New non-basic ligands of serotonin receptor 5-HT₆ as a result of virtual screening based on machine learning methods

<u>Sabina Podlewska</u>, a,b Rafał Kurczaba, Grzegorz Satała, Andrzej J. Bojarskia

^aDepartment of Medicinal Chemistry, Institute of Pharmacology Polish Academy of Sciences, 12 Smętna Street, 31-343 Kraków bFaculty of Chemistry, Jagiellonian University, 3 Ingardena Street, 30-060 Kraków

e-mail: smusz@if-pan.krakow.pl

Machine learning (ML) methods are gaining extreme popularity in tasks connected with the bioactive compounds.1 As it is very difficult to optimize all the influencing parameters of ML predictions, various consensus approaches have been developed. The of them combines majority obtained from different ML algorithms into a final answer. In the presented the fingerprint-based study, consensus was used for the search of new 5-HT₆ ligands in the ChemBridge and ChemDiv compound databases.

ChemBridge db 677 029 cmds

DATABASES SCREENED

ChemDiv db 843 113 cmds

training set composition

actives

assumed inactives

in-house db ChEMBL :

ZINC 39 800 cmds

ExtFP: 2548 cmds KlekFP: 6133 cmds MACCSFP: 10 177 cmds

183 cmds

ML **EXPERIMENTS**

ExtFP: 16 662 cmds KlekFP: 10 924 cmds MACCSFP: 18 754 cmds/ 4418 cmds

1 0 1 0 0 0 1 0 ... 1

To the next step of the screening protocol, only those compounds passed, for which the potential activity was indicated for all three representation of molecules. The high number of compounds rejected in this step revealed that the set of molecules selected by individual fingerprints were almost disjoint.

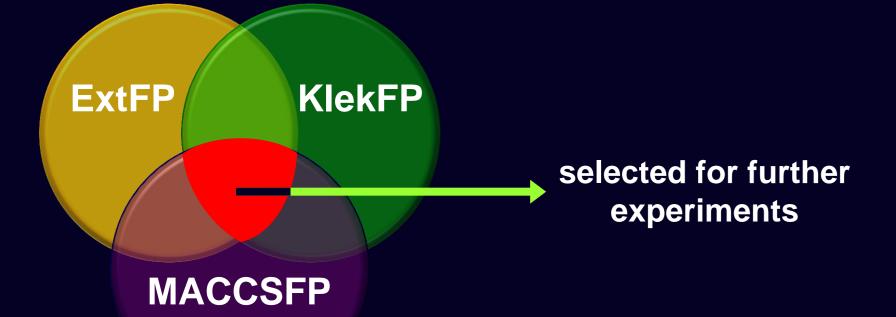
FINGERPRINT-BASED CONSENSUS

597 cmds

The training set for ML experiments was formed by compounds with experimentally confirmed activity towards 5-HT₆R (fetched from the ChEMBL and inhouse IP PAS databases) in a total number of 4418 and a set of 39 800 assumed inactives randomly picked from the ZINC database. All the compounds were represented by three fingerprints from the PaDEL-Descriptor package²: Extended Fingerprint (ExtFP), Klekota&Roth Fingerprint (KlekFP) and MACCS Fingerprint (MACCSFP), capturing different pieces of information about the structure and properties of the analyzed molecules. The ChemBridge and ChemDiv compounds were evaluated by the modified version of the Support Vector Machine (SVM) algorithm: Sequential Minimal Optimization (SMO),3 the WEKA package implementation was used.







SIMILARITY 81 cmds **ANALYSIS**

818 cmds

A = Number of bits 'on' simultaneously in cmd 1 and cmd 2 = 3

 $\mathbf{B} = \text{Number of bits 'on' in cmd 1, but not in cmd 2} = \mathbf{2}$

from further consideration.



The compounds purchasing was supported by the docking to the 5-HT₆R homology models constructed on the 5-HT_{1B}R template.⁴

74 cmds

12 cmds

1 hit

DOCKING

IN VITRO

TESTS

773 cmds

cmd 1

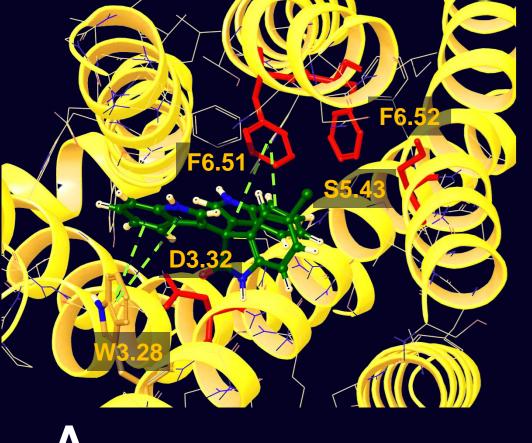
As the aim of the study was to find ligands that would be structurally

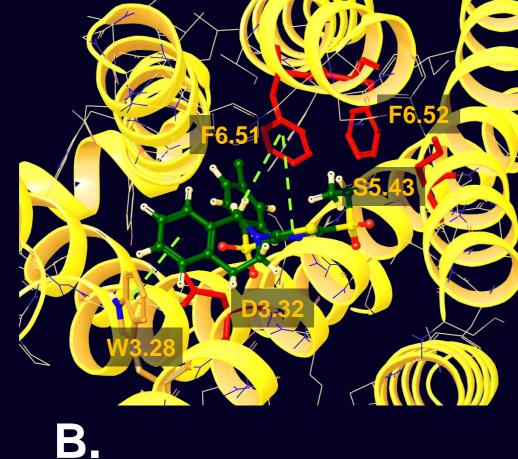
dissimilar to known 5-HT₆R binders, the similarity coefficients

(Tanimoto metric (Tc) was used as a measure) towards all known

5-HT₆R ligands from the training set were calculated. All structures

with the similarity coefficients values higher than 0.7 were rejected







(1 hit)

 $\mathbf{C} = \text{Number of bits 'on' in cmd 2, but not in cmd 1 = 0}$

To provide the maximum coverage of chemical space of the structures tested, the compounds were clustered and on the basis of the visual examination of the docking results, a set of 23 compounds was ordered. As one compound was out of stock, 22 compounds were handed over to the in vitro examination.

Figure 1. Docking results of the two hits found in the study (A. – in ChemBridge db, B. – in ChemDiv db).

The purchased compounds underwent in vitro examination of their affinity for serotonin receptor 5-HT₆, and also to three other serotonin receptor subtypes: 5-HT_{1A}, 5-HT_{2A}, and 5-HT₇ in the radioligand binding affinity tests. For two of the compounds, the activity (expressed as K_i) below 1000 nM towards 5-HT₆R was found (Table 1). One of the compounds (hit found in the ChemBridge db) is characterized by good 5-HT₆R selectivity over the other serotonin receptor subtypes, whereas the hit from ChemDiv db also binds to 5-HT_{2A}R $(5-HT_6R K_i = 119 nM, 5-HT_{2A}R K_i = 296 nM).$

The analysis of the docking results (Figure 1) indicates that the compounds fit well in the binding cavity of 5-HT₆R interacting with amino acid residues reported as important for 5-HT₆R activity. Although a hydrogen bond with D3.32 is missing due to non-basicity of ligands, the network of the remaining ligand-protein interactions provides sufficient strength for the compounds to bind the 5-HT₆R. For both hits, face-to-face and edge-to-face π - π interactions with receptor residues are observed, there is also a number of amino acids from both the hydrophobic and the polar subpocket that interact with the ligands' moieties.

The obtained hits are structurally new 5-HT₆R ligands, and they can also be considered to be non-standard, belonging to the group of non-basic compounds, which is proved by the pK_a analysis (Table 1). Though several reports have proven that the presence of a basic nitrogen atom enabling formation of the interaction of its protonated form and D3.32 is not indispensable for 5-HT₆R anchoring,⁵ the fraction of non-basic compounds within known 5-HT₆R ligands is low (about 7% within the set of active compounds included in the training set) and the majority of 5-HT₆R ligands keep fitting the standard pharmacophore model, which requires the possession of a positive ionizable group.

Table 1. The results of *in vitro* experiments and pK_a analysis for the two active compounds found in VS.

Structure/Vendor/Cmd ID	K _i [nM]				n/
	5-HT ₆	5-HT _{1A}	5-HT _{2A}	5-HT ₇	pK _a
ChemBridge/7706240	670	2450	15 830	18 080	-6.84
СhemDiv/C848-0334	119	12 220	296	15 770	-8.66

In summary, the applied ML-based virtual screening protocol enabled was found to be fast and efficient way of compounds library evaluation and provided finding two structurally new non-standard 5-HT₆R ligands.

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