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RESEARCH PAPER



EXPLORING 2D AND 3D QSAR STUDIES OF INDOLE/ BENZOXIMIDAZOLE-5-CARBOXIMIDINE DERIVATIVES AS ANTICANCER AGENTS FOR THE DEVELOPMENT OF PREDICTIVE MODEL

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2D QSAR and 3D QSAR studies of indole/benzoximidazole-5-carboximidine derivatives as anticancer agents by Vlife Sciences MDS molecular modelling package has been performed to explore the physico-chemical properties and spatial disposition of the chemical groups towards the biological activity. The 2D-QSAR studies were carried out using the partial least squares (PLS) method coupled with stepwise variable selection, with $r^2 = 0.5960$ and $q^2 = 0.4062$ and the 3D-QSAR studies were performed using stepwise variable selection k-nearest-neighbour molecular field analysis (kNNMF) approach; with cross-validated correlation coefficient (q^2) of 0.6453 and a predicted r^2 for the external test (pred_ r^2) of 0.7316.

Key words: QSAR, kNNMFA, PLS, Indole/benzoximidazole-5-carboximidine, Anticancer agents.

INTRODUCTION

Cancer is the second leading cause of death in the developed world. Cancer accounted 7.9 million deaths (around 13% of all deaths) in 2008 (Zali *et al* 2011). Regular use of some established screening tests can prevent the development of cancer through identification and removal or treatment of premalignant abnormalities (American Cancer Society, 2013). Currently, inspite of intensive research and some major advances in treatment, cancer claims the life of nearly one out of four. It is second to heart diseases responsible for 35% of deaths in United States (Copper, 1992). The failure of the curative treatment of cancer patients often occurs as a result of intrinsic or acquired drug resistance of the tumor to chemotherapeutic agents. The resistance of tumors occurs not only to a single cytotoxic drug used, but also occurs as a crossresistance to a whole range of drugs with different structures and cellular targets (Ozben, 2006). There are more than 100 distinct types of cancer and subtypes of tumors can be found within specific organs (Hanahan and Weinberg, 2000). The urokinase (uPA) pathway of plasminogen activation plays a key role in tissue remodelling, cancer cell invasion and in metastasis. uPA is one of the serine proteases



that catalyzes the conversion of plasminogen to plasmin, an active enzyme that is able to degrade a variety of extracellular matrix proteins. The involvement of urokinase-type plasminogen activator receptor in the pathology of human cancers is well documented. High levels of uPAR in tumour tissues and plasma from patients with various human cancers are associated with poor prognosis and increased risk of tumour recurrence and metastasis. The uPAS (urokinase plasminogen activating system) is involved in the extracellular conversion of the ubiquitous inactive plasminogen to the broad-spectrum serine protease plasmin, implicated in numerous pathophysiological process requiring the remodelling of extracellular matrix (ECM) and basement membranes (BM) (Ulisse et al 2009). Inhibition of expression of these components leads to a reduction in the invasive and metastatic capacity of many tumors (Choong and Nadesapillai, 2003).

Quantitative structure-activity relationship models (QSAR models) are regression or classification models used in the chemical and biological sciences and engineering. Like other regression models, QSAR regression models establish a linear relationship between a set of molecular descriptors of chemicals and the biological activity of the chemical while classification QSAR models shows a non-linear relationship between a set of molecular descriptors of chemicals and the biological activity of the chemical (Bansal *et al* 2011; Kumar, 2011; Sharma *et al* 2011; Jain *et al* 2013; Pahwa and Papreja, 2014).

QSAR studies can reduce the costly failures of drug candidates in clinical trials by filtering the combinatorial libraries (Sethi, 2012). In continuation of the research of molecular modelling, in this study, we report the 2D and 3D QSAR analysis of indole/benzox- imidazole-5carboximidine derivatives as anti-cancer agents by VlifeSciences MDS molecular modeling package.

MATERIALS AND METHODS

Selection of molecules and Data set

A dataset of thirty nine indole/benzoximidazole-5-carboximidine derivatives (Bhongade and Gadad, 2004) reported to have inhibitory activity on urokinase plasminogen activator (uPA) was used in the present 2D and 3D QSAR analysis. The inhibitory concentration values reported as pIC_{50} (-log IC_{50}) were used for the studies. The structures along with their $_{PIC_{50}}$ values are represented in **Table 1**.

Table 1. Chemical structures of data set used for 2D and 3D QSAR Studies with actualand predicted activity from the best model

Molooulo	Structures	Activit	$\mathbf{y}(\mathbf{PIC}_{50})$
wioiecule	Structures	Actual	Predicted
S1		-0.74	-0.81
S2		-0.447	-0.55
S 3		-0.568	-0.64
S4		-0.87	-0.44

S5		0.556	0.89
S6	H = H = H	0.045	-0.32
S7		0.259	-0.09
S8	H_{H}	0.25	0.36
S9		-0.556	0.02
S10		0.39	0.92
S11		-0.556	-0.80
S12		-0.278	-0.05
S13		-0.591	-0.48

S14		0.552	0.52
S15		-0.38	-0.31
S16	$H_{N} + H_{H} + H_{H$	1.25	0.79
S17		1.45	0.51
S18		0.552	0.84
S19		1.42	1.70
S20	H = H = H = H = H = H = H = H = H = H =	1.602	1.73
S21		-1.113	-1.02
S22		-0.5	-0.82

S23	-1.041	-0.80
S24	0.259	0.25
S25	1.698	1.75
S26	0.44	0.24
S27	2.096	1.29
S28	2.045	1.98
S29	-0.3	-0.21

S30		-0.477	0.70
S31	H = H = H = H = H = H = H = H = H = H =	-0.518	-0.48
\$32	H = H = H = H = H = H = H = H = H = H =	-1.13	-1.25
\$33		0.301	0.61
S34	H_{H}	1	0.84
\$35	H H H H H H H H H H H H H H H H H H H	1.36	1.59
S36		1.25	1.54
\$37		1	1.09
S38	$H_{H} H_{H} H_{H$	-0.903	-1.06



2D QSAR

All the compounds for 2D QSAR was subjected to energy minimization by MMFF (Molecular mechanics force field method).Various 2D descriptors like topological, physicochemical, alignment-independent descriptors were calculated after which by invariable column was removed and the training and test set was selected by Manual Selection Method. The model for the 2D-QSAR study was generated using PLS with forward backward as the variable selection method.

3D QSAR

3D-QSAR refers to the application of force field calculations requiring three-dimensional structures based on protein crystallography or molecule superimposition (Ibezim et al 2009). For studies, the molecules are converted from 2D to 3D structures, optimized by MMFF (Molecular mechanics force field method) and then were aligned using Template based Alignment method by taking most active molecule (Figure 1) as the reference molecule and basic moiety (Figure 2) as the template. The alignment is shown in Figure 3. The QSAR model was builded by KNN method using forwardbackward as variable selection method . It examines the steric fields and the electrostatic fields.



Fig. 1. Reference molecule used for alignment by template based alignment

RESULTS AND DISCUSSION 2D QSAR

The best QSAR model was selected among the various models generated by PLS (Partial Least Square analysis). The 2D QSAR equation and the statistical parameters generated are shown in



Fig. 2. Basic moiety as a template for alignment



Fig. 3. 3D view of aligned molecules

Table 2. The QSAR model showed $r^2 = 0.5960$ and standard error of 0.6907. The stability of model judged by leave-one-out procedure (q^2 =0.4062) suggesting that the models can be useful for meaningful predictions. Furthermore, the predictive potential of model was observed by the pred_ $r^2 = 0.1208$. The descriptors contributing to the biological activity as generated were slogP, EpsilonB, T_O_Cl_7 and H-Donor. The correlation matrix given by **Table 3** and the values less than 0.6 indicated the absence of multi colinearities in the model. **Figure 4** gives a pictorial representation of different 2D parameters and their contributions towards anticancer activity.

Equation	<i>p</i> IC ₅₀ = 1.05 slogP +22.7091 Delta EpsilonB -1.9378 T_O_Cl_7 + 1.1410 H-Donor count -10.1773					
	n = 33	Degree of freedom $= 29$	F test = 14.2619			
Statistics	$r^2 = 0.5960$	$q^2 = 0.4062$	$pred_{r}^{2} = 0.1208$			
	$r^2 se = 0.6907$	$q^2 se = 0.8373$	$pred_{r^{2}se} = 0.7331$			

Table 2. Statistical results of 2D	QSAR equation a	generated by PLS method
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Table 3.	Correlation	matrix for	the	descriptors	contributing	to the	2D QS	SAR model
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	Mol. wt.	SdsNE-index	Score
Mol. wt.	1	-0.413695	1
SdsNE-index	-0.413695	1	1



Fig. 4. Contribution chart of selected 2D descriptors for anticancer activity

slogp

This descriptor signifies log of the octanol/water partition coefficient

T_O_Cl_5

This is the count of number of Oxygen atoms (single double or triple bonded) separated from chlorine atom by 5 bond distance in a molecule.

H-Donor count

Number of hydrogen bond donor atoms

Uni-column statistics as shown in **Table 4** for training and test set, were generated to check correctness of selection criteria for training and test set molecules. Higher standard deviation in training set indicates wide distribution of activity of molecules as compared to test set molecules.

Figure 5 shows the graph plotted between actual and predicted biological activity. Training set (points in red) as well as test set (points in blue) are well closed to regression line and also the training set are encircling the test set showing good predictive ability of the model. The predicted activity values for the compounds in the training set and test set, along with their corresponding observed activity values, are given in **Table 5**.

Table 4. Uni-column statistics for training set and test set

Set	Column Name	Average	Max	Min	Std Dev	Sum
Training	pIC ₅₀	0.1645	2.0960	-1.7400	1.0345	5.4290
Test	pIC ₅₀	0.2763	1.3600	-0.5180	0.6823	1.6580



Fig. 5. Fitness plot between observed and predicted biological activities of training (blue spot) and test (red spot) molecules of 2D model.

3D QSAR

3D-QSAR was used to optimize the steric requirement. 3D data points were generated that contributed to k Nearest Neighbour Molecular Field Analysis (kNN MFA) 3D-QSAR model. This is followed by generation of a common rectangular grid around the molecules. The steric interaction energies were computed at the lattice points of the grid using a methyl probe of charge +1. The data points generated by 3D-QSAR are shown in **Figure 6**. The best model generated with kNN MFA method showed a q2, pred_r2 and K nearest neighbour as 0.8105, 0.7015 and 2 respectively as shown in **Table 6**. The predicted activity values for the compounds

Molecule	Actual BA	Predicted BA	Residual
S1	-0.74	-0.813449	0.073449
S2	-0.447	-0.219817	-0.22718
S3	-0.568	0.130168	-0.69817
S4	-0.87	-0.841612	-0.02839
S5*	0.556	-1.01552	1.57152
\$6	0.045	-0.131271	0.176271
S7	0.259	-0.219817	0.478817
S8*	0.25	0.130168	0.119832
S9	-0.556	-1.01552	0.45952
S10*	0.39	0.206531	0.183469
S11	-0.556	-0.841612	0.285612
S12	-0.278	0.183642	-0.46164
S13	-0.591	0.080751	-0.67175
S14	0.552	0.080751	0.471249
S15*	-0.38	-0.466336	0.086336
S16	1.25	0.446082	0.803918
S17	1.45	0.477281	0.972719
S18	0.552	1.15872	-0.60672
S19	1.42	0.55255	0.86745
S20	1.602	1.15587	0.44613
S21	-1.113	-0.037207	-1.07579
S22	-0.5	-0.170716	-0.32928
S23	-1.041	-0.922126	-0.11887
S24	0.259	0.143706	0.115294
S25	1.698	1.29298	0.40502
S26	0.44	0.337396	0.102604
S27	2.096	0.561509	1.534491
S28	2.045	1.45917	0.58583
S29	-3	0.752633	-3.75263
S30	-0.477	-0.478671	0.001671
S31*	-0.518	-0.131271	-0.38673
S32	-1.113	-0.314839	-0.79816
S33	0.301	1.196050	-0.89505
S34	1	1.420900	-0.4209
S35*	1.36	1.495950	-0.13595
S36	1.25	1.551030	-0.30103
S37	1	0.638880	0.36112
S38	-0.903	-1.43510	0.5321
S39	-1.74	-0.476281	-1.26372

Table 5. Observed and predicted activity of training set and test set with their residuals of 2D QSAR

*Test set

in the training set and test set, along with their corresponding observed activity values, are given in **Table 7** and the fitness plot in **Figure 7** which shows the graph plotted between actual and predicted biological activity. Training set (points in red) as well as test set (points in blue) are well closed to regression line and showing

good predictive ability of the model. The ranges of data point values were based on the variation of the field values at the chosen points using the most active molecule and its nearest neighbour set. Points generated in kNN MFA 3D-QSAR model were S_1012 (30.0000, 30.0000), E_547 (-0.2724, 0.3311) *i.e.* steric and electrostatic data

Model summary							
kNN Method	Г	'raining S	et Size = 31			Test Set Size	= 8
Statistics	k Nearest Neighbour= 2	n = 31	Degree of freedom = 28	q ² = 0.6453	q²_se = 0.5914	Pred_r ² = - 0.7316	pred_r²se = 0.5230
Selected descriptor and their range	S_1	012 (30.0	000 30.0000)		E_5	47 (-0.2724 0	.3311)

Table 6. Statistical results of 3D QSAR model generated by SW kNN MFA method

Table 7. Observed and predicted activity of training set and test set with their residuals of 3D QSAR

Molecule	Actual BA	Predicted BA	Residual
S1	-0.74	-0.819529	0.073449
S2	-0.447	-0.377798	-0.22718
S3	-0.568	0.306998	-0.69817
S4*	-0.87	-0.647808	-0.02839
S5*	0.556	0.439421	1.57152
S6	0.045	0.057331	0.176271
S7	0.259	1.12333	0.478817
S8	0.25	0.302605	0.119832
S9*	-0.556	-0.158517	0.45952
S10	0.39	-0.647088	0.183469
S11	-0.556	-0.916909	0.285612
S12	-0.278	-0.462462	-0.46164
S13	-0.591	0.335349	-0.67175
S14	0.552	-0.168048	0.471249
S15*	-0.38	-0.527896	0.086336
S16	1.25	0.636405	0.803918
S17	1.45	1.00428	0.972719
S18	0.552	0.857929	-0.60672
S19	1.42	0.478506	0.86745
S20	1.602	1.16161	0.44613
S21	-1.113	-1.34338	-1.07579
S22	-0.5	-0.20481	-0.32928
S23	-1.041	-1.42854	-0.11887
S24	0.259	0.957433	0.115294
S25	1.698	0.897315	0.40502
S26*	0.44	-0.373997	0.102604
S27	2.096	1.12273	1.534491
S28*	2.045	1.00109	0.58583
S29	-3	-0.462813	-3.75263
S30	-0.477	-0.360151	0.001671
S31*	-0.518	-0.664076	-0.38673
S32	-1.113	-0.647785	-0.79816
S33	0.301	-0.736929	-0.89505
S34	1	0.757103	-0.4209
S35*	1.36	1.12951	-0.13595
S36	1.25	1.14399	-0.30103
S37	1	1.30164	0.36112
S38	-0.903	-0.131259	0.5321
S39	-1.74	-0.908508	-1.26372

*Test set



Fig. 6. Relative positions of the steric and electrostatic fields around aligned molecules



Fig. 7. Fitness plot between observed and predicted activities of the training (blue spot) and test (red spot) molecules of 3D model

points at lattice points 1012 and 547 respectively. Positive values in steric field descriptors indicated the requirement of positive steric potential for enhancing the biological activity of indole/benzoximidazole-5carboximidine derivatives. Negative value in electrostatic potential indicated the requirement of negative electrostatic potential for enhancing the biological activity. The positive value of

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showed factors that more steric steric substituents were preferred at the position of data points S 1012 (30.0000,generated 30.0000). Similarly the negative values of electrostatic descriptor suggested the more less requirement of electrostatic substituents at position of generated data point E_547 (-0.2724, 0.3311) for maximum activity.

CONCLUSION

2D and 3D studies were performed on indole/ benzoximidazole-5-carboximidine derivatives for their anticancer activity. 2D QSAR study indicated the requirement of slogP, delta epsilonB and H-Donor count which positively contributed to the biological activity and T_0_Cl_7 removal of which negatively contributed to the biological activity. Points generated in SA kNN-MFA 3D-QSAR model are S_1012 (30.0000, 30.0000), E_547 (-0.2724, 0.3311) *i.e.* steric and electrostatic data points at lattice points 1012 and 547 respectively. 3D-QSAR gave information about nature of substituents like more steric substituents are required at data points S_1012 (30.0000, 30.0000) and less electrostatic substituents are required at data point S_1161 (30.0000, 30.0000) for maximum activity. Above studies rendered significant information which gives detailed structural insights that can provide crucial clues and guidance that can be used in the successful designing of novel highly active analogues against uPA.

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