

QSAR-Guided Optimisation of 5,6-Dimethoxyindanone-Piperazine Derivatives as
Acetylcholinesterase InhibitorsMarcin Gackowski^{1,*}, Weronika Długosz¹, Katarzyna Mądra-Gackowska², Łukasz Szeleszczuk³¹ Department of Toxicology and Bromatology, Faculty of Pharmacy, L. Rydygier Collegium Medicum in Bydgoszcz, Nicolaus Copernicus University in Torun, A. Jurasza 2 Street, PL–85089 Bydgoszcz, Poland² Department of Geriatrics, Faculty of Health Sciences, L. Rydygier Collegium Medicum in Bydgoszcz, Nicolaus Copernicus University in Torun, Skłodowskiej Curie 9 Street, PL–85094 Bydgoszcz, Poland;³ Department of Organic and Physical Chemistry, Faculty of Pharmacy, Medical University of Warsaw, Banacha 1 Street, PL–02093 Warsaw, Poland;

* correspondence: marcin.gackowski@cm.umk.pl

INTRODUCTION & AIM

Alzheimer's disease (AD) is characterised by a progressive cholinergic deficit. Although current acetylcholinesterase (AChE) inhibitors alleviate cognitive symptoms, their brain penetration and tolerability remain sub-optimal [1]. 5,6-Dimethoxyindanone represents the pharmacophore of donepezil; substitution with a piperazine ring generates analogues with promising activity. The aim of this study was to develop a quantitative structure–activity relationship (QSAR) model able to predict the AChE-inhibitory potency (IC₅₀) of 5,6-dimethoxyindanone-piperazine derivatives, thereby guiding the design of improved inhibitors.

METHOD

A set of **15 literature analogues** with experimental IC₅₀ (Ellman assay) was compiled from Mishra *et al.* (donepezil-based MTDLs) and used as the response source for modelling [2]. Conformers were energy-minimised (HyperChem MM⁺ → PM3). **4,885** Dragon 7 descriptors were computed and reduced to **843** by low-variance and multicollinearity filtering ($r \geq 0.95$). Feature selection (Statistica 14) returned **four** variables (Mor22v, HATS8p, VE1_B(p), C-006); an artificial neural network (ANN) **MLP 4-3-1 (BFGS)** was trained on nine compounds and checked by LOO, a 3-compound external test, and a 3-compound validation set.

RESULTS & DISCUSSION

The final model achieved **R² = 0.961**, **Q² = 0.999**, and **MAE = 0.001 μM**; external prediction yielded **R²_{test} = 0.928** with a near-unity regression slope (≈ 0.98) on the parity plot (**Figure 1**).

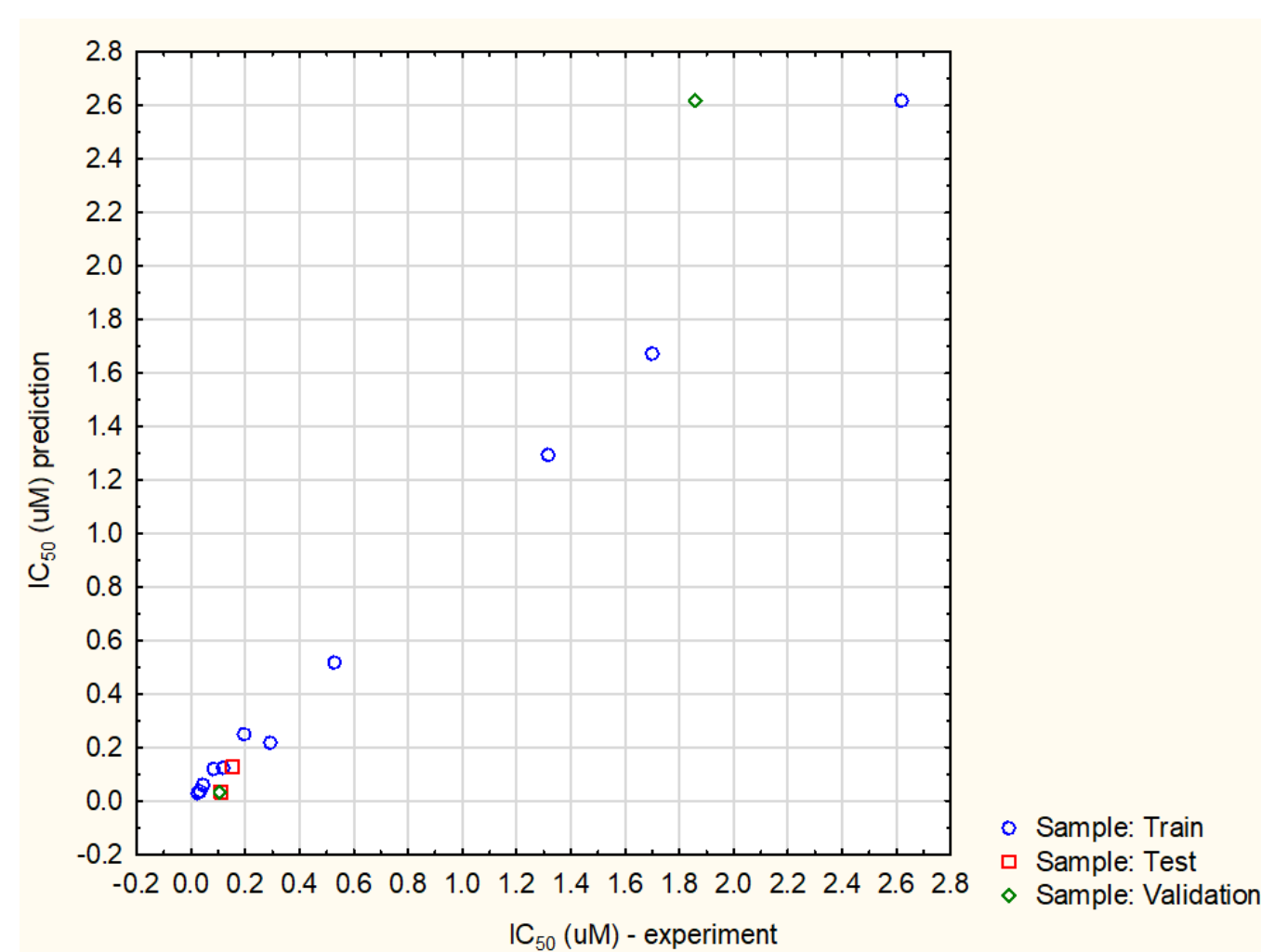


Figure 1. Predicted vs experimental IC₅₀ (μM) for 15 studied analogues.

Sensitivity ranked **C-006 (42.1) > Mor22v (16.4) > VE1_B(p) (8.3) > HATS8p (3.1)**, consistent with the variable-importance profile shown in the **descriptor importance bar chart (Figure 2)**.

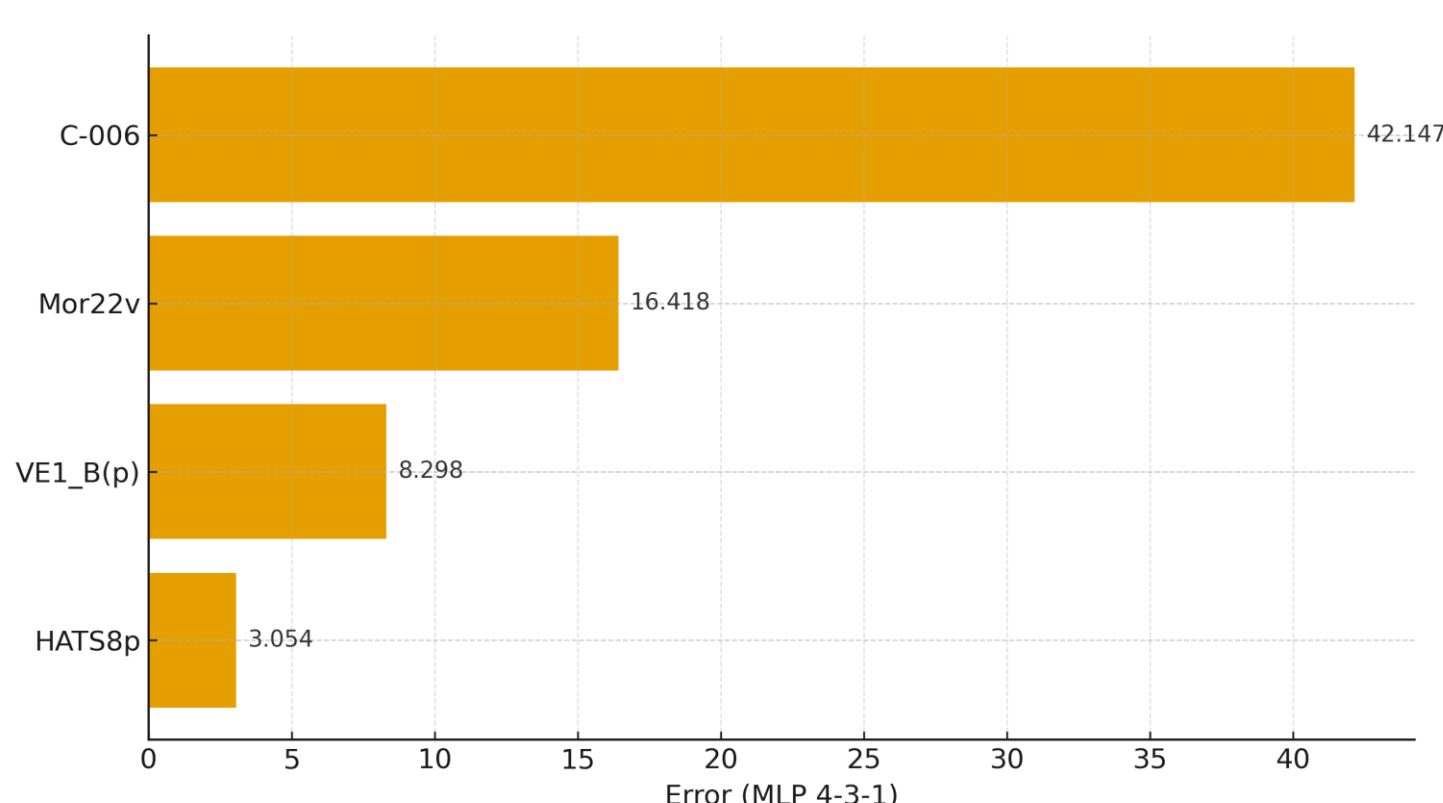


Figure 2. Descriptor importance derived from ANN sensitivity analysis.

Descriptor interpretation:

- **Mor22v (3D-MoRSE)** captures short-range atom-pair contributions and vdW-weighted shape; its prominence matches the geometric constraints of the AChE gorge and correlates with π -fragment placement;
- **HATS8p (GETAWAY)** encodes geometry-weighted **polarizability**, highlighting benefits of π -rich/heteroatom motifs and their spatial dispersion for non-covalent recognition
- **VE1_B(p)** (Burden eigenvalue, polarizability-weighted) reflects global electron-distribution patterns relevant to aromatic stacking/edge contacts within the catalytic and peripheral sites;
- **C-006 (ACF)** counts **CH₂–R–X** fragments, tying potency to substitution density near the indanone–piperazine junction and linker electronics.

Design takeaways:

- Maintain compact molecular volume while **increasing polarizability** (e.g., para-aryl, ether or judicious halo/CF₃) to lift Mor22v/HATS8p without overshooting lipophilicity; tune **CH₂–R–X** around the hinge to optimize **C-006**.
- These rules align with broader AChE-QSAR evidence that descriptor families blending **3D geometry + atom-weighting** (GETAWAY) and **electron-diffraction-like 3D codes** (3D-MoRSE) tend to dominate predictivity.
- Prioritizing analogues with **log P $\approx$ 2–4** should support BBB penetration while limiting non-specific binding.

CONCLUSION

An interpretable ANN-QSAR for 5,6-dimethoxyindanone-piperazine AChE inhibitors shows high internal and external performance and yields actionable rules (enhanced polarizability; targeted CH₂–R–X substitution) to streamline analogue selection for experimental follow-up.

FUTURE WORK / REFERENCES

Expand the chemical domain (≥ 40 analogues), couple training with **BBB/ADMET** in-silico filters, and prospectively validate top-ranked designs in enzyme/cellular assays.

[1] Hampel, H.; Mesulam, M.-M.; Cuello, A.C.; Khachaturian, A.S.; Vergallo, A.; Farlow, M.R.; Snyder, P.J.; Giacobini, E.; Khachaturian, Z.S. Revisiting the Cholinergic Hypothesis in Alzheimer's Disease: Emerging Evidence from Translational and Clinical Research. *J. Prev. Alzheimers Dis.* 2019, 6, 2–15. <https://doi.org/10.14283/jpad.2018.43>.

[2] Mishra, C.B.; Kumari, S.; Manral, A.; Prakash, A.; Saini, V.; Lynn, A.M.; Tiwari, M. Design, Synthesis, In-Silico and Biological Evaluation of Novel Donepezil Derivatives as Multi-Target-Directed Ligands for the Treatment of Alzheimer's Disease. *Eur. J. Med. Chem.* 2017, 125, 736–750. <https://doi.org/10.1016/j.ejmech.2016.09.057>.

[3] Consonni, V.; Todeschini, R.; Pavan, M.; Gramatica, P. Structure/Response Correlations and Similarity/Diversity Analysis by GETAWAY Descriptors. 2. Application of the Novel 3D Molecular Descriptors to QSAR/QSPR Studies. *J. Chem. Inf. Comput. Sci.* 2002, 42, 693–705. <https://doi.org/10.1021/ci0155053>.

[4] Devinyak, O.; Havrylyuk, D.; Lesyk, R. 3D-MoRSE Descriptors Explained. *J. Mol. Graph. Model.* 2014, 54, 194–203. <https://doi.org/10.1016/j.jmglm.2014.10.006>.

[5] Simeon, S.; Anuwongcharoen, N.; Shoombuatong, W.; Malik, A.A.; Prachayasittikul, V.; Wikberg, J.E.S.; Nantasenamat, C. Probing the Origins of Human Acetylcholinesterase Inhibition via QSAR Modeling and Molecular Docking. *PeerJ* 2016, 4, e2322. <https://doi.org/10.7717/peerj.2322>.