-2.38021	-2.55919	-2.74464	-2.81479	-2.17512
64		-2.4624	-2.61129	-2.67446	-2.69233	-2.69243
65		-0.54407	-1.50621	-1.464	-1.50507	-1.30741
66		-0.36173	-1.78588	-1.73863	-1.74121	-1.70141
67		-2.14613	-2.41121	-2.48671	-2.38873	-2.67373
68		-2.27875	-1.42259	-1.50215	-1.15754	-1.59148

69		-1.23045	-0.67261	-0.68706	-0.44822	-1.04778
70		-0.8451	-1.07109	-1.14375	-0.87355	-1.11622
71		-2.54407	-2.93449	-3.13921	-3.1271	-3.17411
72		-2.83885	-2.31807	-2.455	-2.28096	-2.52259
73		-2.11394	-2.6011	-2.83325	-2.65245	-2.63491
74		-2.74819	-2.81163	-2.74266	-3.01938	-2.53783
75		-2.01703	-2.23854	-2.01232	-2.0085	-2.44876
76		-1.17609	-2.0615	-1.94474	-1.86403	-1.55231

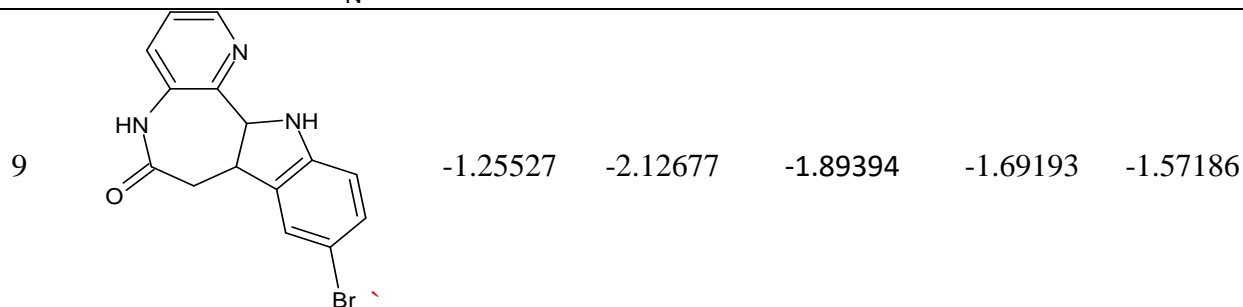
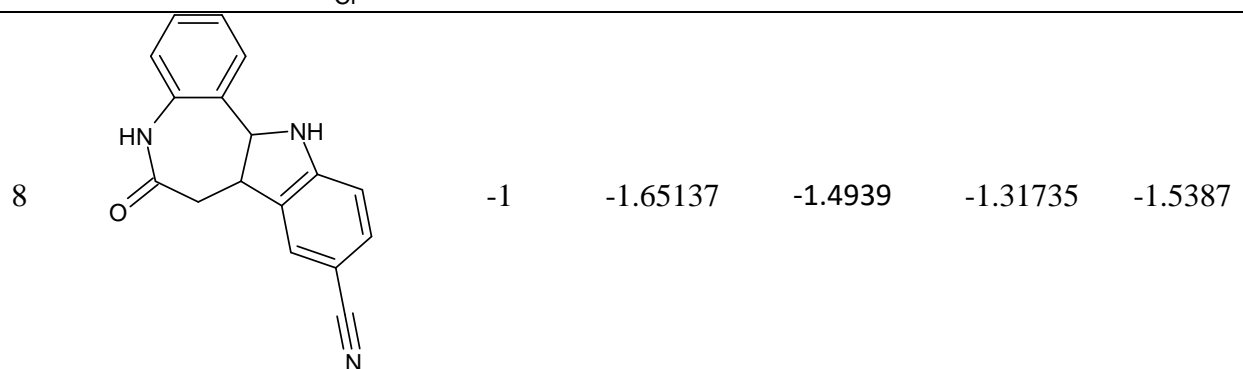
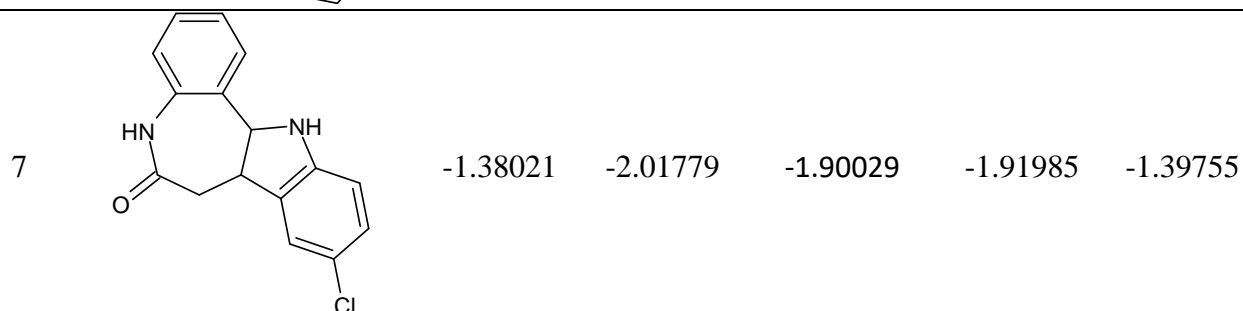
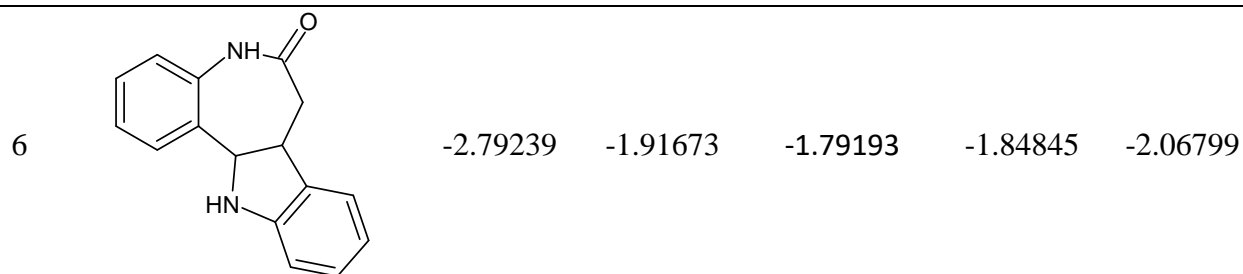
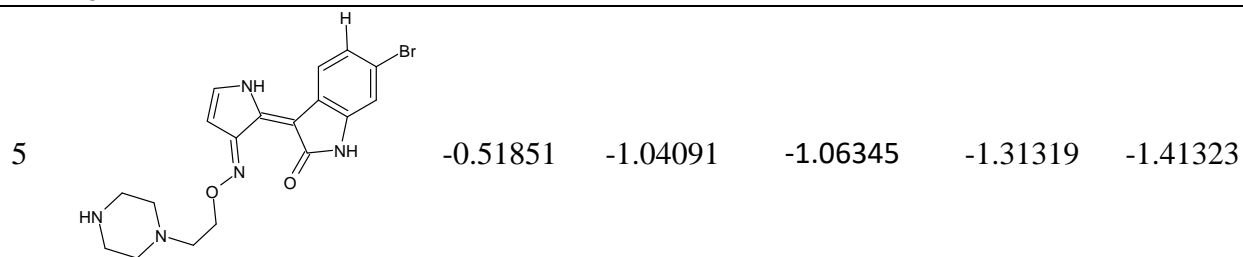
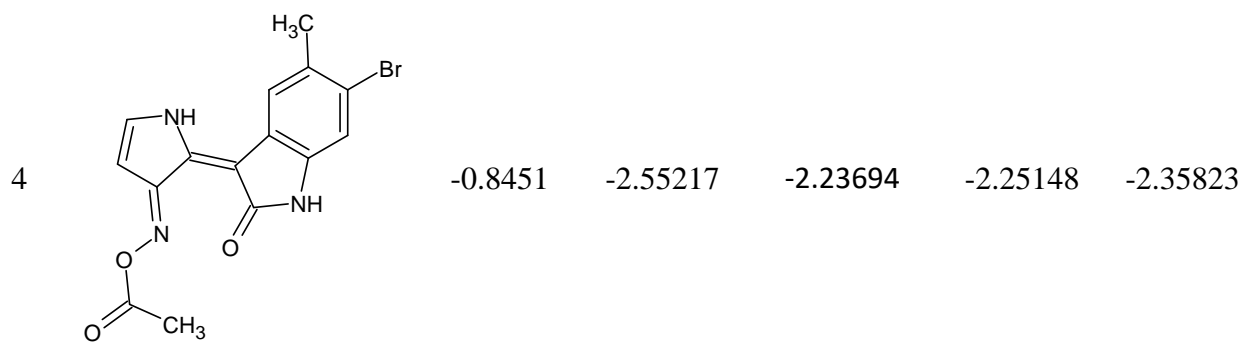
77		-3.17319	-1.72148	-1.55145	-1.3515	-1.21064
78		0.09691	-3.22932	-3.16331	-3.19711	-3.84867
79		-0.30103	-2.70091	-2.4354	-2.73939	-2.95431
80		-3.62325	-0.59672	-0.52066	-0.35065	0.246198
81		-3.80618	-0.97199	-0.83399	-0.76394	-0.55527
82		-3.89209	-1.46444	-1.316	-1.30007	-0.86088
83		-1.24055	-3.40718	-3.76988	-3.57262	-3.54276

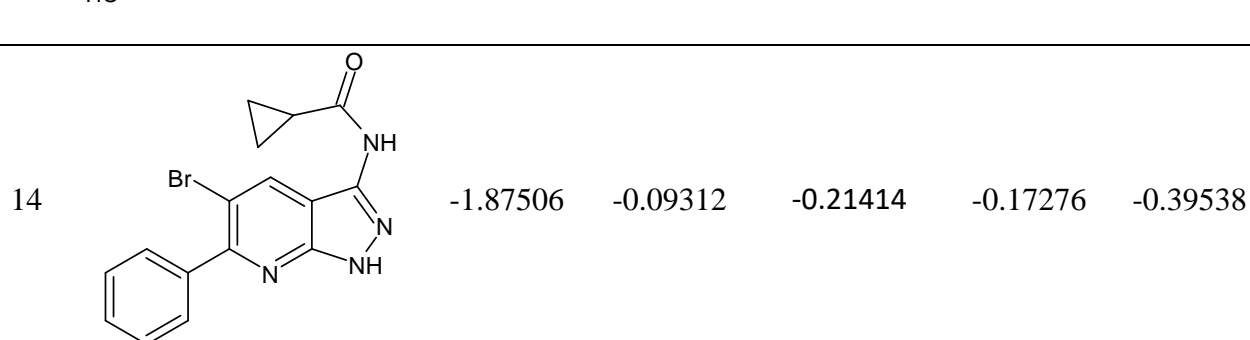
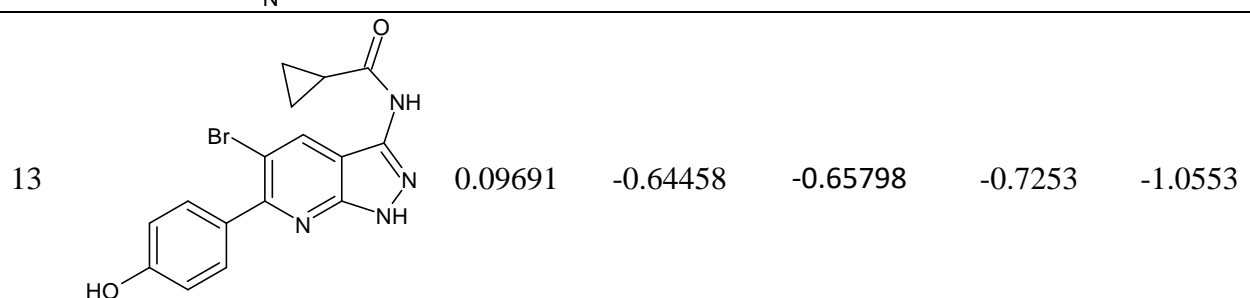
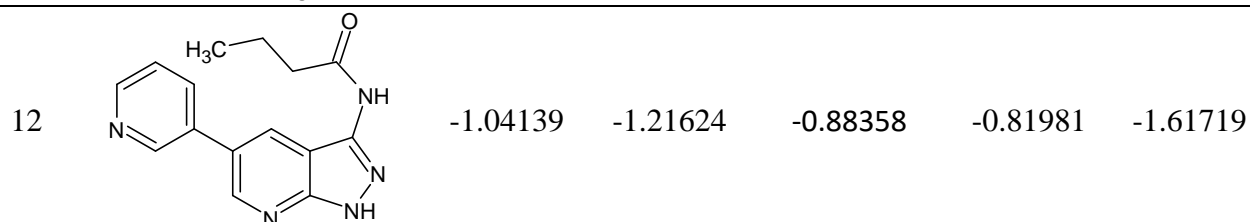
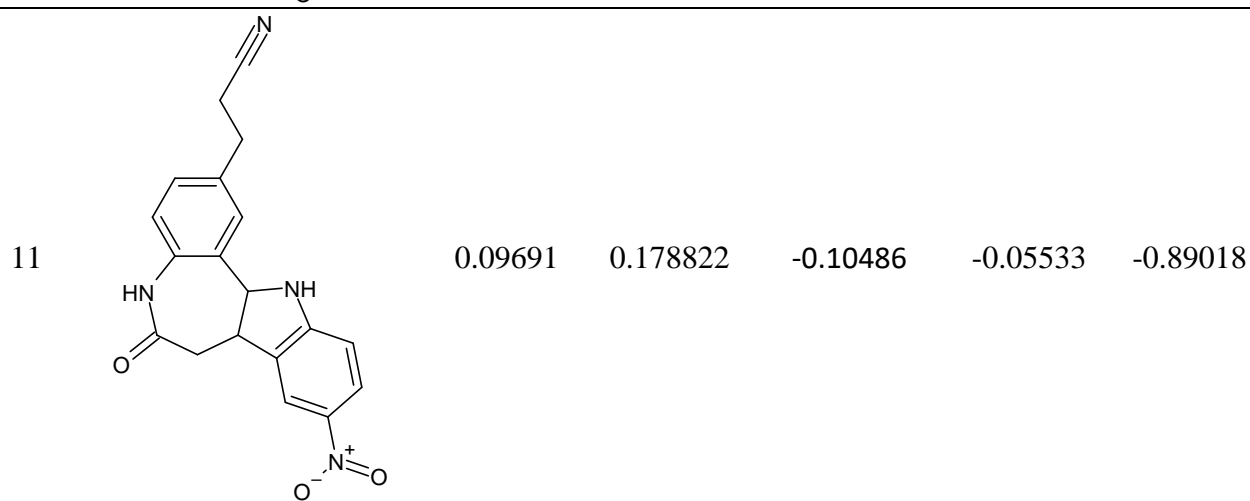
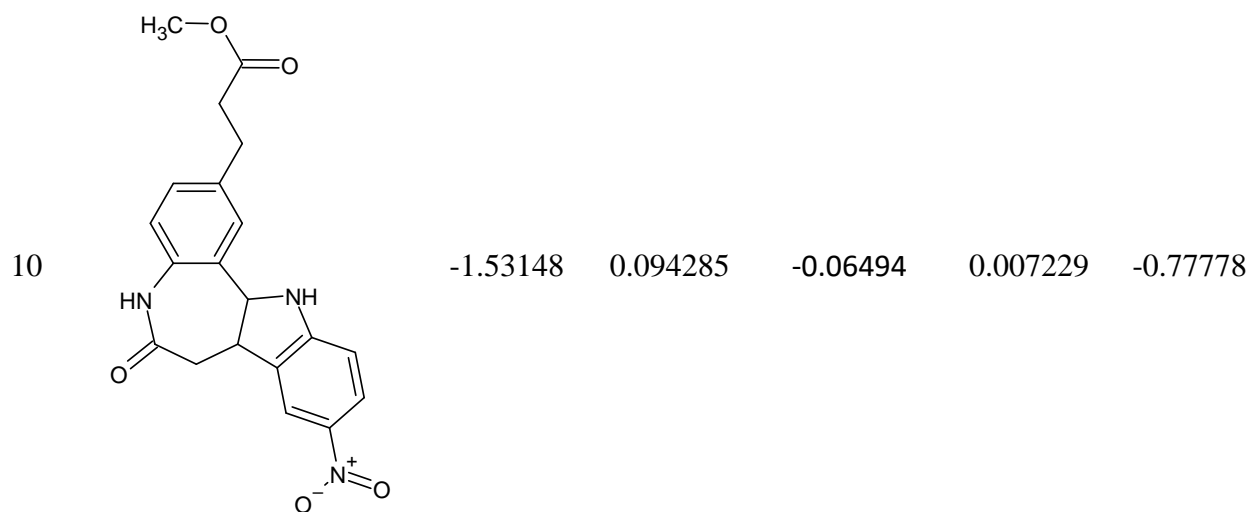
84		-3.39794	-3.86152	-3.7999	-3.51148	-3.4637
85		-1	-1.07088	-1.25888	-1.1567	-1.215
86		-3.47712	-2.84139	-3.0448	-3.45799	-3.67018

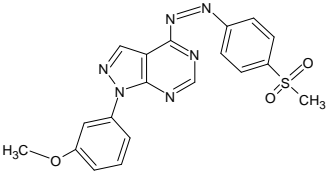
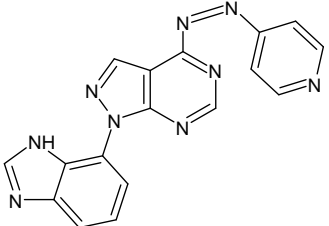
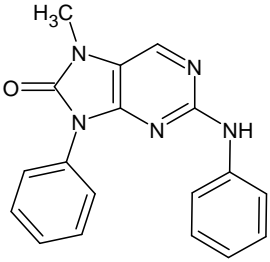
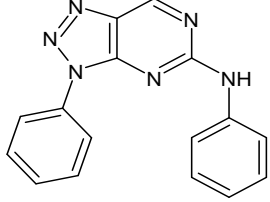
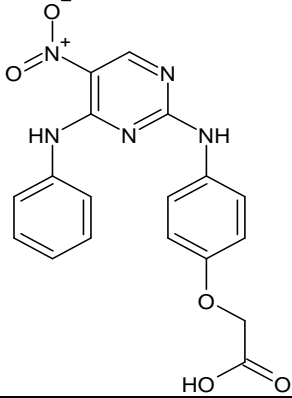
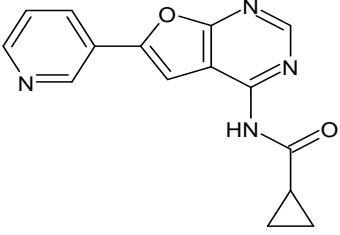
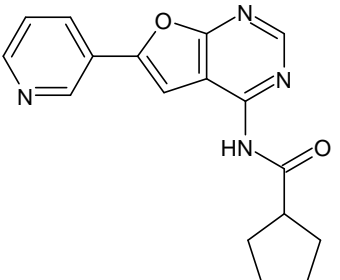
**Table S2.** Actual pIC<sub>50</sub>, and Predicted pIC<sub>50</sub> Values of Test Set Molecules of different QSAR Models.

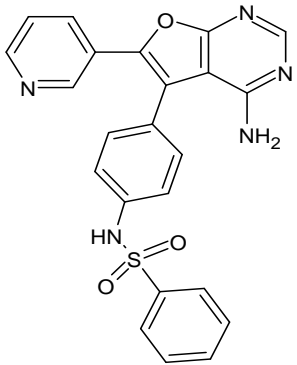
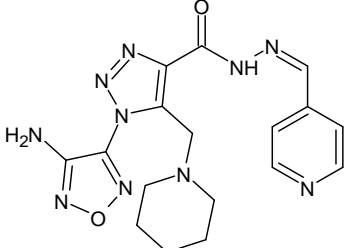
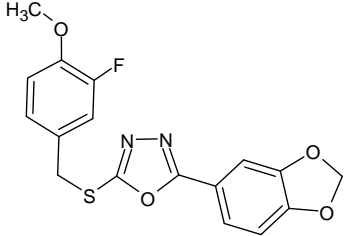
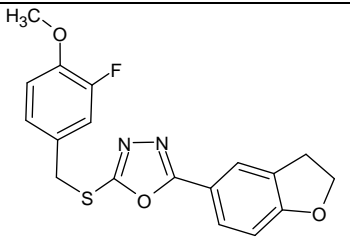
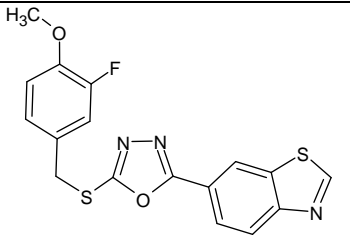
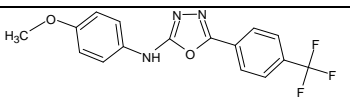
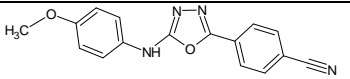
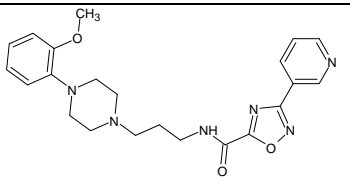
SN	Structure of the compounds	Actual pIC <sub>50</sub>	Predicted pIC <sub>50</sub> (Model 2)	Predicted pIC <sub>50</sub> (Model 3)	Predicted pIC <sub>50</sub> (Model 4)	Predicted pIC <sub>50</sub> (Model 5)
1		-1.30103	-1.24499	-1.18999	-1.05578	-0.90191
2		0.455932	-3.02138	-2.79518	-2.94851	-2.7294
3		0.638272	-2.67948	-2.60372	-2.81586	-3.19567

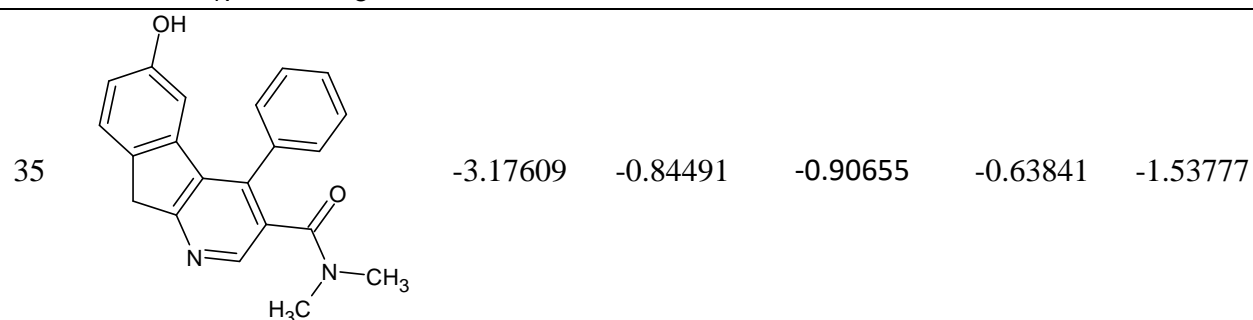
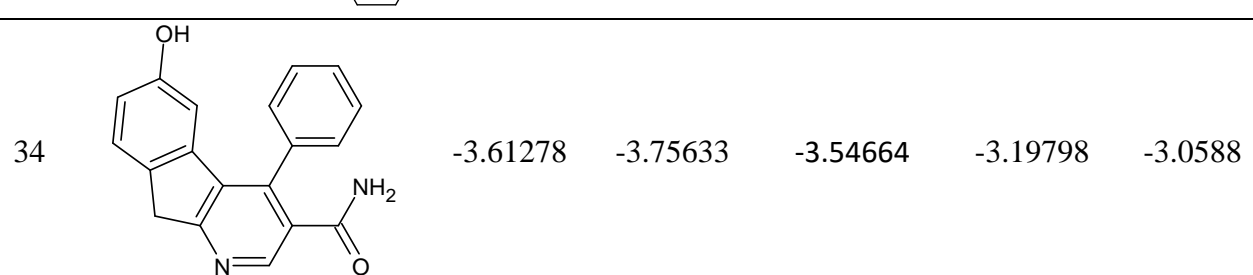
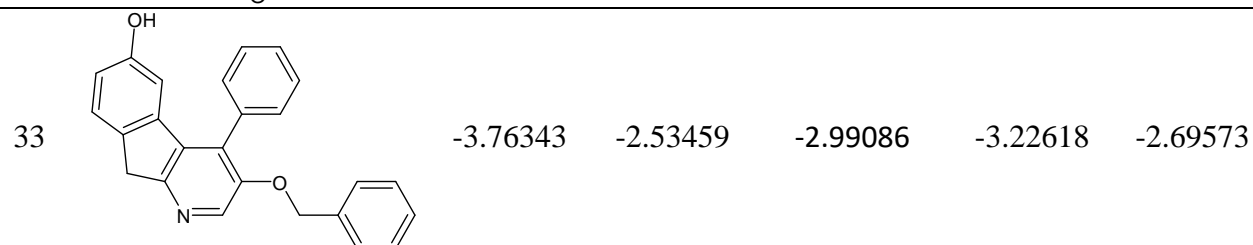
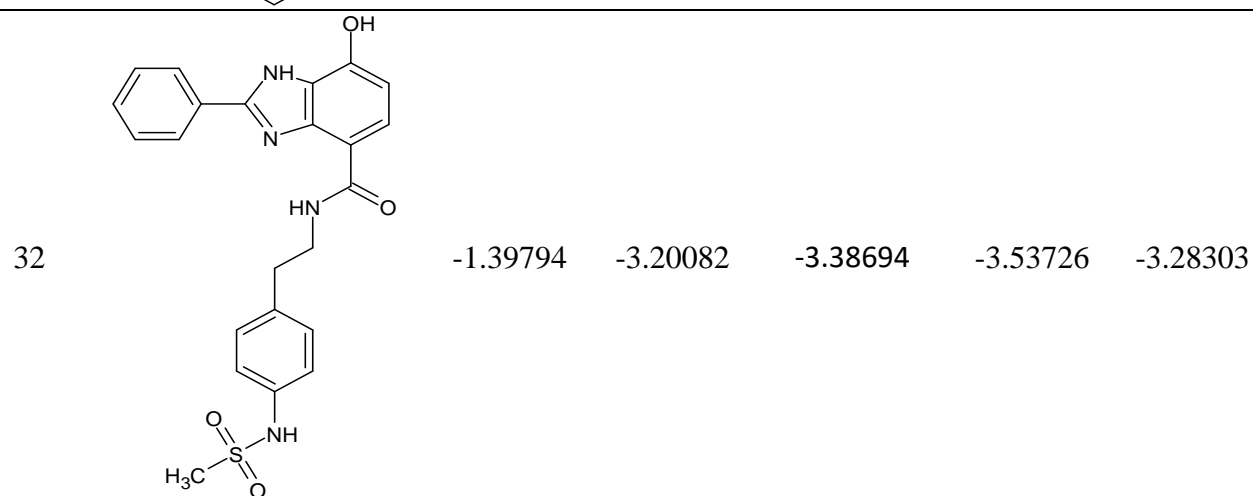
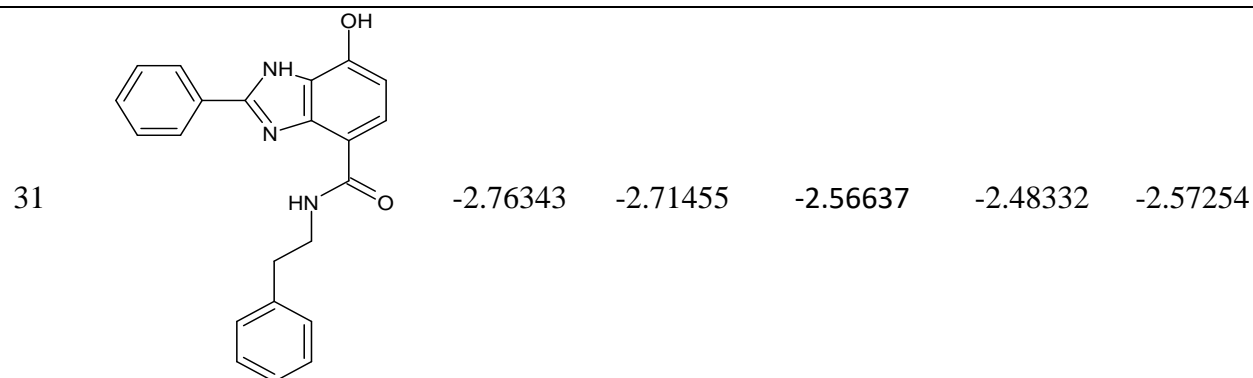
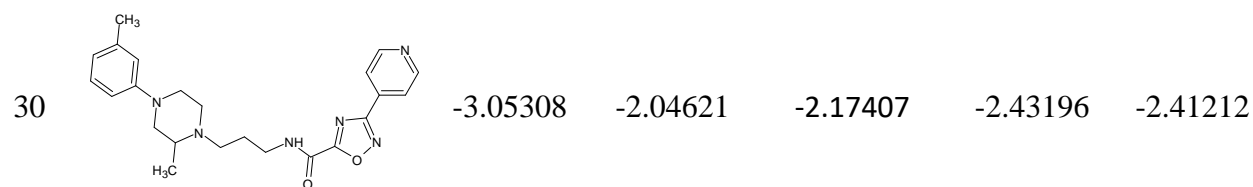


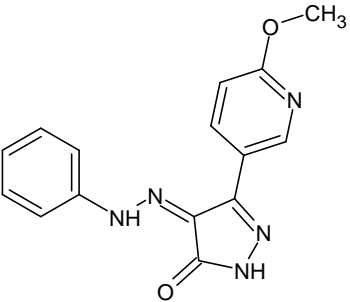
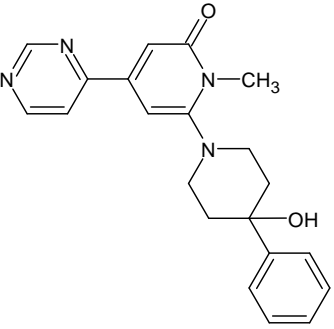
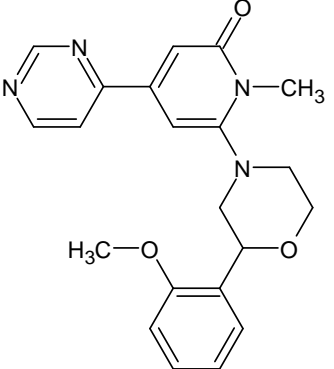




15		-0.39794	-2.31872	-2.72759	-2.70075	-3.17392
16		-0.60206	-2.58918	-2.96401	-2.94737	-2.89934
17		-3.23045	-3.31936	-3.35144	-3.44064	-3.05172
18		-2.79796	-3.02355	-3.4654	-3.42876	-3.05327
19		-1.96379	-2.33595	-2.23061	-2.2877	-1.46029
20		-0.69897	-1.85979	-1.79061	-1.90179	-1.38761
21		-0.69897	-1.22213	-1.40194	-1.55047	-1.73706

22		-1.47712	-0.74298	-0.87667	-1.08011	-1.76131
23		-2	-2.04707	-2.22989	-2.1214	-2.70784
24		-1.81291	-1.38933	-1.37071	-1.29737	-0.88844
25		-1.64345	-1.5615	-1.59767	-1.51346	-1.28357
26		-0.49136	-1.00044	-1.0599	-0.93604	-0.43445
27		-1.72428	-2.47081	-2.54255	-2.33287	-2.4352
28		-1.25527	-1.78717	-1.81222	-1.38524	-1.4032
29		-2.61278	-2.7362	-2.95038	-2.75703	-2.64634



36		-0.65321	-1.07088	-1.25888	-1.1567	-1.215
37		-0.92942	-3.85206	-3.67773	-3.54236	-3.79259
38		-1.20683	-1.40269	-1.37178	-1.62418	-1.34722

**Table S3.** YR Data of different QSAR Models.

Model 2			Model 3			Model 4			Model 5		
Avg R <sup>2</sup>	Avg Q <sup>2</sup> (LOO)	cR p <sup>2</sup>	Avg R <sup>2</sup>	Avg Q <sup>2</sup> (LOO)	cR p <sup>2</sup>	Avg R <sup>2</sup>	Avg Q <sup>2</sup> (LOO)	cR p <sup>2</sup>	Avg R <sup>2</sup>	Avg Q <sup>2</sup> (LOO)	cRp <sup>2</sup>
0.14	-0.23	0.6	0.15	-0.24	0.6	0.15	-	0.7	0.29	-0.68	0.75
		6			8		0.32	0			

(2023) ; <https://revues.imist.ma/index.php/morjchem/index>