



## QSAR Study on HIF – PHD2 Inhibitors by Monte Carlo Method

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### Abstract

The main aim of the present work is to study the quantitative structure activity relationship (QSAR) of structural indicators of a series of 71 pyridine analogues and their inhibitory activity on Hypoxia inducible factor Prolyl Hydroxylase Domain II (HIF – PHD2) using CORAL (<http://www.insilico.eu/coral>) software. To develop the QSAR models, the molecular structure by SMILES [simplified molecular input line entry system] and molecular graph by HSG [Hydrogen suppressed Graph] were used. The datasets were divided into sub-training set, the calibration set, and the test set. The quality of predicted models were examined by splitting the dataset into two types and the models were validated by validation set in which the dataset compounds are not included in the model building steps. The statistically significant predicted model can be used to define the structural characteristics responsible for the increased or decreased inhibition activity on HIF – PHD2.

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**Keywords:** QSAR, Inhibitory activity on HIF – PHD2, Monte Carlo method, CORAL software

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### 1. Introduction

Hypoxia inducible factor (HIF) plays an important role in hypoxic condition by regulating the various essential genes (Semenza, 2004). It consists of two subunits namely HIF - 1 $\alpha$  and 1  $\beta$ . Regulation of various processes namely erythropoiesis, energy utilization, angiogenesis, cellular proliferation and apoptosis are carried out with HIF - 1 $\alpha$  subunit (Brahimi-Horn and Pouysségur, 2009; Chiche, et al., 2010) and the functional level mainly depends on the oxygen concentration i.e. in normoxia, the expression level of HIF - 1 $\alpha$  was suppressed where as in hypoxia their expression is increased (Bruick, 2003).

The level of HIF - 1 $\alpha$  was regulated by hydroxylation process at 4<sup>th</sup> position of Pro 402 and Pro 564 which is catalyzed by prolyl hydroxylase domains PHD1, 2 & 3 which lead to their degradation (Appelhoff, et al., 2004). Especially, PHD2 domain is considered to be a key regulator in the hydroxylation process based on oxygen availability (Metzen, et al., 2005).

The up regulation of HIF - 1  $\alpha$  activity is made possible by preventing the hydroxylation through the use of PHD2 inhibitors (Linden, et al., 2003; Tsukiyama, et al., 2006; Nangaku, et al., 2006; Lee, et al., 2010; Rosen, et al., 2010; Rabinowitz, et al., 2010) .

Hence, inhibition of PHD2 domain can be considered as an important therapeutic drug target to treat various hypoxia related diseases namely anemia, myocardial infarction etc., Many PHD2 inhibitors are available in the market. But developing new and effective HIF – PHD2 inhibitors still remains a problem.

To solve this problem, QSAR models can be developed and used (Ojha and Roy, 2011; Ibezim, et al., 2012). The fundamental basis of QSAR analysis involves calculation of molecular descriptors by means of various methods like multiple linear regression (MLR), artificial neural networks, principle component analysis (PCA) etc., (Rasulev, 2008; Furtula, B. and Gutman 2011; Došlic et al., 2011; Afantitis, 2012).

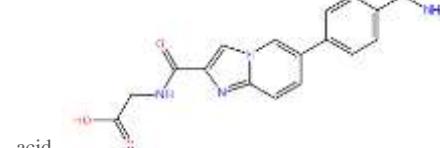
In this study, CORAL software was used to calculate molecular descriptors and to build QSAR models by Monte Carlo method (Toropova, et al., 2011) and to define the molecular structure responsible for HIF – PHD2 inhibition activity.

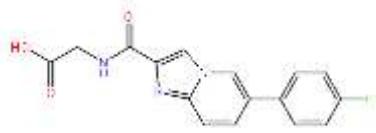
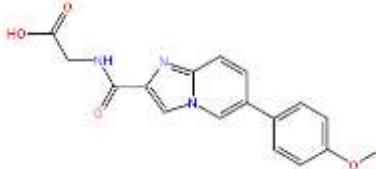
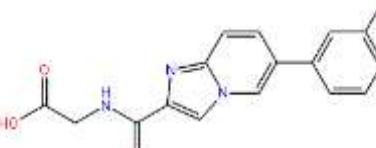
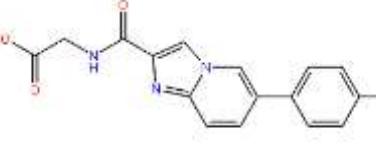
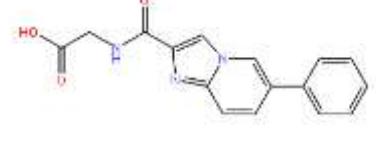
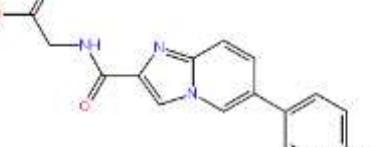
## 2. Method

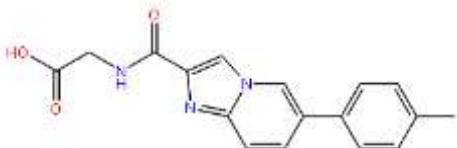
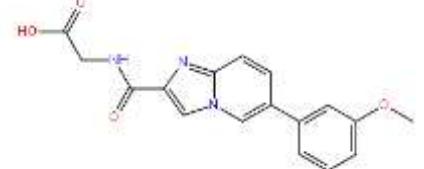
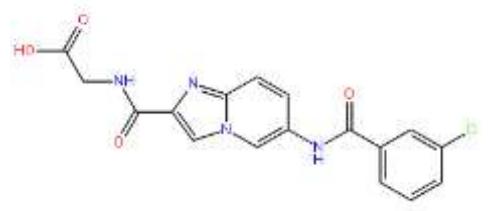
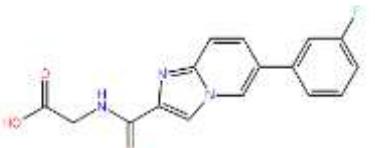
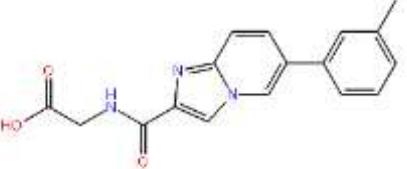
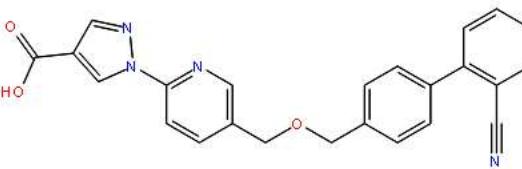
### The data set

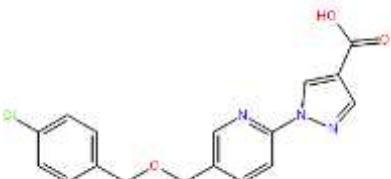
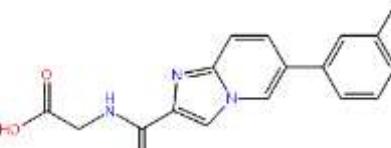
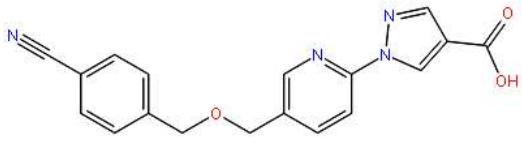
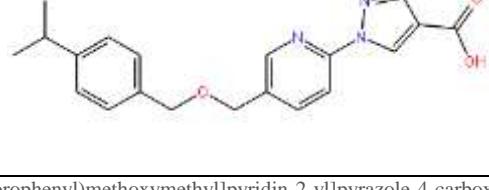
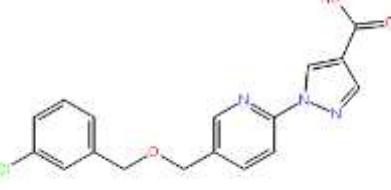
A series of 71 pyridine analogs with HIF –PHD2 inhibition activity (Warshakoon, et al., 2006) has been taken from the Binding database (Table 1). The logarithm of the inhibitory concentration [PIC<sub>50</sub> = - log (IC<sub>50</sub>) nM] has been used as the endpoint. The QSAR models were built up for two random splits.

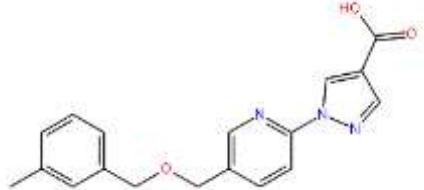
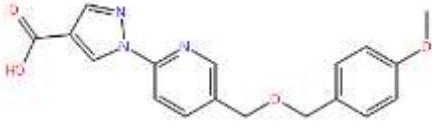
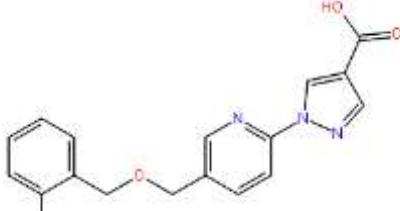
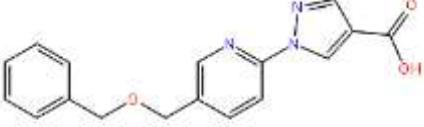
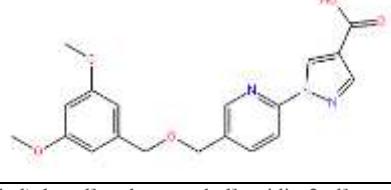
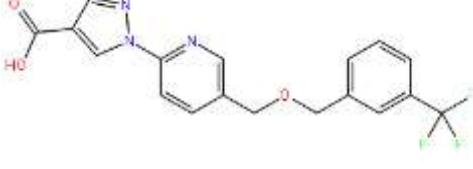
**Table 1 – Pubchem CID, IUPAC name, chemical structure, IC<sub>50</sub>, PIC<sub>50</sub>**

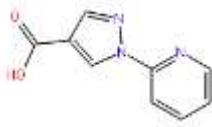
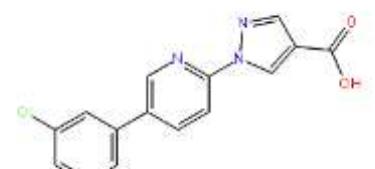
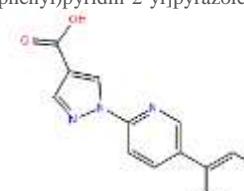
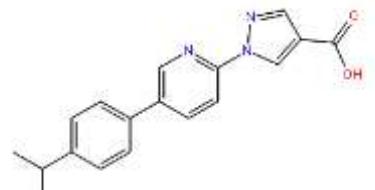
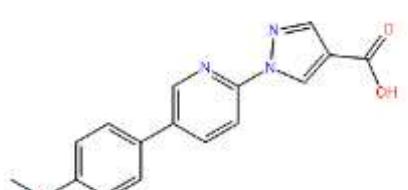
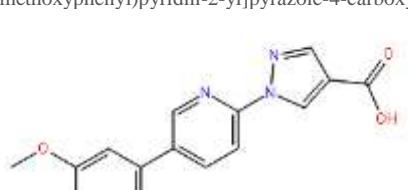
S.NO	Pubchem CID	Structure	Experimental IC <sub>50</sub> (nM)	Predicted IC <sub>50</sub> (PIC <sub>50</sub> ) (Mole)
1.	16126774	2-[(6-naphthalen-2-ylimidazo[1,2-a]pyridine-2-carbonyl)amino]acetic acid 	3600	5.44
2.	44419281	2-[[6-(4-carbamoylphenyl)imidazo[1,2-a]pyridine-2-carbonyl]amino]acetic acid 	5900	5.22
3.	44419265	2-[(6-(4-chlorophenyl)imidazo[1,2-a]pyridine-2-carbonyl)amino]acetic acid 	6800	5.16

				
4.	44419280	2-[[6-(4-methoxyphenyl)imidazo[1,2-a]pyridine-2-carbonyl]amino]acetic acid 	8100	5.09
5.	44419336	2-[[6-(3-chlorophenyl)imidazo[1,2-a]pyridine-2-carbonyl]amino]acetic acid 	12000	4.92
6.	44419282	2-[[6-(4-fluorophenyl)imidazo[1,2-a]pyridine-2-carbonyl]amino]acetic acid 	14000	4.85
7.	44419264	2-[(6-phenylimidazo[1,2-a]pyridine-2-carbonyl)amino]acetic acid 	14200	4.84
8.	44419270	2-[[6-(4-ethylphenyl)imidazo[1,2-a]pyridine-2-carbonyl]amino]acetic acid 	16000	4.79
9.	44419252	2-[[6-(4-methylphenyl)imidazo[1,2-a]pyridine-2-carbonyl]amino]acetic acid	17000	4.76

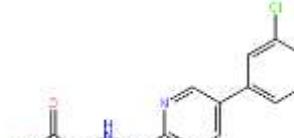
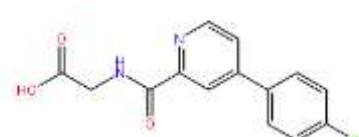
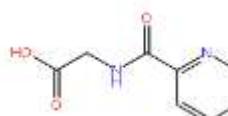
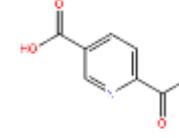
				
10.	44419297	2-[[6-(3-methoxyphenyl)imidazo[1,2-a]pyridine-2-carbonyl]amino]acetic acid 	19000	4.72
11.	44419302	2-[[6-[(3-chlorobenzoyl)amino]imidazo[1,2-a]pyridine-2-carbonyl]amino]acetic acid 	24000	4.61
12.	44419342	2-[[6-(3-fluorophenyl)imidazo[1,2-a]pyridine-2-carbonyl]amino]acetic acid 	24000	4.61
13.	44419346	2-[[6-(3-methylphenyl)imidazo[1,2-a]pyridine-2-carbonyl]amino]acetic acid 	100000	4.00
14.	16126655	1-[5-[[4-(2-cyanophenyl)phenyl]methoxymethyl]pyridin-2-yl]pyrazole-4-carboxylic acid 	190	6.72
15.	44419318	1-[5-[(4-chlorophenyl)methoxymethyl]pyridin-2-yl]pyrazole-4-carboxylic acid	580	6.23

				
16.	6914666	2-[(1-chloro-4-hydroxyisoquinoline-3-carbonyl)amino]acetic acid 	1400	5.85
17.	44419325	1-[5-[(3-methoxyphenyl)methoxymethyl]pyridin-2-yl]pyrazole-4-carboxylic acid 	1600	5.79
18.	44419326	1-[5-[(4-cyanophenyl)methoxymethyl]pyridin-2-yl]pyrazole-4-carboxylic acid 	1600	5.79
19.	44419333	1-[5-[(4-propan-2-ylphenyl)methoxymethyl]pyridin-2-yl]pyrazole-4-carboxylic acid 	1700	5.76
20.	44419319	1-[5-[(3-chlorophenyl)methoxymethyl]pyridin-2-yl]pyrazole-4-carboxylic acid 	1700	5.76
21.	44419329	1-[5-[(3-methylphenyl)methoxymethyl]pyridin-2-yl]pyrazole-4-carboxylic acid	2100	5.67

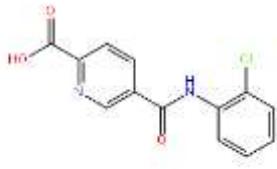
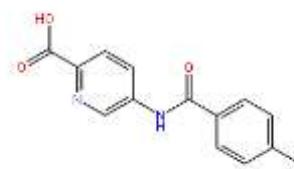
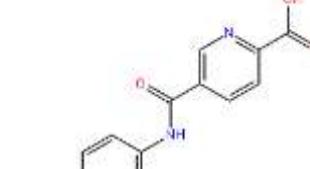
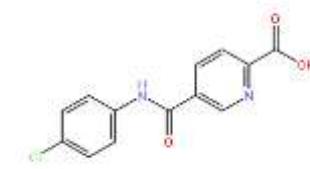
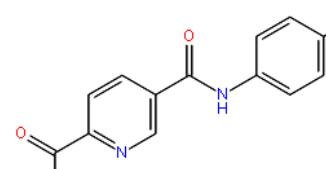
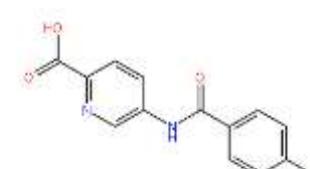
				
22.	44419321	1-[5-[(4-methoxyphenyl)methoxymethyl]pyridin-2-yl]pyrazole-4-carboxylic acid 	2400	5.61
23.	44419320	1-[5-[(2-chlorophenyl)methoxymethyl]pyridin-2-yl]pyrazole-4-carboxylic acid 	2400	5.61
24.	44419317	1-[5-(phenylmethoxymethyl)pyridin-2-yl]pyrazole-4-carboxylic acid 	2700	5.56
25.	44419334	1-[5-[(3,5-dimethoxyphenyl)methoxymethyl]pyridin-2-yl]pyrazole-4-carboxylic acid 	2800	5.55
26.	44419330	1-[5-[[3-(trifluoromethyl)phenyl]methoxymethyl]pyridin-2-yl]pyrazole-4-carboxylic acid 	2900	5.53
27.	8027170	1-pyridin-2-ylpyrazole-4-carboxylic acid	12000	4.92

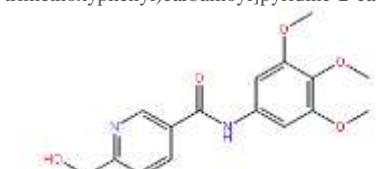
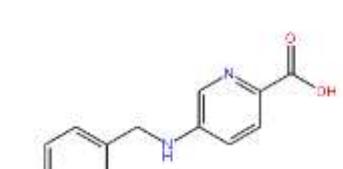
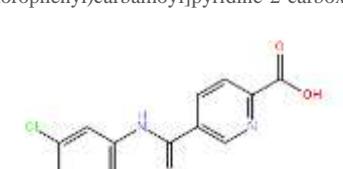
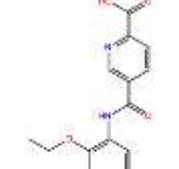
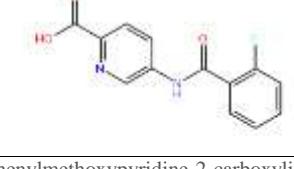
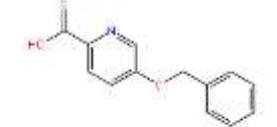
				
28.	44419139	1-[5-(3-chlorophenyl)pyridin-2-yl]pyrazole-4-carboxylic acid 	4900	5.30
29.	44419140	1-[5-(2-chlorophenyl)pyridin-2-yl]pyrazole-4-carboxylic acid 	6500	5.18
30.	44419165	1-[5-(4-propan-2-ylphenyl)pyridin-2-yl]pyrazole-4-carboxylic acid 	6800	5.16
31.	44419160	1-[5-(4-methoxyphenyl)pyridin-2-yl]pyrazole-4-carboxylic acid 	7300	5.13
32.	44419179	1-[5-(3-methoxyphenyl)pyridin-2-yl]pyrazole-4-carboxylic acid 	10000	5.00
33.	44419159	1-(5-pyrimidin-5-ylpyridin-2-yl)pyrazole-4-carboxylic acid	15000	4.82

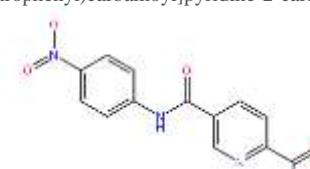
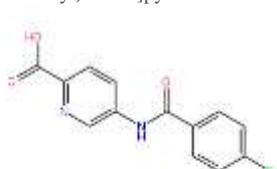
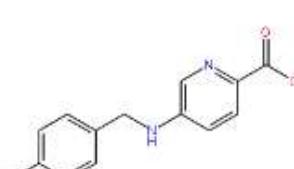
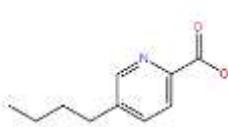
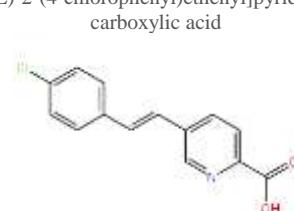
34.	44419147	1-[5-(furan-2-yl)pyridin-2-yl]pyrazole-4-carboxylic acid 	15000	4.82
35.	44419131	2-[[5-(4-chlorophenyl)pyridine-2-carbonyl]amino]acetic acid 	15000	4.82
36.	44419154	1-(5-thiophen-2-ylpyridin-2-yl)pyrazole-4-carboxylic acid 	18000	4.74
37.	44419171	1-[5-(2-methoxyphenyl)pyridin-2-yl]pyrazole-4-carboxylic acid 	19000	4.72
38.	44419133	1-[5-(4-chlorophenyl)pyridin-2-yl]pyrazole-4-carboxylic acid 	20000	4.69
39.	44419124	2-[[5-(4-cyanophenyl)pyridine-2-carbonyl]amino]acetic acid 	39000	4.40

40.	44419123	2-[[5-(4-methylphenyl)pyridine-2-carbonyl]amino]acetic acid 	46000	4.33
41.	44419132	2-[[5-(3-chlorophenyl)pyridine-2-carbonyl]amino]acetic acid 	100000	4.00
42.	24891150	2-[[4-(4-chlorophenyl)pyridine-2-carbonyl]amino]acetic acid 	100000	4.00
43.	11788622	2-(pyridine-2-carbonylamino)acetic acid 	100000	4.00
44.	15121190	5-[(4-(dimethylamino)phenyl)carbamoyl]pyridine-2-carboxylic acid 	4100	5.38
45.	15121179	5-[(4-ethoxyphenyl)carbamoyl]pyridine-2-carboxylic acid 	5000	5.30
46.	7493	pyridine-2,5-dicarboxylic acid 	5500	5.25

47.	15121188	5-[(4-methylphenyl)carbamoyl]pyridine-2-carboxylic acid 	8300	5.08
48.	15121186	5-[(2-fluorophenyl)carbamoyl]pyridine-2-carboxylic acid 	11000	4.95
49.	15121200	5-[(4-ethoxybenzoyl)amino]pyridine-2-carboxylic acid 	11200	4.95
50.	15121202	5-[[4-(dimethylamino)benzoyl]amino]pyridine-2-carboxylic acid 	11300	4.94
51.	15121191	5-[(2-methoxyphenyl)carbamoyl]pyridine-2-carboxylic acid 	14800	4.82
52.	15121187	5-[(4-fluorophenyl)carbamoyl]pyridine-2-carboxylic acid 	16100	4.79
53.	15121182	5-[(2-chlorophenyl)carbamoyl]pyridine-2-carboxylic acid	16300	4.78

				
54.	15121198	5-[(4-methylbenzoyl)amino]pyridine-2-carboxylic acid 	16500	4.78
55.	15121194	5-[(2,4-dimethoxyphenyl)carbamoyl]pyridine-2-carboxylic acid 	16600	4.77
56.	15121185	5-[(4-chlorophenyl)carbamoyl]pyridine-2-carboxylic acid 	17400	4.75
57.	15121193	5-[(4-methoxyphenyl)carbamoyl]pyridine-2-carboxylic acid 	21100	4.67
58.	15121199	5-[(4-chlorobenzoyl)amino]pyridine-2-carboxylic acid 	22500	4.64
59.	12640225	5-benzamidopyridine-2-carboxylic acid 	25600	4.59

60.	15121195	5-[(3,4,5-trimethoxyphenyl)carbamoyl]pyridine-2-carboxylic acid 	26500	4.57
61.	15121181	5-(phenylcarbamoyl)pyridine-2-carboxylic acid 	26500	4.57
62.	12640191	5-[(4-fluorophenyl)methylamino]pyridine-2-carboxylic acid 	31000	4.50
63.	15121183	5-[(3-chlorophenyl)carbamoyl]pyridine-2-carboxylic acid 	32200	4.49
64.	15121189	5-[(2-ethoxyphenyl)carbamoyl]pyridine-2-carboxylic acid 	32900	4.48
65.	15121204	5-[(2-fluorobenzoyl)amino]pyridine-2-carboxylic acid 	33800	4.47
66.	18379352	5-phenylmethoxypyridine-2-carboxylic acid 	39000	4.40

67.	15121196	5-[(4-nitrophenyl)carbamoyl]pyridine-2-carboxylic acid 	44000	4.35
68.	15121201	5-[(4-fluorobenzoyl)amino]pyridine-2-carboxylic acid 	51200	4.29
69.	12640191	5-[(4-fluorophenyl)methylamino]pyridine-2-carboxylic acid 	80000	4.09
70.	3442	5-butylpyridine-2-carboxylic acid 	149000	3.82
71.	15121207	5-[(E)-2-(4-chlorophenyl)ethenyl]pyridine-2-carboxylic acid 	150000	3.82

## 2.2 Splitting

Development of statistically significant QSAR models were based on the placing of dataset compounds into training and test set compounds (Roy et al., 2011; Puzyn, et al., 2012). The following criteria were used while splitting the dataset compounds. (i) In each subset the uniform range of end point is maintained (ii) Random splits and (iii) the splits should not be identical. The percentage deviation in the splits is detailed in Table 2 which revealed that the splits are in enough random.

**Table 2 Percentage of identity of splits 1–2**

	Set	Split1%	Split2%
Split1	Sub training	100	33.8
	Calibration		4.44
	Test		50
	Validation		0
Split2	Sub training		100
	Calibration		

	Test		
	Validation		

$$* \text{Identity\%} = \frac{N_{ij}}{0.5 * (N_i + N_j)} \times 100 \quad (\text{Toropov, et al., 2013})$$

Where,

$N_i$ ;  $j$  is the number of substances which are distributed into the same set for both  $i$ -th split and  $j$ -th split (set = sub-training, calibration, test, validation)

$N_i$  is the number of substances which are distributed into the set for  $i$ -th split

$N_j$  is the number of substances which are distributed into the set for  $j$ -th split

### 2.3 Optimal descriptors

If the molecular structure was represented by hybrid form i.e. a combination of SMILES and HSG (Hydrogen suppressed graph), statistically significant QSAR models were obtained. The hybrid optimal descriptors were used to build up model for the  $\text{pIC}_{50}$  of PHD2 inhibitors:

$$\text{Hybrid DCW (T; Nepoch)} = \text{SMILES DCW (T; Nepoch)} + \text{HSGDCW (T; Nepoch)}$$

Where,

$$\text{SMILES DCW (T, } N_{\text{epoch}}) = \sum \text{CW (SSSk)}$$

$$\text{HSGDCW (T, } N_{\text{epoch}}) = \sum \text{CW (A}_K) + \sum \text{CW (} ^0\text{EC}_K) + \sum \text{CW (} ^2\text{EC}_K) \dots \dots \quad (2)$$

$T$  is threshold for definition of rare (noise) molecular features:  $T = 1$  and  $2$  were examined.

$N_{\text{epoch}}$  is the number of the epochs of the Monte Carlo optimization:

$N_{\text{epoch}} = 150$  have been selected;

Where,

$\text{SSSk}$  is three-components SMILES attributes,

$A_k$  is chemical element, such as, C, N, O, etc., for HSG,

$^0\text{EC}_k$  is the Morgan extended connectivity of zero order (i.e., the vertex degree) in the HSG,

$^2\text{EC}_k$  is the Morgan extended connectivity of second order (i.e., the vertex degree) in the HSG.

$\text{CW}(x)$  is the correlation weights for  $x$  (some molecular feature which can be extracted from SMILES or from HSG). Table 3 contains an example of the  $\text{CW}(x)$  calculated with the Monte Carlo method. Table 4 contains an example of the calculation with the correlation weights.

**Table 3 Correlation weights for calculation of Hybrid DCW (T; Nepoch) for the case of split 1 (Eq 4)**

Structural attribute (SA)	CW(SA)	$N_{\text{TRN}}$	$N_{\text{CLB}}$	$N_{\text{TST}}$
EC0-C...2...:	-0.3468	33	25	10
EC0-C...2...:	-0.3468	33	25	10
EC0-C...2...:	-0.3468	33	25	10
EC0-C...3...:	-1.7853	33	25	10
EC0-C...2...:	-0.3468	33	25	10
EC0-C...3...:	-1.7853	33	25	10
EC0-C...2...:	-0.3468	33	25	10

EC0-C...2...:	-0.3468	33	25	10
EC0-C...3...:	-1.7853	33	25	10
EC0-C...2...:	-0.3468	33	25	10
EC0-C...3...:	-1.7853	33	25	10
EC0-C...2...:	-0.3468	33	25	10
EC0-C...3...:	-1.7853	33	25	10
EC0-N...2...:	-3.1436	33	25	10

EC0-C...3...:	-1.7853	33	25	10
EC0-C...2...:	-0.3468	33	25	10
EC0-C...2...:	-0.3468	33	25	10
EC0-C...3...:	-1.7853	33	25	10
EC0-O...1...:	1.5020	33	25	10
EC0-N...2...:	-3.1436	33	25	10
EC0-C...2...:	-0.3468	33	25	10
EC0-C...3...:	-1.7853	33	25	10
EC0-O...1...:	1.5020	33	25	10
EC0-O...1...:	1.5020	33	25	10
EC2-C...9...:	2.6074	17	14	6
EC2-C...9...:	2.6074	17	14	6
EC2-C...11...:	-1.0254	32	21	9
EC2-C...18...:	0.6983	11	6	6
EC2-C...14...:	0.4531	17	13	8
EC2-C...18...:	0.6983	11	6	6
EC2-C...12...:	-0.4728	32	25	10
EC2-C...12...:	-0.4728	32	25	10
EC2-C...17...:	-0.1240	18	17	6
EC2-C...11...:	-1.0254	32	21	9
EC2-C...18...:	0.6983	11	6	6
EC2-C...14...:	0.4531	17	13	8
EC2-N...19...:	1.8369	5	2	5
EC2-C...14...:	0.4531	17	13	8
EC2-C...18...:	0.6983	11	6	6
EC2-N...14...:	0.1925	5	3	5
EC2-C...18...:	0.6983	11	6	6
EC2-C...12...:	-0.4728	32	25	10
EC2-C...12...:	-0.4728	32	25	10
EC2-C...15...:	1.6991	29	20	10
EC2-O...6...:	0.5313	20	14	6
EC2-N...11...:	-0.1270	9	6	6
EC2-C...9...:	2.6074	17	14	6
EC2-C...11...:	-1.0254	32	21	9
EC2-O...4...:	0.8428	8	6	5
EC2-O...4...:	0.8428	8	6	5
C...1...=...:	3.5585	33	25	10
C...=...1...:	2.7832	33	25	10
C...C...=...:	0.1044	31	24	10
C...C...=...:	0.1044	31	24	10
C...=...C...:	-0.4267	32	25	10
=...C...2...:	0.1210	31	24	10
C...2...C...:	0.0	1	1	0
=...C...2...:	0.1210	31	24	10
C...=...C...:	-0.4267	32	25	10

=...C...(...:	-0.6044	31	24	10
C...(...C...:	-0.1797	28	22	6
=...C...(...:	-0.6044	31	24	10
C...=...C...:	-0.4267	32	25	10
C...C...=...:	0.1044	31	24	10
C...C...2...:	1.7773	6	4	3
C...2...=...:	1.7832	31	23	10
C...=...2...:	2.3175	31	23	10
=...C...1...:	9.6230	33	25	10
C...1...(...:	2.2540	23	16	6
C...(...1...:	2.1240	16	11	4
3...C...(...:	0.0	14	0	0
C...3...=...:	0.0	1	1	0
C...=...3...:	0.0	1	1	0
N...C...=...:	3.1260	32	24	10
C...N...4...:	0.0	1	0	0
N...4...C...:	0.0	1	1	0
=...C...4...:	0.0	1	1	0
C...=...C...:	-0.4267	32	25	10
=...C...(...:	-0.6044	31	24	10
N...(...C...:	-2.9816	7	5	6
=...N...(...:	-2.2782	5	3	5
N...=...C...:	0.0284	32	24	10
=...C...4...:	0.0	1	1	0
C...4...C...:	0.0	1	0	0
=...C...4...:	0.0	1	1	0
C...=...C...:	-0.4267	32	25	10
=...C...3...:	-2.4375	14	12	8
C...3...(...:	0.0	1	1	0
C...(...3...:	1.1699	10	9	3
(...C...(...:	-3.3790	33	25	10
C...(...=...:	-0.6845	33	25	10
O...=...(...:	2.1553	33	25	10
=...O...(...:	3.8477	33	25	10
O...(...N...:	1.1280	12	9	5
C...N...(...:	1.3770	18	11	6
N...C...C...:	2.0206	8	6	5
C...C...(...:	0.6054	18	16	9
C...(...=...:	-0.6845	33	25	10
O...=...(...:	2.1553	33	25	10
=...O...(...:	3.8477	33	25	10
O...(...O...:	-4.9960	33	25	10

\* NTRN, NCLB, and NTST are the numbers of the x in the sub training, calibration, and test set

**Table 4 - calculation for hybrid DCW (1, 9) = 18.53975**

Molecular features	Correlation Weight, CW(x)
<b>Features extracted from SMILES</b>	
(...C...(...:	-3.37900
(...O...(...:	0.84875
1...C...(...:	-0.62300
2...C...(...:	1.15425
2...C...1...:	0.73137
3...N...(...:	0.71775
=...C...(...:	-0.60438
=...C...1...:	9.62300
=...C...2...:	0.12100:

=...C...3...:	-2.43750
=...N...(...:	-2.27825
=...N...3...:	2.69250
=...O...(...:	3.84775
C...(...1...:	2.12400
C...(...2...:	1.94331
C...(...3...:	1.16988:
C...(...=...:	-0.68450:
C...(...C...:	-0.17969:
C...1...(...:	2.25400:
C...1...=...:	3.55850:
C...1...C...:	3.14644:

C...2...(...:	5.15325:
C...2...=...:	1.78325:
C...3...C...:	-1.32813:
C...=...(...:	0.99800:
C...=...1...:	2.78325:
C...=...2...:	2.31750:
C...=...C...:	-0.42669:
C...C...(...:	0.60538:
C...C...1...:	5.22375:
C...C...2...:	1.77725:
C...C...=...:	0.10438:
C...N...(...:	1.37700:

C..N...1...:	2.69050:
C..N...3...:	1.31250:
C..N...=...:	2.21575:
C..O...(.):	-1.31050:
C..O...C...:	0.65344:
Features extracted from HSG	
EC0-C...1...:	2.96975:
EC0-C...2...:	-0.34675:
EC0-C...3...:	-1.78525:
EC0-F...1...:	3.72275:
EC0-Cl..1...:	0.24419:
EC0-N...2...:	-3.14363:
EC0-N...3...:	-1.30569:
EC0-O...1...:	1.50200:
EC0-O...2...:	0.40425:
EC2-C...10..:	-2.29787:
EC2-C...11..:	-1.02544:
EC2-C...12..:	-0.47275:
EC2-C...13..:	0.24700:
EC2-C...14..:	0.45313:
EC2-C...15..:	1.69913:
EC2-C...16..:	-1.93250:

EC2-C...17..:	-0.12400:
EC2-C...18..:	0.69831:
EC2-C...3...:	7.99900:
EC2-C...4...:	1.53425:
EC2-C...5...:	1.62500:
EC2-C...7...:	-4.12600:
EC2-C...8...:	2.72275:
EC2-C...9...:	2.60738:
EC2-F...5...:	3.43750:
EC2-Cl..5...:	3.17488:
EC2-N...11..:	-0.12700:
EC2-N...12..:	2.08975:
EC2-N...13..:	-1.00400:
EC2-N...14..:	0.19250:
EC2-N...18..:	-1.00300:
EC2-N...19..:	1.83694:
EC2-O...10..:	-2.08494:
EC2-O...4...:	0.84275:
EC2-O...5...:	0.70894:
EC2-O...6...:	0.53125:
EC2-O...8...:	2.55850:
EC2-O...9...:	-2.14463:

N...(1...:	-1.00000:
N...(2...:	1.68550:
N...(C...:	-2.98156:
N...1...C...:	1.53025:
N...3...(...:	1.28025:
N...3...C...:	1.68950:
N...=...C...:	0.02844:
N...C...(...:	2.03625:
N...C...2...:	2.94150:
N...C...=...:	3.12600:
N...C...C...:	2.02062:
O...(C...:	-2.52725:
O...(F...:	1.25300:
O...(Cl..:	2.71294:
O...(N...:	1.12800:
O...(O...:	-4.99600:
O...=...(...:	2.15525:
O...C...(...:	0.12600:
O...C...1...:	-0.02825:
O...C...C...:	-3.12100:

Threshold=2;

Number of SMILES Attributes (SA) =160;

Number of active SA=96

In CORAL software, the QSAR models were built up by calculating the CW(x) which provides the maximum of target function (TF) (Toropov, et al., 2008; 2011).

$$TF = R + R' - |R - R'| \times \text{Const}$$

where R and R' are correlation coefficients between pIC<sub>50</sub> and Hybrid DCW(T; Nepoch); Const is an empirical constant (In this case it is 0.1). Several runs of the Monte Carlo optimization was carried out to define preferable threshold and Nepoch with best quality of QSAR model followed by validation of the model performed with external validation dataset.

### 3. Results and Discussion

The best one variable models statistical quality are given in Table 5 and are represented by the following formula

$$pIC_{50} = C_0 + C_1 \times {}^{\text{Hybrid}}\text{DCW}(T, N_{\text{epoch}}) \dots \dots (3)$$

Table 5 Statistical characteristics of one-variable models for HIF – PHD2 inhibition activity (PIC<sub>50</sub>) with the threshold T = 0, 1 & 2 and the number of epochs of the Monte Carlo optimization Nepoch = 150

**Table 5 Statistical characteristics of one variable model**

Split-1	Run	T	Nact	Sub training					Calibration					Test						
				N	r2	q2	s	Mae	F	N	r2	q2	s	Mae	F	N	r2	q2	s	Mae
1	0	160	33	0.9822	0.9804	0.071	0.042	1707	25	0.9370	0.9281	0.423	0.334	342	10	0.6512	0.4226	0.423	0.334	15
2	0		33	0.9820	0.9803	0.071	0.042	1694	25	0.9372	0.9283	0.403	0.292	343	10	0.6287	0.4015	0.424	0.305	14
3	0		33	0.9821	0.9803	0.071	0.043	1705	25	0.9370	0.9281	0.396	0.287	342	10	0.6446	0.4229	0.474	0.359	15
1	1	127	33	0.9820	0.9802	0.071	0.042	1688	25	0.9373	0.9284	0.410	0.298	344	10	0.4880	0.1931	0.608	0.298	8

	2	1		33	0.98 22	0.98 04	0.071	0.04 2	1713	25	0.93 70	0.92 80	0.401	0.290	342	10	0.63 31	0.42 76	0.54 3	0.41 0	14
	3	1		33	0.98 19	0.98 01	0.070	0.04 2	1682	25	0.93 73	0.92 84	0.406	0.029 5	344	10	0.47 58	0.19 32	0.63 6	0.45 3	7
Aver age																					
1	2	96		33	0.98 31	0.98 13	0.069	0.04 4	1798	25	0.93 51	0.92 56	0.468	0.349	331	10	0.78 99	0.68 06	0.31 3	0.24 9	30
2	2		33	0.98 27	0.98 09	0.070	0.04 5	1758	25	0.93 54	0.92 60	0.473	0.353	333	10	0.81 85	0.71 38	0.29 7	0.24 4	36	
3	2		33	0.98 28	0.98 10	0.070	0.04 4	1767	25	0.93 55	0.92 61	0.469	0.350	334	10	0.72 96	0.58 56	0.43 2	0.32 1	22	
Split- 2																					
	1	0	155	34	0.95 28	0.94 85	0.134	0.08 3	646	24	0.99 47	0.99 38	0.338	0.255	4125	10	0.80 08	0.68 55	0.26 3	0.20 2	32
	2	0		34	0.95 32	0.94 90	0.134	0.08 1	652	24	0.99 57	0.99 49	0.336	0.251	5094	10	0.73 94	0.49 16	0.32 6	0.22 4	23
	3	0		34	0.95 18	0.94 74	0.136	0.08 3	632	24	0.99 56	0.99 48	0.343	0.255	4983	10	0.69 38	0.50 57	0.27 8	0.21 9	18
	1	1	137	34	0.95 28	0.94 86	0.134	0.08 0	646	24	0.99 57	0.99 49	0.343	0.254	5084	10	0.61 39	0.28 57	0.31 8	0.23 2	13
	2	1		34	0.95 08	0.94 64	0.137	0.08 2	619	24	0.99 62	0.99 55	0.326	0.242	5754	10	0.82 23	0.73 49	0.23 6	0.18 6	37
	3	1		34	0.95 37	0.94 95	0.133	0.08 1	659	24	0.99 54	0.99 46	0.347	0.257	4744	10	0.88 28	0.83 14	0.18 7	0.13 9	60
Aver age																					
	1	2	104	34	0.94 37	0.93 82	0.147	0.09 8	536	24	0.99 67	0.99 60	0.333	0.248	6732	10	0.52 45	0.20 21	0.34 7	0.24 9	9
	2	2		34	0.94 40	0.93 86	0.146	0.09 8	540	24	0.99 58	0.99 51	0.335	0.246	5267	10	0.51 53	0.16 87	0.35 6	0.26 2	9
	3	2		34	0.94 79	0.94 29	0.141	0.09 5	582	24	0.99 69	0.99 63	0.337	0.249	7173	10	0.56 29	0.28 29	0.35 4	0.27 0	10

Best models are indicated by bold

\* Nact = number of molecular features

n = number of substances in the set,

$r^2$  = square correlation coefficient between experimental and calculated values of PIC50,

$q^2$  = cross-validated squared correlation coefficient,

s = standard error of estimation and F = Fischer F-ratio.

In both the splits, best statistical quality was obtained at threshold equals to 2 & 1 and the average values of the  $N_{epoch}$  are 12 and 27 for split 1 & split 2 respectively. Further, the PIC<sub>50</sub> models for Split1 and 2 are as follows

### Split 1

$$\text{PIC}_{50} = 2.3687(\pm 0.0181) + 0.0621 (\pm 0.0006) * \text{DCW} (2, 8) \dots\dots (4)$$

n = 33,  $R^2 = 0.9827$ ,  $q^2 = 0.9809$ , s = 0.070 (sub training set)

n = 25,  $R^2 = 0.9354$ ,  $q^2 = 0.9260$ , s = 0.343(Calibration set)

n = 10,  $R^2 = 0.8185$ ,  $q^2 = 0.7138$ , s = 0.297,  $R_m^2 = 0.7154$ (should be larger than 0.5) (Test set)

### Split 2

$$\text{PIC}_{50} = 3.0005 (\pm 0.0057) + 0.0491 (\pm 0.0003) * \text{DCW} (1, 9) \dots\dots (5)$$

$n = 34, R^2 = 0.9537, q^2 = 0.9495, s = 0.133, F = 659$  (sub training set)

$n = 24, R^2 = 0.9954, q^2 = 0.9946, s = 0.347$  (Calibration set)

$n = 10, R^2 = 0.8828, q^2 = 0.8314, s = 0.187, R_m^2 = 0.6730$ (should be larger than 0.5) (Test set)

$n = 10,$

Where,

$n$ = Number of compounds in the dataset,

$r$  = correlation coefficient,

$q^2$  = leave-one-out cross validated correlation coefficient

$F$  = Fischer F-ratio

$R_m^2$  = Predictive ability of the model

The robustness of the predicted models were further validated by using Y-scrambling (Mitra, et al., 2010) and the obtained values are given in Table 6

**Table 6 Y-randomization results for test set**

Probe of Y-scrambling	Split 1,Eq. 4 $R_r^2$	Split 2, Eq. 5, $R_r^2$
$R^2$	0.8185	0.8828
1	0.0781	0.0782
2	0.1119	0.0754
3	0.2572	0.0222
4	0.1146	0.1688
5	0.1919	0.1444
6	0.0918	0.0088
7	0.0093	0.994
8	0.0048	0.1214
9	0.0052	0.0012
10	0.0691	0.3721
$[^C R_p^2 = R * \sqrt{R^2 - Rr^2}]$	0.7421	0.7170

From the obtained correlation weights of Monte Carlo method of optimization in each split, it is possible to detect the structural features responsible for the increased or decreased inhibition activity of compounds against HIF - PHD2. Structural features having positive correlation values indicate that the feature may enhance the inhibition activity as well as increased end point. Similarly, the features having negative correlation values may represent the decreased inhibition activity. Based on this knowledge, we concluded that the presence of nitrogen is the promoter of the inhibition activity and vice versa and the presence of side chain atoms may decrease the inhibition activity (Table -7). The obtained predicted inhibitory values, experimental values and the residuals are also given in Table 8. The obtained results reveals that the predicted models can be effectively used to compute inhibitory activity of novel pyridine based molecule against HIF – PHD2 domains and may be used as a drug to treat various disorders of hypoxic conditions.

#### **4. Conclusion**

Statistical QSAR models for HIF – PHD2 domain inhibition activity for pyridine analogs were developed by using CORAL software (Table – 5). The developed models explain the structural feature promoters for the increased or decreased HIF – PHD2 domain inhibition activity (Table 7). These features may be effectively used to predict HIF – PHD2 inhibition

activity for a newly developed pyridine analogs (Table -8; Fig 1). The predicted model in two splits were validated with external dataset compounds also (Table 9)

**Table 7 - Stability of the correlation weights for molecular structures extracted from SMILES**

	S. NC	Pubchem CID	Observe d C <sub>50</sub> (PIC <sub>50</sub> )	Predicted PIC50	Residu al	Molecular features, x	Correlation weights, CW(x) Run 1		
						C...1...=...:	5.3780		
1.		+ 1612677 4	5.44		0.114	C...C...=...:	1.0136		
2.		# 4441928 1	5.22		-0.176	C...2...C...:	0.0		
3.		+ 4441926 5	5.16		-0.222	=...C...(.:)	0.7773		
4.		# 4441933 6	4.92		-0.183	C...=...C...:	-0.3095		
5.		+ 4441928 2	4.85		0.008	=...C...(.:)	0.7773		
6.		# 4441926 4	4.84		-0.407	=...N...(.:)	0.0575		
7.		- 4441927 0	4.79		-0.350	N...=...C...:	1.0020		
8.		+ 4441925 2	4.76		0.013	C...4...C...:	0.0		
9.		# 4441929 7	4.72		-0.123	C...=...C...:	-0.3095		
10.		# 4441930 2	4.61		0.140	=...C...3...:	0.5615		
11.		- 4441934 2	4.61		-0.070	(...C...(.:)	2.9980		
12.		+ 4441934 6	4.00		0.259	C...(.:=...):	0.4990		
13.		- 1612665 5	6.72		0.046	O...=...(.:)	0.4990		
14.		# 4441931 8	6.23		-0.544	O...=...(.:)	0.5000		
15.		- 6914666	5.85		0.103	=...O...(.:)	1.7460		
16.		# 4441932 5	5.79		0.160	O...(.O...):	-3.0040		
17.		- 4441932	5.79		0.076				

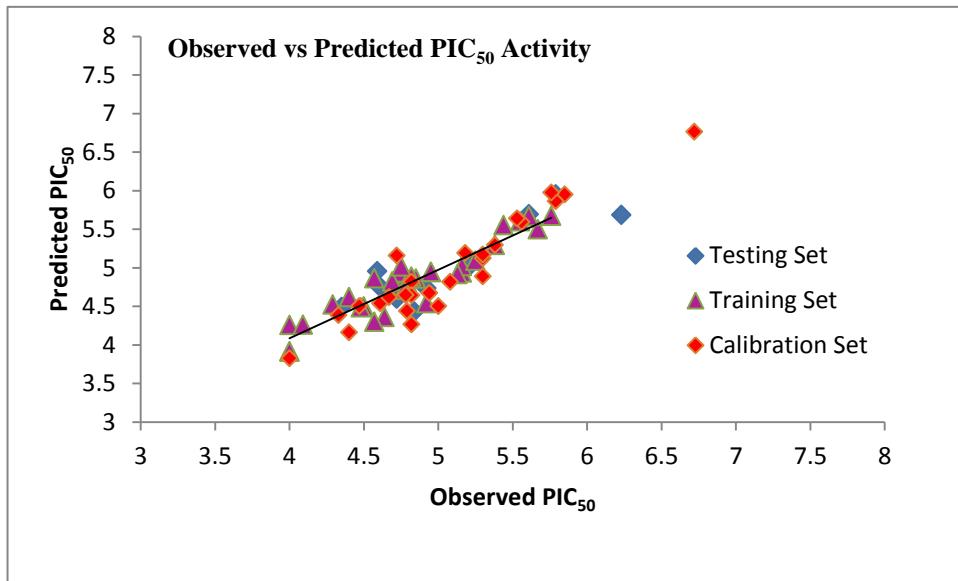
<b>Experimental PIC50, predicted PIC50</b>									
18.	+	4441933 3	6	5.76				-0.088	
19.	-	4441931 9	6	5.76				0.218	
20.	+	4441932 9	6	5.67				-0.171	
21.	+	4441932 1	6	5.61				0.057	
22.	#	4441932 0	6	5.61				0.085	
23.	-	4441931 7	6	5.56				0.036	
24.	+	4441933 4	6	5.55				0.051	
25.	-	4441933 0	6	5.53				0.110	
26.	+	4441913 9	6	4.92				-0.380	
27.	-	4441914 0	6	5.30				-0.174	
28.	-	4441916 5	6	5.18				0.011	
29.	+	4441916 0	6	5.16				-0.140	
30.	+	4441917 9	6	5.13				-0.211	
31.	-	4441915 9	6	5.00				-0.495	
32.	-	4441914 7	6	4.82				0.00	
33.	-	4441913 1	6	4.82				-0.554	
34.	+	4441915 4	6	4.82				0.064	

35.	+	4.74		0.198
36.	-	4.72		0.440
	4441913 3		5.16	
37.	+	4.69		0.131
	4441912 4		4.821	
38.	-	4.40		-0.239
	4441912 3		4.161	
39.	-	4.33		0.055
	4441913 2		4.385	
40.	+	4.00		-0.086
	2489115 0		3.914	
41.	+	4.00		-0.087
	1178862 2		3.913	
42.	-	4.00		-0.172
	1512119 0		3.828	
43.	+	5.38		-0.084
	1512117 9		5.296	
44.	-	5.30	4.889	-0.411
45.	+	5.25		-0.157
	1512118 8		5.093	
46.	-	5.08		-0.260
	1512118 6		4.82	
47.	+	4.95		-0.007
	1512120 0		4.943	
48.	+	4.95		-0.005
	1512120 2		4.945	
49.	-	4.94		-0.266
	1512119 1		4.674	
50.	-	4.82		-0.175
	1512118 7		4.645	
51.	+	4.79		0.022
	1512118 2		4.812	
52.	-	4.78		-0.130
	1512119 8		4.65	
53.	+	4.78		-0.046
	1512119 4		4.734	
54.	+	4.77		-0.055
	1512118 5		4.715	
55.	+	4.75		0.267
	1512119 3		5.017	
56.	-	4.67		-0.050
	1512119 9		4.62	
57.	+	4.64		-0.280
	1264022 5		4.36	
58.	#	4.59	4.957	0.367

	1512119 5			
59.	+	4.57		0.296
	1512118 1		4.866	
60.	+	4.57		-0.269
	1264019 1		4.301	
61.	+	4.50		-0.001
	1512118 9		4.499	
62.	-	5.30		-0.129
	1512120 4		5.171	
63.	+183793 52	4.48	4.485	0.005
64.	-	4.47		0.032
	1512119 6		4.502	
65.	+	4.40		0.220
	1512120 1		4.62	
66.	#	4.35		0.141
	1264019 1		4.491	
67.	+3442	4.29	4.524	0.234
68.	+	4.09		0.172
	1512120 7		4.262	

**Table 9- Validation of the predicted model using external dataset compounds**

S.No	Compound ID	Observed	Predicted	Split	Residuals
1.	44419280	3.910	4.912, 4.121	1 & 2	-1.00 & -0.21
2.	15121183	4.510	4.60	2	-0.09
3.	8027170	4.080	3.920	1	0.16

**Figure 1 Plot of observed Vs Predicted PIC<sub>50</sub>**

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