



Data Article

Dataset on *in-silico* investigation on triazole derivatives via molecular modelling approach: A potential glioblastoma inhibitors



Abel Kolawole Oyebamiji^{a,g,*}, Oluwatumininu Abosede Mutiu^b,
Folake Ayobami Amao^c, Olubukola Monisola Oyawoye^d,
Temitope A Oyedepo^e, Babatunde Benjamin Adeleke^f,
Banjo Semire^g

^a Department of Basic Sciences, Adeleke University, P.M.B. 250, Ede, Osun State, Nigeria

^b Department of Chemical Sciences, Osun State University, Osogbo, Osun State, Nigeria

^c Department of Mathematics, Faculty of Science, Adeleke University, P.M.B. 250, Ede, Osun State, Nigeria

^d Department of Microbiology, Laboratory of Molecular of Biology, Immunology and Bioinformatics, Adeleke University, P.M.B. 250, Ede, Osun State, Nigeria

^e Department of Biochemistry, Adeleke University, P.M.B. 250, Ede, Osun State, Nigeria

^f Department of Chemistry, University of Ibadan, Ibadan, Oyo State, Nigeria

^g Computational Chemistry Laboratory, Department of Pure and Applied Chemistry, Ladoké Akintola University of Technology, P.M.B. 4000, Ogbomoso, Oyo State, Nigeria

ARTICLE INFO

Article history:

Received 7 September 2020

Revised 18 December 2020

Accepted 24 December 2020

Available online 30 December 2020

Keywords:

Triazole

Glioblastoma

Inhibitors

In-silico

DFT

QSAR

Docking

ADMET

ABSTRACT

In this work, ten molecular compounds were optimised using density functional theory (DFT) method via Spartan 14. The obtained descriptors were used to develop quantitative structural activities relationship (QSAR) model using Gretl and Matlab software and the similarity between predicted IC_{50} and observed IC_{50} was investigated. Also, docking study revealed the non-bonding interactions between the studied compounds and the receptor. The molecular interactions between the observed ligands and brain cancer protein (PDB ID: 1q7f) were investigated. Adsorption, distribution, metabolism, excretion and toxicity (ADMET) properties were also investigated.

* Corresponding author.

E-mail address: abeloyebamiji@gmail.com (A.K. Oyebamiji).

Specifications Table

Subject	Computational Chemistry
Specific subject area	Drug Discovery and Development
Type of data	Figure Table QSAR model
How data were acquired	Spartan'14, Pymol 1.7.4.4, Autodock tool 1.5.6, AutoVina 1.1.2, Discovery Studio 2017.
Data format	Raw data
Parameters for data collection	B3LYP, 6–31G*, Pymol 1.7.4.4, Discovery studio 2017R, Autodock tool 1.5.6 and Autodock vina 1.1.2.
Description of data collection	The research work started with optimizing the selected compounds using DFT. The obtained descriptors from the optimized compounds were extracted and used to develop QSAR model using MLR and Genetic Algrithm. Also, the developed QSAR model was used to predict the biological activites of new set of triazole based drug-like comounds and further subjected to docking. The results obtained were collected and interpreted.
Data source location	Computational Chemistry Research Laboratory, Department of Pure and Applied Chemistry, Ladoke Akintola University of Technology, P.M.B. 4000, Ogbomosho, Oyo State, Nigeria.
Data accessibility	The observed and calculated data can be accessed with the data article

Value of the Data

- The data obtained from investigated triazole derivatives in this research will assist scientists to know the molecular descriptors that describe its anti-glioblastoma activity.
- Data in this research will disclose the role of individual molecular descriptors obtained from optimised compounds in the developed QSAR model.
- The obtained binding affinity will reveal the ability of each compound to inhibit brain tumor protein (PDB ID: 1q7f).
- ADMET properties of the observed and proposed molecular compounds were also investigated in order to define the nature of triazole derivatives in receptor.

1. Data Description

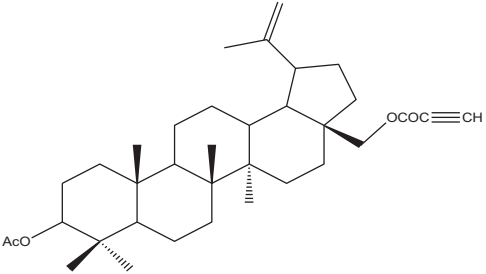
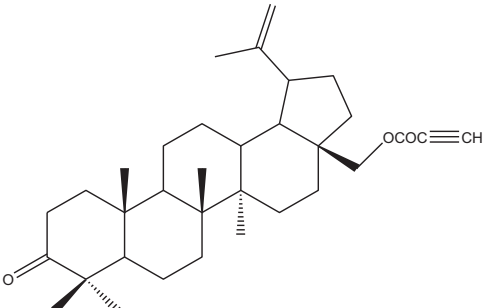
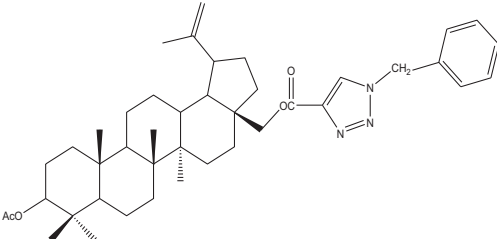
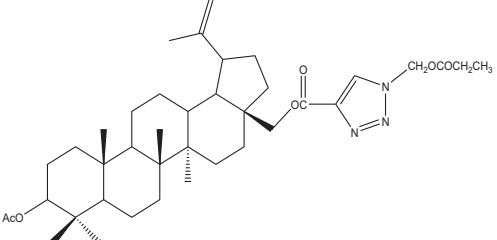
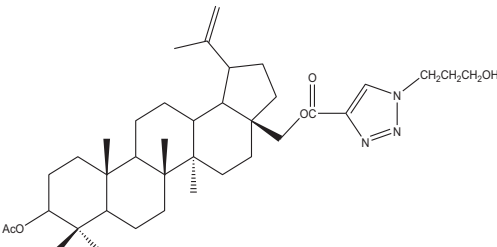
The 2D structures of the molecules used in this research were shown in [Table 1](#). The observed compounds used in this work were obtained from the research carried out by Ewa et al., (2018) [1]. The compounds with inhibition concentration (IC_{50}) of $\leq 10 \mu M$ were selected and subjected to quantum chemical calculation using density functional theory via B3LYP (6–31G*basis set).

Thirteen descriptors ([Table 2](#)) which describe anti-glioblastoma activities of the investigated triazole derivative were obtained and they were used for further research. The descriptors obtained were highest occupied molecular orbital energy (E_{HOMO}), lowest unoccupied molecular orbital (E_{LUMO}), band gap (BG), molecular weight (MW), area, volume, polar surface area (PSA), ovality, dipole moment (DM), log P, polarisability (POL), hydrogen bond donor (HBD) and hydrogen bond acceptor (HBA).

[Table 3](#) revealed the developed QSAR model (which help to probe into biological activities of triazoles derivatives) from the calculated molecular descriptor obtained from

Table 1

The Schematic diagram of the observed Triazole derivatives [1].

SN	Molecular Structures	IUPAC Name
1		3-Acetyl-28-propynoylbetulin
2		28-Propynoylbetulone
3		3-Acetyl-28-[1-(4-fluorobenzyl)-1H-1,2,3-triazol-4-yl]carbonylbetulin
4		3-Acetyl-28-(1-ethylacetyl-1H-1,2,3-triazol-4-yl)carbonylbetulin
5		3-Acetyl-28-[1-(3-hydroxypropyl)-1H-1,2,3-triazol-4-yl]carbonylbetulin

(continued on next page)

Table 1 (continued)

SN	Molecular Structures	IUPAC Name
6		2-Amino-3-[4-(3-acetyl-28-betulinylylcarbonyl)-1H-1,2,3-triazol-1-yl]propanoic acid
7		28-[1-(4-Fluorobenzyl)-1H-1,2,3-triazol-4-yl]carbonylbetulone
8		28-[1-(4-Cyanobenzyl)-1H-1,2,3-triazol-4-yl]carbonylbetulone
9		28-[1-(3'-Deoxythymidine-5'-yl)-1H-1,2,3-triazol-4-yl]carbonylbetulone
10		28-[1-(1-Deoxy-β-D-glucopyranosyl)-1H-1,2,3-triazol-4-yl]carbonylbetulone

Table 2

Calculated molecular descriptors with anti-glioblastoma activities.

	E _{HOMO}	E _{LUMO}	BG	DM	MW	AREA	VOL	PSA	OVA	LOG P	POL	HBD	HBA
1	-6.30	-2.75	3.55	3.72	536.79	571.38	598.14	40.09	1.66	8.09	89.06	0	2
2	-6.29	-1.49	4.80	3.76	492.74	521.02	551.1	33.37	1.60	8.35	84.95	0	2
3	-6.36	-0.99	5.37	6.72	673.95	706.89	726.39	51.01	1.81	10.23	99.03	0	5
4	-6.33	-1.00	5.33	7.57	651.93	692.8	704.58	71.86	1.81	8.21	97.27	0	6
5	-6.39	-0.96	5.43	7.58	623.92	668.32	681.66	71.04	1.78	8.10	95.39	1	6
6	-6.36	-1.02	5.34	6.29	652.92	682.91	695.04	109.53	1.80	6.86	96.49	1	7
7	-6.25	-1.04	5.21	5.98	643.88	659.42	682.81	59.30	1.76	10.02	95.53	0	5
8	-6.28	-1.92	4.36	4.46	650.90	674.84	697.86	74.64	1.77	9.90	96.95	0	6
9	-6.28	-1.12	5.16	6.23	759.98	760.65	777.32	125.34	1.86	7.12	103.21	2	11
10	-6.26	-1.15	5.11	4.81	697.91	692.16	711.58	138.97	1.80	6.03	97.89	4	10

Table 3

Calculated QSAR model for the observed triazole derivatives.

Equation	F	P-value	R ²	Adjusted R ²	MSE
IC ₅₀ = -88,509.7 - 513.940(E _{HOMO}) + 500.156(E _{LUMO}) - 174.603(VOL) + 11.3407(Log P) + 2137.77(POL) + 0.587370(PSA) + 1.01540(AREA)	31.03	P < 0.0001	0.990	0.958	0.085

Table 4

Assessment for validation of Developed QSAR model.

QSAR model validation parameters	Standard value	Developed QSAR model value	Remark
Correlation coefficient (R ²)	≥0.5	0.990	Pass
Adjusted Correlation coefficient	≥0.6	0.958	Pass
Confidence interval at 95% confidence level i.e. P-value	<0.05	0.031	Pass

Table 5Observed IC₅₀ and predicted IC₅₀.

	Observed IC ₅₀	Predicted IC ₅₀	Residual	Genetic Algorithm (GA)	Residual
1	0.67	0.45	0.217310	0.616731	0.053269
2	0.19	0.49	-0.307571	0.136731	0.053269
3	0.85	0.50	0.342669	0.816023	0.033977
4	0.78	0.74	0.0302183	0.746023	0.033977
5	7.75	7.91	-0.161626	7.716023	0.033977
6	1.22	1.19	0.0226067	1.186023	0.033977
7	0.45	0.28	0.167543	0.416023	0.033977
8	6.45	6.72	-0.270293	6.416796	0.033204
9	0.17	0.67	-0.500773	0.137068	0.032932
10	7.45	6.99	0.459915	7.417068	0.032932

optimised compounds using Gretl software and Matlab [2,3]. The selected descriptors used in developing QSAR model were E_{HOMO}, E_{LUMO}, Vol, Log P, Pol, PSA and Area and the statistical factors considered for QSAR validation were correlation coefficient (R²), adjusted correlation coefficient (Adj.R²), P-Value, F-Value and MSE. The calculated value for correlation coefficient (R²), Adjusted correlation coefficient (Adj. R²), P-Value and F-Value were 0.990, 0.958, P < 0.0001, 31.03 and 0.085 as shown in Table 4.

Table 5 showed the calculated inhibition concentration (IC₅₀) for the investigated molecular compounds. The correlation between the predicted inhibition efficiency (IC₅₀) and observed efficiency (IC₅₀) were displayed in Fig. 1. In this work, six (6) molecular compounds were proposed using the developed QSAR model and the inhibition concentration of individual proposed compound was predicted and displayed in Table 6.

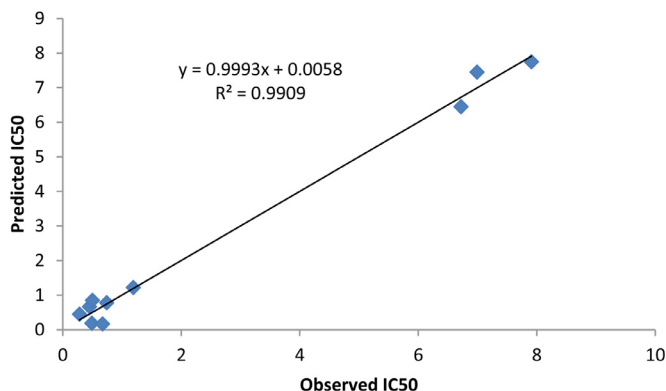


Fig. 1. Graphical description of correlation between predicted IC_{50} and Observed IC_{50} .

Table 6

Schematics structures of the proposed compounds with the inhibition concentration.

	R_1	R_2	IC_{50}
1	OCH_3	CH_3	−13.54
2	OC_2H_5	CH_3	−9.60
3	NH_2	CH_3	−16.79
4	CH_3	CH_3	−7.72
5	CH_2F	CH_3	−27.30
6	CHF_2	CH_3	−32.98

Also, Table 7 showed four molecular compounds (**2**, **7**, **9** and **10**) with −9.5 kcal/mol, −11.2 kcal/mol, −10.0 kcal/mol, and −9.4 kcal/mol respectively. The selected compounds were subjected to ADMET study using admetSAR server and the factor considered were based on adsorption, distribution, metabolism, excretion and toxicity of the investigated ligands. The obtained ADMET values were compared to the standard compound used (Carmustine).

The calculated molecular interaction observed between the optimised triazole derivatives and brain tumor protein (PDB ID: 1q7f) [4] were reported in Table 8. The binding affinity calculated for each complex was −8.4 kcal/mol, −9.5 kcal/mol, −8.6 kcal/mol, −8.8 kcal/mol, −8.5 kcal/mol, −8.1 kcal/mol, −11.2 kcal/mol, −9.0 kcal/mol, −10.0 kcal/mol and −9.4 kcal/mol for compound **1–10** and the interaction between the observed complexes were shown in Fig. 2.

2. Design, Materials and Methods

The studied triazole derivatives (Table 1) were drawn using ChemDraw Ultra 8.0 and were optimised using Spartan 14 [5]. The optimization was accomplished using B3LYP with 6–31 G*

Table 7
Obtained calculated ADMET Properties.

Mode	Compound 2			Compound 7			Compound 8			Compound 9			Compound 10			Compound 11		
	Result	Probability		Result	Probability		Result	Probability		Result	Probability		Result	Probability		Result	Probability	
Blood-Brain Barrier	BBB+	0.9079		BBB+	0.8802		BBB+	0.5456		BBB-	0.8875		BBB-	0.9564		BBB+	0.9533	
Human Intestinal Absorption	HIA+	0.9900		HIA+	0.9962		HIA+	0.9947		HIA+	0.9430		HIA+	0.6024		HIA+	1.0000	
Caco-2 Permeability	Caco2+	0.6469		Caco2-	0.5649		Caco2-	0.831		Caco2-	0.6729		Caco2-	0.6997		Caco2-		
P-glycoprotein Substrate	Substrate	0.6290		Substrate	0.8512		Substrate	0.8125		Substrate	0.8454		Substrate	0.8269		Non-substrate	0.7552	
P-glycoprotein Inhibitor	Inhibitor	0.9030		Inhibitor	0.9365		Inhibitor	0.9495		Inhibitor	0.6937		Inhibitor	0.7651		Non-inhibitor	0.7970	
Renal Organic Cation Transporter	Inhibitor	0.7882		Inhibitor	0.8550		Inhibitor	0.9370		Inhibitor	0.5500		Inhibitor	0.5758		Non-inhibitor	0.8778	
	Non-inhibitor	0.7387		Non-inhibitor	0.5700		Non-inhibitor	0.5301		Non-inhibitor	0.8682		Non-inhibitor	0.9224		Non-inhibitor	0.8177	
Subcellular localization	Mitochondria	0.8457		Mitochondria	0.6253		Mitochondria	0.6304		Mitochondria	0.5907		Mitochondria	0.4545		Mitochondria	0.7342	
CYP450 2C9 Substrate	Non-substrate	0.8652		Non-substrate	0.8442		Non-substrate	0.8067		Non-substrate	0.7938		Non-substrate	0.7848		Non-substrate	0.7656	
CYP450 2D6 Substrate	Non-substrate	0.9104		Non-substrate	0.8250		Non-substrate	0.8210		Non-substrate	0.8343		Non-substrate	0.8260		Non-substrate	0.8491	
CYP450 3A4 Substrate	Substrate	0.7739		Substrate	0.6987		Substrate	0.7062		Substrate	0.7076		Substrate	0.6901		Non-substrate	0.6720	
CYP450 1A2 Inhibitor	Non-inhibitor	0.8848		Non-inhibitor	0.7102		Non-inhibitor	0.7503		Non-inhibitor	0.8277		Non-inhibitor	0.7723		Non-inhibitor	0.9045	
CYP450 1A2 Inhibitor	Non-inhibitor	0.6679		Non-inhibitor	0.5957		Non-inhibitor	0.6198		Non-inhibitor	0.6658		Non-inhibitor	0.7210		Non-inhibitor	0.9070	
CYP450 2D6 Inhibitor	Non-inhibitor	0.9248		Non-inhibitor	0.8454		Non-inhibitor	0.8666		Non-inhibitor	0.8863		Non-inhibitor	0.9026		Non-inhibitor	0.9231	
CYP450 2C19 Inhibitor	Inhibitor	0.5296		Inhibitor	0.581		Non-inhibitor	0.5391		Non-inhibitor	0.7017		Non-inhibitor	0.7290		Non-inhibitor	0.9025	
CYP450 3A4 Inhibitor	Non-inhibitor	0.6446		Inhibitor	0.7561		Inhibitor	0.7227		Inhibitor	0.9283		Inhibitor	0.6378		Non-inhibitor	0.9031	
CYP Inhibitory Promiscuity	Low CYP	0.5796		High CYP	0.8442		High CYP	0.7893		High CYP	0.6255		High CYP	0.5083		Low CYP	0.9131	
	Inhibitory			Inhibitory			Inhibitory			Inhibitory			Inhibitory			Inhibitory		
Human Ether- α -go-go-Related Gene Inhibition	Promiscuity			Promiscuity			Promiscuity			Promiscuity			Promiscuity			Promiscuity		
AMES toxicity	Weak inhibitor	0.9102		Weak inhibitor	0.6081		Weak inhibitor	0.5223		Weak inhibitor	0.7555		Weak inhibitor	0.9532		Strong inhibitor	0.7278	
AMES toxicity	Non-inhibitor	0.7874		Non-inhibitor	0.5622		Non-inhibitor	0.7159		Non-inhibitor	0.7011		Non-inhibitor	0.5654		Non-inhibitor	0.9190	
Carcinogens	Non-AMES toxic	0.8923		Non-AMES toxic	0.5292		Non-AMES toxic	0.5228		Non-AMES toxic	0.5140		Non-AMES toxic	0.5885		AMES toxic	0.9577	
Fish Toxicity	Non-carcinogens	0.8769		Non-carcinogens	0.8221		Non-carcinogens	0.8539		Non-carcinogens	0.7862		Non-carcinogens	0.9015		Carcinogens	0.6880	
Tetrahymena Pyriformis Toxicity	Fish FHMT	0.9996		High FHMT	1.0000		High FHMT	0.9999		High FHMT	0.9998		High FHMT	0.9999		High FHMT	0.6546	
	High TPT	0.9996		High TPT	0.9968		High TPT	0.9931		High TPT	0.9874		High TPT	0.9924		High TPT	0.9857	
Honey Bee Toxicity Biodegradation	High HBT	0.8781		Low HBT	0.6610		Low HBT	0.5742		Low HBT	0.6662		Low HBT	0.6038		Low HBT	0.7045	
	Not ready biodegradable	0.9800		Not ready biodegradable	1.0000		Not ready biodegradable	1.0000		Not ready biodegradable	0.9870		Not ready biodegradable	0.9803		Not ready biodegradable	0.5596	

Table 8

Scoring and residues involved in the interaction between the studied complex.

	Scoring (kcal/mol)	Residues involved in the interactions	Types of Non-bonding interaction involved
1	−8.4	VAL-835, VAL-788, VAL-921, LEU-1sss009, ILE-965	Conventional Hydrogen Bond, Alkyl
2	−9.5	GLY-964, VAL-921, ALA-787, ARG-837, ILE-965	Carbon Hydrogen Bond, Alkyl
3	−8.6	ILE-965, VAL-1007, ALA-787, ALA-834, VAL-922, ARG-837	Carbon Hydrogen Bond, Alkyl
4	−8.8	ASP-924, ARG-837, ALA-834, VAL-877	Conventional Hydrogen Bond, Carbon Hydrogen Bond, Pi-Alkyl, Alkyl
5	−8.5	ASP-924, ILE-965, VAL-950, THR-878, LEU-1009, ALA-1008, ARG-837	Conventional Hydrogen Bond, Carbon Hydrogen Bond, Pi-Alkyl, Alkyl
6	−8.1	THR-986, GLN-987, GLY-969, ASN-968, ILE-965, VAL-922, ARG-837, VAL-835	Conventional Hydrogen Bond, Carbon Hydrogen Bond, Alkyl
7	−11.2	ARG-837, ALA-1008, ASP-1006, VAL-877, VAL-833, LEU-1009, ILE-965	Conventional Hydrogen Bond, Halogen(Fluorine), Pi-Anion, Pi-Alkyl, Alkyl
8	−9.0	ILE-965, GLY-969, VAL-922, ARG-837, ALA-1008, ALA-787	Carbon Hydrogen Bond, Alkyl
9	−10.0	ILE-965, ALA-787, ALA-834, VAL-922, ARG-837, ALA-790	Conventional Hydrogen Bond, Carbon Hydrogen Bond, Pi-Alkyl, Pi-Sigma, Alkyl
10	−9.4	ILE-965, ALA-787, ALA-1008, VAL-922, ASN-838, ARG-837	Conventional Hydrogen Bond, Carbon Hydrogen Bond, Pi-Alkyl, Alkyl
Carmustine	−5.0	VAL-835, ARG-837, VAL-879	Conventional Hydrogen Bond
Proposed Compounds			
P1	−8.6	PHE-916, ILE-961, TYR-959	Alkyl, Pi-Alkyl
P2	−8.7	PHE-916, ILE-961, TYR-959	Alkyl, Pi-Alkyl
P3	−8.5	VAL-788, VAL-835, ARG-837, ILE-965	Conventional Hydrogen Bond, Unfavourable Donor-Donor, Alkyl
P4	−8.7	PHE-916, ILE-961, TYR-959	Alkyl, Pi-Alkyl
P5	−8.6	PHE-1005, PHE-916, ILE-961, TYR-959	Alkyl, Pi-Alkyl
P6	−8.9	ARG-837, VAL-788, ALA-787, VAL-835, ALA-834, ILE-965, VAL-921	Conventional Hydrogen Bond, Halogen, Alkyl

as basis set which produce descriptors that were used for further investigation. The selected calculated descriptors obtained from the optimised compounds were used to build robust QSAR model in order to relate the biological activity of the studied compounds to the calculated molecular parameters [6]. This was achieved using mathematical methods (multiple linear regression method) via Gretl 1.9.8. The observed inhibition concentration (IC_{50}) served as dependent variable while the calculated descriptors served as independent variables; thus, the QSAR model was developed. Several factors such as correlation coefficient (R^2), P-Value, F-value were considered to know the level of efficiency of the developed QSAR model. More so, validation of the developed QSAR model was implemented by observing some mathematical factors (cross validation correlation coefficient (C.V R^2), adjusted correlation coefficient) which could be calculated using Eq. (1) and 2 [7].

$$C.VR^2 = 1 - \frac{\sum (Y_{obs} - Y_{cal})^2}{\sum (Y_{obs} - \bar{Y}_{obs})^2} \quad (1)$$

$$R_a^2 = \frac{(N-1) \times R^2 - P}{N-1-P} \quad (2)$$

Absorption, Distribution, Metabolism, Excretion and the Toxicity properties of the studied triazole derivatives were done via online software (admetSAR) (<http://lmmd.ecust.edu.cn/admetSar1>) [8]. The factors considered were Blood Brain Barrier, Caco-2 cell permeability, Human Intestinal Absorption, Ames test. Also, four software (Pymol

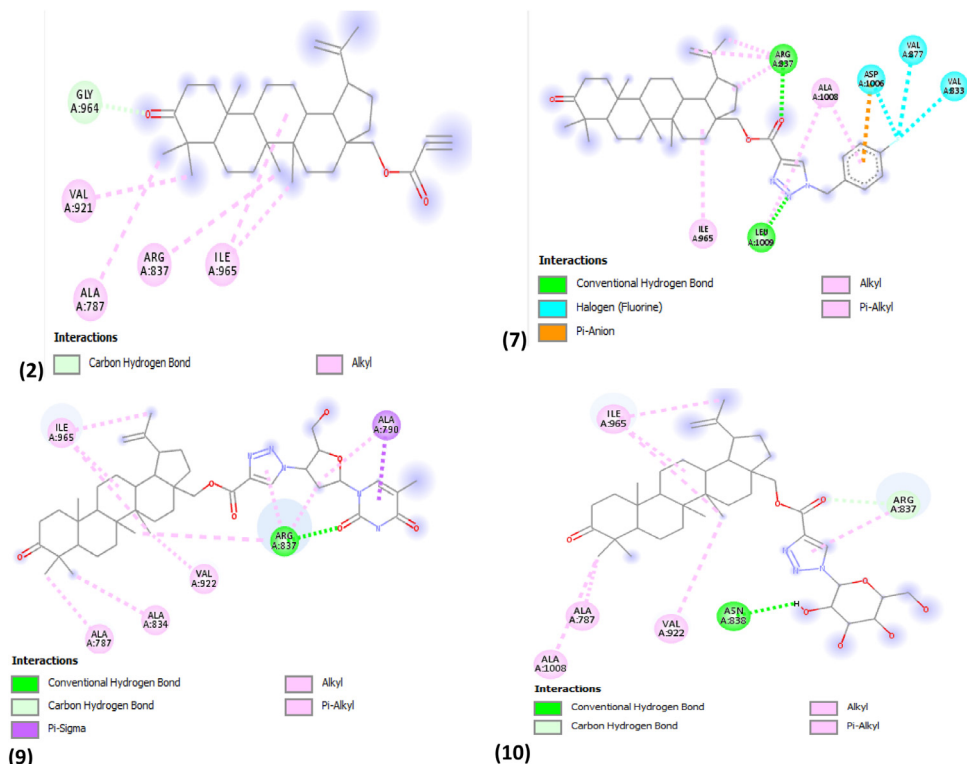


Fig. 2. 2D structures of brain tumor protein (PDB ID: 1q7f) and compound **2**, **7**, **8**, **9** and **10** respectively.

(for treating downloaded protein), Autodock Tool (for locating binding site in the downloaded protein and for converting ligand and receptor to.pdbqt format from.pdb format), Auto dock vina (for docking calculation) and discovery studio (for viewing the non-bonding interaction between the docked complexes) were used to accomplish docking study between triazole derivative and brain tumor protein (PDB ID: 1q7f). The observed grid box was as follows: center ($X=12.534$, $Y=23.847$, $Z=40.848$) and size ($X=68$, $Y=64$, $Z=72$) as well as the spacing was set to be 1.00 \AA .

Ethics Statement

Not Applicable.

CRediT Author Statement

Abel Kolawole **OYEBAMIJI**: Conceptualization, Methodology, Writing- Original draft preparation; Oluwatumininu Abosede **MUTIU**: Software; Folake Ayobami **AMAO**, Data curation; Olubukola Monisola **OYAWOYE**: Writing- Reviewing and Editing; Temitope A **OYEDEPO**: Writing- Reviewing and Editing; Babatunde Benjamin **ADELEKE**: Visualization; Banjo **SEMIRE**: Supervision, Software, Validation.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Acknowledgement

We are grateful to the computational chemistry research laboratory, Department of Pure and Applied Chemistry, Ladoko Akintola University of Technology, Nigeria for the computational resources and Mrs E.T. Oyebamiji for the assistance in the course of this work. Also, this research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

- [1] B. Ewa, K.-T. Monika, C. Elwira, L. Małgorzata, B. Stanisław, Novel triazoles of 3-acetylbetulin and betulone as anti-cancer agents, *Med. Chem. Res.* 27 (2018) 2051–2061.
- [2] A.Beheshti, E.Pourbasheer, M. Nekoei, S. Vahdani, QSAR modeling of antimalarial activity of urea derivatives using genetic algorithm–multiple linear regressions, *J. Saudi Chem. Soc.*, (2012), 10.1016/j.jscs.2012.07.019
- [3] A. Ousaa, B. Elidrissi1, M. Ghamali, S. Chtita, A. Aouidate, M. Bouachrine, T. Lakhli, Quantitative structure-toxicity relationship studies of aromatic aldehydes to *Tetrahymena pyriformis* based on electronic and topological descriptors, *J. Mater. Environ. Sci.* 9 (1) (2018) 256–266.
- [4] A.E. Thomas, B.D. Wilkinson, R.P. Wharton, A.K. Aggarwal, Model of the brain tumor–pumilio translation repressor complex, *Genes Dev.* 17 (2015) 2508–2513.
- [5] Spartan 14 program, Wavefunction, Irvine, USA.
- [6] A.K. Oyebamiji, I.O. Abdulsalami, B. Semire, Dataset on Insilico approaches for 3,4-dihydropyrimidin-2(1H)-one urea derivatives as efficient *Staphylococcus aureus* inhibitor, *Data Brief* 32 (2020) 106195.
- [7] R.O. Oyewole, A.K. Oyebamiji, B. Semire, Theoretical calculations of molecular descriptors for anticancer activities of 1, 2,3-triazole-pyrimidine derivatives against gastric cancer cell line (MGC-803): DFT, QSAR and docking approaches, *Heliyon* 6 (2020) e03926.
- [8] S. Jie, C. Feixiong, X. You, L. Weihua, T. Yun, Estimation of ADME properties with substructure pattern recognition, *J. Chem. Inf. Model.* 50 (2010) 1034–1041.