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2D AND 3D QSAR STUDIES ON THIAZOLES AND OXADIAZOLES HAVING ANTIPLATELET ACTIVITY BY MULTIPLE REGRESSIONS FORWARD, PRINCIPLE COMPONENT REGRESSION FORWARD AND PARTIAL LEAST SQUARE REGRESSION FORWARD METHOD

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Abstract

Thiazole analogues' antiplatelet action was recently discovered. Principal component analysis, partial least squares, multiple regression, and k-NN MFA 3-Dimensional Simulations of QSAR have created. Considering the q2 and pred r2 values, either of these models was chosen. Through cross validation (pred r2) and q2 validation, the chosen model demonstrated strong intrinsic and extrinsic prognosis for the training-set and test-set dimensions of 63 and 10 analogues respectively. To create correlations between the physical and chemical characteristics of chemicals as well as their platelet inhibition actions and to produce a trustworthy quantitative prediction model, thiazole derivative QSAR analysis has been employed. The best model demonstrated by the 3-Dimensional QSAR analysis was completed using the partial least-square regression-forward technique with a r^2 value of 0.93, while the best model for the 2-Dimensional QSAR study was reported using the multiple regression-forward method with a r^2 value of 0.912 and strong predictive power. Future designs of more effective anticancer congeners may be based on the findings from QSAR investigations.

Keywords: Antiplatelet Action, Thiazole analogs, and 3-Dimensional and 2-Dimensional QSAR.

Introduction

The term Quantitative Structure-Activity Relationship (QSAR) refers to a a plan for creating computational or quantitative designs It employs a chemometric approach in an effort to find a significant correlation association among structure/functionThe structure in drug design relates to the characteristics or descriptors of the analogues, and the function of their substituents corresponding to an experimental measure of interaction energy fields endpoint in biology or biochemistry, such as lethality, effectiveness, high affinity, or rate constants. Chemometric methods involve GA, ANN, PCR, PCA, PLS, MLR etc. When a property in addition to pharmacological activities is involved, the term "quantitative structure-property relationship" (-QSPR) is often used. Over the course of more than a century, several QSAR techniques have been steadily developed and are indeed statistical inferences tools, notably in development of medicines and agrochemicals.

By way of Crammers 3-dimensional QSAR and, Vedani's-fifth, Hopfinger's -fourth and Free-sixth Wilson's aspects, approaches had advanced from Hansch and Free-one Wilson's or 2-dimensional linear free energy correlations. The term "classical" QSAR approaches refers to all one-, two-, and related procedures. Every chemical used ties to the same in the research receptor at the equivalent location. The primary distinction between all of these formalisms, however, is in how each one approaches, depicts, and extracts the quantitative correlations among of properties and potency of the molecules. Due to the opportunity limitations and the reliance on electrostatic, steric, or hydrophobic characteristics

Materials and Methods

The data set for the QSAR investigation includes every synthesized derivative with antioxidant activity. This dataset's antioxidant activity is described as IC50 digits. Chemically, the structures were created using 2-Dimensional Draw software and V-Life MDS apps then transformed to 3-Dimensional. (V-Life sciences Pvt Ltd Pune). The MMFF 94 force field and Gasteiger Marsili charges were used to single point optimise each structure until a gradient of 0.001 kcal/A0 was achieved. By using template base alignment, the optimised molecule should be aligned. Table includes the general structures and appropriate replacements.



Figure 1 illustrates a 3-Dimensional representation of the alignment of the GS 1a to GS 11 derivatives using the template base.



Figure 2 illustrates a 3-Dimensional representation of the alignment of the GS 2ia to GS 4c derivatives using the template base.



Figure 3 illustrates a 3-Dimensional representation of the alignment of the GS 5ia to GS 7id derivatives using the template base.



Figure 4 illustrates a 3-Dimensional representation of the alignment of the GS 8ia to GS 8im derivatives using the template base.



Figure 5 illustrates a 3-Dimensional representation of the alignment of the GS 9ia to Gs 9ii derivatives using the template base.

Sr. No.	Comp. No.	Activity	log	Negative log
1	GS1a	156.19	2.183	-2.183
2	GS1b	164.49	2.206	-2.206
3	GS1c	144.58	2.160	-2.160
4	GS1d	63.68	1.804	-1.804
5	GS1e	97.41	1.988	-1.988

6	GS1f	36.86	1.566	-1.566
7	GS1g	98.54	1.993	-1.993
8	GS1h	206.20	2.304	-2.304
9	GS1i	131.35	2.108	-2.108
10	GS1j	100.33	2.001	-2.001
11	GS1k	187.25	2.272	-2.272
12	GS11	63.12	1.800	-1.800
13	GS2ia	181.57	2.272	-2.272
14	GS2ib	97.07	1.981	-1.981
15	GS2ic	123.49	2.045	-2.045
16	GS2id	92.35	1.956	-1.956
17	GS2ie	58.22	1.764	-1.764
18	GS2if	120.47	2.071	-2.071
19	GS2ig	124.29	2.118	-2.118
20	GS2ih	13.09	1.107	-1.107
21	GS2ii	32.46	1.439	-1.439
22	GS2ij	62.10	1.823	-1.823
23	GS2ik	25.72	1.465	-1.465
24	GS3a	35.18	1.457	-1.457
25	GS3b	84.18	1.851	-1.851
26	GS3c	11.78	1.065	-1.065
27	GS4a	40.33	1.507	-1.507
28	GS4b	89.18	1.850	-1.850
29	GS4c	13.63	1.238	-1.238
30	GS5ia	131.35	2.019	-2.019
31	GS5ib	17.30	1.230	-1.230
32	GS5ic	106.89	2.023	-2.023
33	GS5id	18.53	1.260	-1.260
34	GS6ie	92.03	1.963	-1.963
35	GS6ia	100.75	2.103	-2.103
36	GS6ib	31.14	1.485	-1.485

37	GS6ic	20.27	1.319	-1.319
38	GS7ia	81.34	1.881	-1.881
39	GS7ib	146.91	2.177	-2.177
40	GS7ic	92.67	1.966	-1.966
41	GS7id	27.19	1.236	-1.236
42	GS8ia	99.85	2.001	-2.001
43	GS8ib	94.54	1.975	-1.975
44	GS8ic	12.65	1.102	-1.102
45	GS8id	97.87	1.992	-1.992
46	GS8ie	93.81	1.963	-1.963
47	GS8if	32.01	1.516	-1.516
48	GS8ig	48.41	1.655	-1.655
49	GS8ih	109.48	2.019	-2.019
50	GS8ii	90.61	1.857	-1.857
51	GS8ij	119.71	2.068	-2.068
52	GS8ik	26.86	1.419	-1.419
53	GS8il	132.64	2.1211	-2.120
54	GS8im	160.51	2.551	-2.551
55	GS9ia	54.51	1.633	-1.633
56	GS9ib	109.19	2.021	-2.021
57	GS9c	25.49	1.418	-1.418
58	GS9id	41.29	1.517	-1.517
59	GS9ie	20.81	1.310	-1.310
60	GS9if	86.64	1.838	-1.838
61	GS9ig	68.25	1.735	-1.735
62	GS9ih	19.32	1.268	-1.268
63	GS9ii	161.04	2.217	-2.217

Table No- 1

Pharmacological Performance

1. Database of Pharmacological Performance for QSAR Interpretation

These novel molecules' antioxidant activity and structural details are listed in the table, which is crucial for 2D and 3D-QSAR research.

1.1 Computational Specifications

All compound structures were depicted using the 2D-Sketch software (MDS 2020). In MDS, the 2D-analogs were transformed into 3D-analogues. Merck Molecular Force Field (MMFF) and charges were used to batch optimize each chemical and reduce its energy consumption.

1.2 2D-QSAR Molecular Simulation

1.2.1 Calculation of Descriptors:

Using the descriptor computation feature included in the MDS technology, the Physicochemical Parameter, Alignment Independent, may be computed. There are calculated to be close to several hundred descriptions. Using the "delete invariable column tool," the column that has both zero-value reading and invariability is eliminated.

1.2.2 Assignment of the Parameter

For creating a Statistical model, there are one hundred molecular descriptors accessible. Not every molecular attribute is crucial for figuring out the biological activity. It is necessary to use a variable selection approach, which is crucial in assessing activity, to choose the best subset of the descriptors. The step-by-step forward-backward systemic variable selection approach can be used to pick the variables. The log of the IC50 value, which may be employed as a dependent variable in a QSAR analysis, is created from the IC50 value. Create a separate variable for each additional attribute.

1.2.3 Quantitative Approaches

Statistics analysed in to be able to create Statistical simulate through using subset of variables which have the highest statistical significance in predicting the pharmacology potency using an appropriate statistical approach in conjunction with a variable selection method.

1.2.4 Training and test data readiness:

Two sets, a training and test-sets, can be created according to set of data. Template base alignment should be used to align optimized molecules. Table contains the general structures and the relevant replacements.

1.2 3D-QSAR Molecular Simulation:

Training and test- data readiness:

Training and test-set may be created using the 3-Dimensional QSAR data collection. By using template base alignment, the optimized compound must be aligned. Table includes basic structures and the appropriate replacements. Similar to 2-Dimensional QSAR of the same molecule, descriptor computation, variable selection, and statistical approaches are used.

Quantitative			2-Dimensional QSAR specification				
Structural -	Two Set	Assigned	Component/Coe	Constan	Analytical statistics		
Activity		Variables/	fficient	t			
Relationship		Descriptors					
Techniques							
Multiple	Training-Set	Quadrupol-	0.018 (± 0.02), -	0.85	n = 63, Degree of		
regressions-	dimensions	2,	0.010 (± 0.01),		freedom = 14, F-test =		
Forward	Size = 63,	MomInertia	0.0277 (± 0.018),		68.19, r2 se =0.02, q2 se		
Techniques	Test-Set	-X, Zcomp-	0.0752 (± 0.031)		= 0.04, pred_r2 =-3.48,		
	dimensions =	Dipole,			pred_r2se =0.30, r2 =		
	10	QMDipole -			0.96, q2 =0.92,		
		Y					
Principle	Training-Sets	Quadrupol-	0.005, -0.112,	1.641	Optimum Components =		
Component	dimensions	2, Zcomp-	0.022		4, $n = 63$ Degree of		
Regression-	Size= 63,	Dipole			freedom = 15,		
Forward	Test-Sets				F-test = 21.47, r2 se =		
Techniques	dimensions =				0.069, q2 s = 0.100,		
	10				$pred_r2 = -1.14,$		
					pred_r2se=0.215, r2 =		
					0.758, q2 = 0.616		
Quantitative		3- Di	mensional QSAR s	specificatio	n		
Structural -	Two Set	Assigned	Component/Coe	Constan	Analytical statistics		
Activity		Variables/	fficient	t			
Relationship		Descriptors					
Techniques							
Multiple	Training-Sets	E_78	-0.110 (±0.08)	1.767	n = 63, Degree of		

Regression-	dimensions	E_289	0.052 (±0.062)		freedom = 10, F-test =
GS 1a – Gs	Size = 63,	E_141	0.024 (±0.069)		2.52, r2 se =0.28, q2 se =
1k	Test-Set				1.12
	dimensions =				pred_r2= 0.72, pred_r2se
	10				$= 0.13, r^2 = 0.64, q^2 =$
					0.26
Model i)	Balance Equati	on I		1	
	Log-MIC =-0.1	10 (±0.08)E_7	$78 + 0.052 (\pm 0.062)$	E_289+0.0	24 (±0.069)E_141 + 1.76
Multiple	Training-Sets	S_49	5.869 (± 1.72)	0.14	n = 63, Degree of
Regression-	dimensions	E_27	-0.134 (± 0.019)		freedom = 12, F-test
GS 2ia to GS	Size = 63,	H_6	-2.167 (± 0.34)		=5.14, r2 se $=0.17$, q ² se
4c	Test-Set				=0.12
	dimensions =				$pred_r^2 = -8.29$, $pred_r^2$ se
	10				$= 0.14, r^2 = 0.69, q^2$
					=0.11,
Model ii)	Balance Equati	on II	I	I	I
	Log-MIC = 5.8	69 (± 1.72) S_	-0.134 (± 0.019) E_	_272.167	(± 0.34) H_6 + 0.14
Multiple	Training-Sets	H_19	2.12 (± 0.19)	6.2	n = 63, Degree of
Regression	dimensions	H_33	0.54 (± 0.24)		freedom =11, F-test =
GS 5ia to GS	Size = 63,	S_14	$-4.01 (\pm 0.56)$		8.05, r^2 se = 0.04, q^2 se =
7id	Test-Set				0.06
	dimensions =				$pred_r^2 = -74.62,$
	10				$pred_r^2 se = 0.23, r^2 =$
					$0.85, q^2 = 0.54,$
Model iii)	Balance Equati	on III		1	
	Log-MIC = 2.1	2 (± 0.19) H_1	9 0.54 (± 0.24) H_3	34.01 (±	0.56) S_142 + 6.2
Multiple	Training-Sets	H_39	5.91 (± 0.03)	10.55	n = 63, Degree of
Regression	dimensions	S_12	164.37 (± 37.01)		freedom = 12, F-test =
GS 8ia to GS	Size = 63,	H_18	-6.17 (± 0.03)		11.38, $r^2 se = 0.03$, $q^2 se =$
8im	Test-Set				0.07
	dimensions =				$pred_r^2 = -0.11$, $pred_r^2se$
	10				$= 0.063, r^2 = 0.87, q^2 =$
					0.65,

Model iv)	Balance Equation IV					
	Log-MIC = 5.9	2 (± 0.04) H_3	9 +154.37 (± 37.02) S_12 + -6	5.16 (± 0.03) H_18 + 10.55	
Multiple	Training-Sets	H_30	$-0.502 (\pm 0.001)$	-3.74	n = 63, Degree of	
Regression	dimensions	S_11	-7.15 (± 1.53)		freedom = 12, F-test	
GS 9ia to GS	Size = 63,	S_31	-7.32 (± 0.12)		$=217.1, r^2 se =0.008, q^2 se$	
9ia	Test-Set				=0.02	
	dimensions =				$pred_r^2 = -12.2$, $pred_r^2$ se	
	10				= 0.146, r^2 =0.99, q^2 =	
					0.96,	
Mode v)	Balance Equati	on V	1			
	Log-MIC = -0.4	502 (± 0.001) H	H_30+-7.15 (± 1.53))S_117.32	$2 (\pm 0.12) \text{ S}_34-3.74$	
Principle	Training-Sets	E_94, S_74,	-0.106, 3.517, -	0.72	Optimum Components =	
Component	dimensions	S_112,	0.119, 0.117		4, $n = 63$, Degree of	
Regression-	Size = 63,	E_52			freedom = 11, F-test =	
Forward	Test-Set				0.45, r2 se =0.03, q2 se =	
Techniques	dimensions =				0.1 5, pred_r2 =-2.64,	
	10				pred_r2se =0.27, r2	
					=0.95, q2 =0.90,	
Model vi)	Balance Equati	on VI	•			
	Log-MIC = -0.2	106E_94 +3.51	7S_74 -0.119 S_11	2 + 0.117 I	E_52 +0.72	
Partial Least	Training-Sets	E_94, S_74,	-0.08, 3.61, -	0.74	Optimum Components =	
Square	dimensions	S_11, E_53	0.22, 0.13		4 n = 63 Degree of	
Regression-	Size = 63,				freedom = 11, F test	
Forward	Test-Sets				=115.29, r2se= 0.010, q2	
Techniques	dimensions =				se = 0.04 pred_r2 = -2.21,	
	10				$pred_r2se = 0.28,$	
					r2=0.96, q2 =0.92,	
Model vii)	Balance Equati	on VII				
	Log-MIC = -0.0	08 E_94 + 3.61	S_74 -0.22, S_112	2 + 0.13 E_	53 + 0.74	

Table N-. 2 : Equations and QSAR techniques for 2-Dimensional and 3- Dimensional

Result and Discussion:

Utilizing the programme V-life MDS -4.6, derivatives of thiazole and oxadiazole

chemicals were taken into account for the construction of QSAR models. For an efficient QSAR computation, these datasets are split into training and test-sets. We made sure that molecules in the training and test-sets dimensions were evenly distributed in terms of physical and chemical environment and activity while choosing the training and test sets. The remaining factors were chosen as independent variables, while pharmacological activity was chosen as the dependent variable. For this class of chemicals, the training and test sets dimensions of derivatives were chosen at random, and the models/equations were then verified through both intrinsic and extrinsic processes. For discussion, a few QSAR simulations of statistical significance were selected.

Multiple linear regression models in 2-Dimensional QSAR with forward stepwise demonstrate strong correlation among pharmacological activity and variables. The coefficients of determination QMDipole-Y, MomInertia-X, Quadrupole-2, Zcomp-Dipole and with r2 values of 0.96 and 0.75, being order to articulate 76 percent of the variation in the reported activity indices. Each descriptor made a valuable contribution to the model's creation. The model's accuracy is shown by the poor threshold deviation of r2se =0.07, r2 se =0.03. The model was internally validated using the end up leaving method.

Cross-validated r2 values of 68 percent for the model's intrinsic predictive ability (q2 = 0.92, q2 = 0.61) indicate that it has a strong intrinsic predictive ability. Additionally, a 99.5 percent reliability in the created model's nonrandomness was demonstrated by the randomization test, which led to its selection as the QSAR model. The total empirical probability value of the model is 99.5 percent, as indicated by the F-test=78.19, 20.37, which also indicates that the model's failure probability is 01.0 in 10,000. The variables reveal a interrelationship between variables used for resulting QSAR model that is progressive. The favourable coefficients imply adding these atoms of carbon to molecules results in an increase in antiplatelet action.

The first matrix of the quadrupole moments' magnitude is indicated by the quadrupole-2 descriptor. Its significant QSAR model contribution indicates that it will boost potency. Its significant value implies that increasing the quantity of these atoms would improve the antiplatelet activity. These atoms enhance the dipole moment., ZcompDipole, MomInertiaX and QMDipoleY descriptors are examples of a form of dipole-dipole interactions, and their contributions to the platelet aggregation-inhibition actions show that excellent group have strong antioxidant potential.



Figure 6 illustrates 3-Dimensional perspective of an aligned analogues and the contribution of GS 1a - GS 1k descriptors.



Figure 7 illustrates 3-Dimensional perspective of an aligned analogues and the contribution of GS 2ia to GS 4c descriptors



Figure 8 illustrates 3-Dimensional perspective of an aligned analogues and the contribution of GS 5ia to GS 7id descriptors



Figure 9 illustrates 3-Dimensional perspective of an aligned analogues and the contribution of GS 8ia to GS 8im descriptors



Figure 10 illustrates 3-Dimensional perspective of an aligned analogues and the contribution of GS 9ia to GS 9iI descriptors

Multiple linear regressions with forward stepwise and the generated equations in 3-Dimensional QSAR demonstrate strong correlation among biological activity and variables. With r2 = 0.95, r2 = 0.64, r2 = 0.85, r2 = 0.69, r2 = 0.87, r2 = 0.99, and r2 = 0.96, which really is adequate to explain variance in the reported activity indices. The value of q2, which measures a model's intrinsic predictive capability, and pred r2, who evaluates a model's potential to forecast the behaviour of an external test set, serve as the criteria for selecting a model. Our model appears to be accurate and dependable, according to the cross-validated regression analysis (q2), which was regarded as a gauge of prediction dependability.

The suggested A chance of less than 00.001 exists for the Prediction model. produced by chance, according to the randomization tests. Steric variables and electrostatic variables that contribute to models include E 289, E-141, S-4, H-19, H-33, H-12, H-18, S-11, S-34, S-91, E-94, S-14, S-5, E-71, H-30, E-277, S-74, S-11, H-6, E-52, E-9 E-78, The models' indicative power is represented by the q2 values (q2= 0.96, q2= 0.92, q2= 0.54, q2= 0.24, q2= 0.65, q2 = 0.92, q2= 0.90, q2= 0.11, q2= 0.61).

The derived QSAR equation is statistically significant, as shown by the values of F test, r2 se, q2 se, pred r2, and pred r2se, r2, q2, and it demonstrates that the model's predictive capacity is 75% (Intrinsic validation) and 70%. (Extrinsic validation). Smaller bulky residues are selected in that location because steric potential there's really advantageous for activity, according to steric descriptors. In a 3-Dimensional image, the field energies of the steric and electrostatic interactions among the probe (methyl) and the compounds are shown. Steric and

electrostatic force contributions show that both forces are more significant than the other.

The preferable substitution (a larger or smaller bulkier group) to create increased antioxidant potential is implied by the steric effect, which occurs when the phenyl ring is in the o- or m- position. The electro+ve (Electron withdrawing) groups is favoured at the four position of the Ph-ring, which is supported by an electrostatic description with a significant positive impact surrounding that location.

	Molecule	Graph	E_77	E_287	E_143
V 1	GS-1a.mol	Contribution (%) Contribution	-1.206	-1.03	-1.497
₩ 2	GS-1f.mol	Contribution (96) E 143 E 143 E 143 Descubing (96)	-0.659	-0.714	-0.408
V 3	GS-1j.mol	Contribution (96) Contribution	-1.403	0,384	-0.93
V 4	GS-1d.mol	Contribution (96) E 287 E 28	-1.278	0.298	-0.777
V 5	G5-1c.mol	Contribution (96) Contribution	-2.779	0.21	-2.974
V 6	G5-1b.mol	Contribution(06) Contribution(06) E_J7 E_287 E_143 E_143 E_143 Contribution(06)	-2.169	1.033	-0.639
v 7	G5-11.mol	Contribution (96) Contribution	-1.278	0.433	-0.384
V 8	G5-1i.mol	Contribution Co	-0.565	1.395	0.479

Fig.11 Descriptor participation graphs : GS 1a to GS 1k

	Molecule	Graph	E_77	E_287	E_143
V 1	G5-1a.mol		-1.206	-1.03	-1.497
2	GS-1f.mol		-0.659	-0.714	-0.408
V 3	GS-1j.mol		-1.403	0.384	-0.93
V 4	GS-1d.mol		-1.278	0.298	-0.777
⊻ 5	GS-1c.mol		-2.779	0.21	-2.974
V 6	GS-1b.mol		-2.169	1.033	-0.639
7	G5-11.mol		-1.278	0.433	-0.384
₹ 8	GS-1i.mol		-0.565	1.395	0.479

Fig.12 Descriptor participation Pi- graphs : GS 1a to GS 1k

	Molecule	Graph	S_490	E_277	H_66
۲ I	G5-4c.mol	Contribution(%)	-0.021	2.721	0.551
<u>ا</u> و	GS-4a.mol	Contribution(0) Descriptors	-0.018	2.334	0.517
ي s ا	GS-3b.mol	Contribution (5) Descriptors	-0.03	2.363	0.473
¥	G5-2+f.mol	Contribution (%)	-0.028	2.708	0.455
ल s	G5-21-e.mol	Contribution(%)	-0.046	3.099	0.447
الا 6	GS-2H-mol	Contribution(00) Contribution(00) Descriptors	-0.028	3.109	0.436
ا ۲	65-21-d.mol	Contribution(0) Descriptors	-0.039	2.1	0.438
¥ 8	G5-3c.mol	Contribution (%)	-0.028	1.721	0.459
¥ 9	Gs-4b.mol	Contribution(%)	-0.006	2.946	0.454
₩ 10	G5-2i-h.mol	Contribution (%)	-0.054	2.392	0.452
V 11	GS-2t-b.mol	Contribution (%)	-0.022	2.634	0.486

Fig.13 Descriptor participation graphs : GS 2ia to GS 4c

	Molecule	Graph	S_490	E_277	H_66
۲ ا	G5-4c.mol		-0.021	2.721	0.551
۷ 2	G5-4a.mol		-0.018	2.334	0.517
و ع	G5-3b.mol		-0.03	2,363	0.473
v 4	GS-21-f.mol		-0.028	2.708	0.455
ک د	GS-21-e.mol		-0.046	3.099	0.447
ک و	GS-21-k.mol		-0.028	3.109	0.436
۷ 7	GS-21-d.mol		-0.039	2.1	0.438
N 8	G5-3c.mol		-0.028	1.721	0.459
v 9	Gs-4b.mol		-0.006	2,946	0.454
V 10	GS-2I-h.mol		-0.054	2,392	0.452
V 11	GS-21-b.mol		-0.022	2,634	0,486

Fig.14 Descriptor participation Pi-graphs : GS 2ia to GS 4c

	Molecule	Graph	H_194	H_334	S_142
۷ 1	GS-6i+b.mol	Contribution (%)	0.831	0.567	-0.
V 2	GS-71-d.mol	Contribution (%)	0.779	0.473	-0.
۷ 3	GS-71-a.mol	Contribution (%)	0.77	0.467	-0.
V 4	GS-71-b.mol	Contribution (%)	0.808	0.55	-0.
۶ ک	GS-71-c.mol	Contribution (%)	0.832	0.583	-0.
۶ و	G5-5i-a.mol	Contribution (%)	0.995	0.631	-0.
7 و	G5-5i+e.mol	Contribution (%)	1.028	0.75	-0.
₹8	GS-5i+c.mol	Contribution (%)	0.981	0.6	-0.

Fig.15 Descriptor participation graphs : GS 5ia to GS 7id

	Molecule	Graph	H_194	H_334	S_142
V 1	GS-6i+b.mol		0.831	0.567	-0.378
v 2	GS-71-d.mol		0.779	0.473	-0,423
V 3	GS-71+a.mol		0.77	0,467	-0,423
V 4	GS-71-b.mol		0.808	0.55	-0,423
۶ کا	GS-7i-c.mol		0.832	0.583	-0.423
₹ 6	GS-5i-a.mol		0,995	0.631	-0.298
¥ 7	GS-5i-e.mol		1.028	0.75	-0.299
¥ 8	GS-5i-c.mol		0.981	0.6	-0,298

Fig.16 Descriptor participation Pi-graphs : GS 5ia to GS 7id

	Molecule	Graph	H_392	S_126	H_184
۷ 1	GS-8i-c.mol	Contribution (46) H_392 F_128 H_184 H_184	0,349	-0.058	0,845
۷ 2	GS-8i-K.mol	Contribution(46) P 133 P 133 P 233 Descriptors H_184	0,313	-0,058	0,818
۷ 3	GS-8i-l.mol	Contribution (4) H_393 F_138 H_383	0,331	-0,058	0.83
۷ 4	G5-81-E.mol	Contribution (%) H_332 F_128 H_382 H_184 H_184	0.352	-0.057	0.842
V 5	GS-9i-f.mol	Contribution (10) Contribution (10) Contribution (10) Descriptors H_184	0,338	-0,058	0.823
V 6	G5-8i-m.mol	Contribution(9b) Contribution(9b) H_322 F_328 - 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0.36	-0.058	0,836
۲ 7	GS-8i-g.mol	Contribution(46) Contribution(46) P_322 Percentation(46) Desculation(46) P_322 P	0.308	-0.058	0.793
V 8	GS-8I-j.mol	H 133 H 133	0,439	-0,057	0,905
و ی	GS-8i-d.mol	Contribution(0) Contribution(0) F 1 F 233 F 1 F 1 F 1 F 1 F 1 F 1 F 1 F 1	0.435	-0,057	0,933

Fig.17 Descriptor participation graphs : GS 8ia to GS 8im

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	Molecule	Graph	H_392	S_126	H_184
V 1	GS-8i-c.mol		0.349	-0.058	0.845
V 2	G5-8i-k.mol		0.313	-0.058	0.818
v 3	GS-8i-I.mol		0.331	-0.058	0.83
V 4	GS-8I-E.mol		0.352	-0.057	0.842
V 5	GS-8i-f.mol		0.338	-0.058	0.823
V 6	GS-8i-m.mol		0.36	-0.058	0.836
V 7	G5-8i⊦g.mol		0,308	-0.058	0.793
V 8	GS-8i-j.mol		0.439	-0.057	0.905
y 9	G5-8i-d.mol		0.435	-0.057	0.933

Fig.18 Descriptor participation Pi-graphs : GS 8ia to GS 8im

	Molecule	Graph	H_300	S_115	S_341
V 1	G5-9i-d.mol	Contribution (06) H_300 S_341 -	0.143	-0.265	-0.01
∨ 2	GS-9i-i.mol	Contribution(%)	0.323	-0.271	-0.044
V 3	G5-9i-h.mol	Contribution(%) P_300 S_341 S_341 S_341	0.069	-0.271	-0.04
V 4	G5-9i-b.mol	Contribution (%)	0.553	-0.275	-0.039
V 5	G5-9i-g.mol	Contribution (46)	0.542	-0.27	-0.044
V 6	G5-9i-f.mol	Contribution(46) Contribution(46) 5_341 S_341 S_341 Descriptors	0.327	-0.272	-0.021

Fig.19 Descriptor participation graphs : GS 9ia to GS 9ii

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	Molecule	Graph	H_300	S_115	S_341
V 1	GS-9i-d.mol		0.143	-0.265	-0.01
V 2	GS-9i-i.mol		0.323	-0.271	-0.044
V 3	GS-9i-h.mol		0.069	-0.271	-0.04
♥ 4	GS-9i-b.mol		0.553	-0.275	-0.039
₹	GS-9i-g.mol		0.542	-0.27	-0.044
V 6	G5-9i-f.mol		0.327	-0.272	-0.021

Fig.20 Descriptor participation Pi-graphs: GS 9i a to GS 9ii



Fig. 21: Fitness graph comparing GS 1a – GS 1k between reported activity and expected activity



Fig. 22: Fitness graph comparing GS 2ia – GS 4c between reported activity and expected activity





Fig. 23: Fitness graph comparing GS 5ia to GS 7id between reported activity and expected activity



Fig. 24: Fitness graph comparing GS 8ia to GS 8im between reported activity and expected activity



Fig. 25: Fitness graph comparing GS 9ia to GS 9iI between reported activity and expected activity

Conclusions

Equation-1 has an intrinsic predictive ability of 92 percent (q2) and an extrinsic predictive ability of 32 percent (pred r2se) and explains 98 percent (r2 = 0.64) of the training set's dimensions total variance. The training set's dimensions total variance is explained by equation- 2 in 96 percent of cases (r2 = 0.69), and it also possesses intrinsic (q2) and extrinsic (pred r2se) predictive abilities of 92and 26 percent, respectively.

Equation-3 has intrinsic (q2) and extrinsic (pred-r2se) prediction abilities of 94% and 29%, respt., and demonstrate 97% (r2=0.87) of the entirety variation in the training-set dimensions. By using the forward method, the descriptor extent is H-66, H-19, H-33, H-39, H-18, H-30, H-29 (0.44 to 0.45), which signifies that a smaller bulky substituent group is preferred in that area. +Ve hydrophobic descriptor range suggests that +Ve water-insoluble potential is favourable for extend in the antiplatelet activity.

The development of 2-Dimensional and 3-Dimensional QSAR models and equations with moderate-to-high thiazole derivatives prediction accuracy. Hydrophobicity's significance as a 3-Dimensional feature was established, and it was discovered that electrostatic and steric impacts also support antioxidant action. The acquired models could aid in the development of

novel active thiazoles with antioxidant properties.

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