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Chemical structure and antifungal activity of mint essential oil components

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Abstract: The objective of this research was to determine chemical composition and to evaluate the antifungal activity of essential oil of *Mentha piperita*. By the application of GC/MS analysis of essential mint oil, 27 components were identified. The major components were menthol (39.9 %), menton (23.51 %), menthyl acetate (7.29 %), 1.8-cineol (5.96 %), isomenton (5.24 %), isomenthol (3.17 %), trans-caryophyllene (2.88 %), limonene (2.14 %), pulegon (1.38 %), beta-pinene (1.14 %) and piperiton (1.03 %). The quantitative structure–retention relationship (QSRR) was employed to predict the retention time (RT) of *Mentha piperita* essential oil compounds obtained in GC/MS analysis, using twelve molecular descriptors selected by genetic algorithm. The selected descriptors were used, as inputs of an artificial neural network, to build an RT predictive QSRR model. The coefficient of determination was 0.983, during training cycle, indicating that this model could be used for prediction of RT values for essential oil compounds in *Mentha piperita* essential oil extracts. Essential oil of *Mentha piperita* showed antifungal activity on all tested isolates in the minimal inhibitory concentration range of 0.2–1.7 µl/ml and a minimal fungicidal concentration (*MFC*) range of 1.7–454.5 µl/ml. The most powerful antifungal activity of mint was observed in *C. cladosporioides* of *MFC* value 1.7 µl/ml. *P. aurantiogriseum* showed the lowest sensitivity of *MFC* value 454.5 µl/ml.

Keywords: QSRR; ANN; genetic algorithm; antimicrobial potential.

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INTRODUCTION

Nowadays, a global interest towards an application of various natural agents in regards to food protection from microbiological spoilage and the possibility of longer food storing period, is rapidly increasing. The researches of alternative antifungal agents provide an opportunity of plant essential oil application, as well as their extracts, for the food protection purposes from mycotoxigenic molds and the products of their metabolism.[1]

The chemical structure of the main components is very important for antifungal activity of essential oils. The presence and position of hydroxyl groups in the molecule, the presence of aromatic core, spatial orientation and fat solubility have an effect on the antifungal activity.[2]

The antifungal activity of essential oils depends on a combination and ratio of various compounds – constituents of the oil. Monoterpenes, the terpenes with ten carbon atoms, are present in a more evaporative fraction of essential oils, while the terpenes with 15 and more carbon atoms are present in less evaporative fractions.[3] Monoterpenes are the major constituents of essential oils, and most of them possess antifungal, antiaflatoxigenic and antioxidative activity.[4] Antimicrobial activity of terpenes depend on the chemical structure. Phenolic compounds are more efficient than non-phenolic compounds due to a hydroxyl group, and also the presence of aromatic rings. An efficacy of non-phenolic compounds depends on the type of alkyl groups, whereas, the alkenyl is more active than the alkyl.[5] Farag *et al.*[6] quoted that active compounds, which possess the hydroxyl group (–OH), have shown a high antimicrobial impact. Alkenyl substituent (–CH=CH–), also as in limonene, increases the antimicrobial impact in comparison to alkyl substituent (–C≡C–), also as in *p*-cymene. Likewise, the presence of acetate structure increases the activity of the component. For example, geranyl acetate has shown the stronger antimicrobial impact towards geraniol test microorganisms.[7] The presence of oxygen group in monoterpenes and their carbonylated products significantly increases antifungal activities.[8]

The objective of this research was to determine the chemical composition and to evaluate the antifungal activity of essential oil of *Mentha piperita* against selected isolates of mold. Also, the aim of this work was to establish a new quantitative structure–retention relationship (QSRR) model for predicting the RTs of some *Mentha piperita* essential oil in gas chromatography using the genetic algorithm (GA) variable selection method and the artificial neural network (ANN) technique.

EXPERIMENTAL

Gas chromatography/mass spectrometry (GC/MS)

GC/MS analyses were carried out using Agilent 5975C Series GC-MSD system (7890A GC and 5975C inert MSD) operating in the EI mode at 70 eV, equipped with a HP-5MS capillary column (30 m×0.25 mm; film thickness 0.50 μm).

GC–MSD method used for analysis was modified method by Mimica-Dukić *et al.*[9] 1 µl of diluted essential oil of each sample (100× dilution in *n*-heptane) was injected in splitless mode, and inlet temperature was held at 250 °C. Helium was used as a carrier gas in constant flow mode at 1 ml/min. The oven temperature was programmed as follows: 70 °C raised to 104 °C (2 °C/min) and held for 2 min, then raised to 180 °C (2 °C/min) and not held, and finally raised to 200 °C (4 °C/min) and held for 10 min. MSD was operated in scan mode in 40-400 *m*/*z* range, with ion source and transfer line temperatures held at 230 and 280 °C, respectively.

The identification of the compounds was based on comparison of their Kovats indices (*KI*), their retention times (*RT*) and mass spectra with NIST05/Adams libraries spectra and literature.[10] ChemStation software (Agilent Technologies) was used for data analysis, and curves used for experimental estimation of *KI* were plotted and drawn using SciDaVis (http://scidavis.sourceforge.net/) software.

QSSR analysis

A four-core PC computer (i5-2500K CPU, 3.30GHz) with the Windows 7 operating system was used for calculation. The *RT* prediction was based on the molecular descriptors found in the PaDel descriptor database (http://www.yapcwsoft.com/dd/padeldescriptor).[11,12] Since PaDel database gives an enormous amount of data for each observed compound, it was necessary to use a genetic algorithm (GA), using Heuristic Lab (https://dev.heuristiclab.com/trac.fcgi/)[13] to select the most relevant molecular descriptors for RT prediction. Genetic algorithm[14,15] is a stochastic optimization method inspired by evolution theory. In this work, it was used to select the most appropriate molecular descriptors for developing a reliable *RT* predictive model for mint essential oil.

Statistical investigation of the data has been performed mainly by the Statistica 10 software (StatSoft, Inc. Statistica, ver. 10, data analysis software system).[16]

The PaDel database was used to explore the 1875 molecular descriptors (1444 1D and 2D descriptors and 431 3D descriptors), which included: constitutional descriptors, topological descriptors, connectivity indices, information indices, 2D and 3D autocorrelations descriptors, Burden eigenvalues descriptors, eigenvalue-based indices, geometrical descriptors, WHIM descriptors, functional group counts, atom-centred fragments and molecular properties.

Artificial neural network (ANN)

A multi-layer perceptron model (MLP) consisted of three layers (input, hidden and output) was used, as proven and quite capable of approximating nonlinear functions.[17] Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm was used for ANN modelling. To improve the behaviour of the ANN, both input and output data were normalized.

ANN calculations were performed with Statistica 10. The setup of the software enabled to automatically search for the optimal type/architecture of ANN. The optimization process was performed on the basis of validation error minimization.

Antifungal activity assessment

Culture of molds. Eleven laboratory origin isolates of mold were selected for antifungal researches, such as: *Alternaria alternata, Aspergillus flavus*, *A. fumigatus*, *A. niger*, *A. versicolor*, *Cladosporium cladosporioides*, *Fusarium proliferatum*, *F. sporotrichioides*, *Penicillium aurantiogriseum*, *P. expansum* and *P. oxalicum*. The identification of isolated species was performed in accordance with the rules described by Samson *et al.*,[18] Samson and Frisvad[19] and Pitt and Hocking,[20] on the basis of macromorphological characteristics of repro-

ductive structures (size, shape, colour, surface of the cell wall, branching, sexual and asexual structures).

Preparation of conidia suspensions. Seven days old cultures grown on angled Sabourand dextrose agar (SDA; HiMedia, Mumbai, India) were used for preparation of the mold conidia suspensions. Conidia suspensions were prepared in physiological solution which contained 0.1 % Tween 80 (HiMedia, Mumbai, India). A concentration of 10^6 conidia/ml was adjusted by the application of hemocytometer (Burker Turk chamber; Precise, Peillonnex, France).

Broth microdilution assay. Commercial essential oil of mint (*Mentha piperita*; Herba oil, Belgrade, Serbia) was used in antifungal research.

Determination of a minimal inhibitory concentration (*MIC*) and minimal fungicidal concentration (*MFC*) was performed by the broth microdilution method, throughout the application of Microtiter plate with 96 wells.

Inside each microtiter plate well 100 µl of Sabouraud dextrose broth (SDB; HiMedia, Mumbai, India) was poured. After pouring of wells with the compatible broth, the first well was added 100 µl of essential oil and stirred properly. By the serial transition of 100 µl, from the first well until the last, the starting concentration of essential oil was serial double diluted. From the last well, after homogenization, 100 µl of the content was rejected. Inoculation was performed with the addition of 10 µl of prepared conidia suspension, in the concentration of 10^6/ml, inside every well. Obtained concentrations of essential oil were: 454.5; 227.2; 113.6; 56.8; 28.4; 14.2; 7.1; 3.5; 1.7; 0.8; 0.4 and 0.2 µl/ml. Three probes were prepared: K1–100 µl SDB and 0.1 % Tween 80, K2–100 µl SDB with 0.1 % Tween 80 and 10 µl of inoculum test isolate and K3–100 µl SDB with 0.1 % Tween 80 and 100 µl essential oil. Microtiter plates were incubated at 25 °C for 72 h.

MIC was selected as the lowest concentration of essential oil in the well, whereby the mold growth was invisible (blur lacks) after the selected incubation period. For *MFC* determination, from the well without any visible growth, the content was seeded into the agar plates. The lowest concentration of essential oil, which showed the total absence of the microorganism growth on agar plate after incubation was marked as *MFC*.

RESULTS AND DISCUSSION

Chemical composition of the essential oil

By the application of GC/MS analysis of essential mint oil, 27 components were identified, which makes 98.98 % of essential oil (Table I).

The major components of the mint essential oil were menthol (39.9 %), mentone (23.51 %), menthyl acetate (7.29 %), 1.8-cineol (5.96 %), isomentone (5.24 %), isomenthol (3.17 %), *trans*-caryophyllene (2.88 %), limonene (2.14 %), pulegon (1.38 %), beta-pinene (1.14 %) and piperiton (1.03 %). Other components were present in an amount of less than 1 %.

Chemical structures of the compounds found in the analyzed essential oils of mint are presented in Fig. S-1 of the Supplementary material to this paper.

QSRR model validation

GA was used to select the most appropriate molecular descriptors for *RT* prediction, and the selection of the most relevant descriptors was realized using the evolution simulation.[21,22] Each element of the population, defined by a set of

TABLE I. The chemical compositions of the tested essential oil

No.	Compound	Content, %	*RT* / min
1.	Alpha-pinene	0.74	4.626
2.	Sabinene	0.42	5.523
3.	Beta-pinene	1.14	5.637
4.	Myrcene	0.2	5.920
5.	*O*-Cymene	0.42	6.994
6.	Limonene	2.14	7.125
7.	1,8-Cineol	5.96	7.210
8.	*trans*-Sabinene hydrate	0.17	8.500
9.	Linalool	0.15	9.781
10.	Isopulegol	0.15	11.861
11.	Menthon	23.51	12.327
12.	Isomenthone	5.24	12.720
13.	Isomenthol	3.17	12.813
14.	Menthol	39.9	13.481
15.	Neo-isomenthol	0.52	13.769
16.	Alpha-terpineol	0.73	14.136
17.	Pulegon	1.38	16.542
18.	Carvone	0.14	16.805
19.	Piperiton	1.03	17.359
20.	3-Para-menthen	0.32	18.593
21.	Menthyl acetate	7.29	19.875
22.	Alpha kubeben	0.09	15.249
23.	*trans*-Caryophyllene	2.88	27.613
24.	Alpha-humulene	0.24	29.710
25.	Beta-farnesene	0.1	30.239
26.	D-germacrene	0.26	31.444
27.	Caryophyllene oxide	0.69	37.419
	Total	98.98	
	Unidentified compound	1.02	

binary values (so called “chromosome”), represented a subset of the descriptors. The number of elements in each set (*i.e.*, observed compounds) was equal to the number of the molecular descriptors. The population of the first generation was selected randomly. Each element gained value of 1 if its corresponding descriptor was included in the subset; otherwise it gained zero value. The number of the elements was kept relatively low to maintain a small subset of descriptors.[23] As a result, the probability of generating zero for a gene was set at least 60 % greater than the probability of generating the value of 1. The used operators were cross-over and mutation. The probability of application of these operators was varied linearly with generation renewal (0.5 % for mutation and 90 % for crossover). A population size of 100 individuals was chosen for GA, and evolution was allowed over 50 generations. For a typical run, evolution of the generations was

stopped when 90 % of the generations took the same fitness. The twelve most significant molecular descriptors selected by GA were:

Autocorrelation descriptors (ATSC8s – Centered Broto–Moreau autocorrelation – lag 8 / weighted by I-state, ATSC2v k the same fitness. The twelve most significant molecular descriptors selected by GA were: Average centered Broto––Moreau autocorrelation – lag 2 / weighted by van der Waals volumes, AATSC2m – Average centered Broto–Moreau autocorrelation – lag 2 / weighted by mass, AATSC2v – Average centered Broto–Moreau autocorrelation – lag 2 / weighted by van der Waals volumes, MATS2e – Moran autocorrelation – lag 2 / weighted by Sanderson electronegativities, MATS7m – Moran autocorrelation – lag 7 / weighted by mass),[23] Detour matrix descriptors (VR3_Dt – Logarithmic Randic-like eigenvector-based index from detour matrix).[32] Atom type electrotopological state descriptors (minsssCH – Minimum atom-type E-State: >CH– and hmax – Maximum H E-State), Chi path cluster descriptor (VPC-4 – Valence path cluster, order 4), BCUT descriptor (BCUTp-1l – n^{th} high lowest polarizability weighted BCUTS)[24–27] and Chi path descriptor (AVP-4 – Average valence path, order 4).[28–30]

The molecular descriptors of compounds found in the analyzed essential oils compounds in mint, are presented in Table S-I. These descriptors encode different aspects of the molecular structure and were applied to develop a QSRR model.

The calibration and predictive capability of a QSRR model should be tested through model validation. The most widely used squared correlation coefficient (r^2) can provide a reliable indication of the fit of the model, thus, it was employed to validate the calibration capability of a QSRR model.

Artificial neural network (ANN)

In order to explore the non-linear relationship between *RT*s and the selected descriptors, ANN technique was used to build models. The ANN results, including the weight coefficients, depend on the initial presumptions of parameters which are vital for ANN development and fitting. Likewise, the number of neurons in the hidden layer can alter the result of the ANN model. In order to avoid this problem each topology was run 10,000 times to avoid random correlation due to initial assumption and random initialization of the weights. According to results, the highest r^2 values during the training cycle were obtained when the 13 descriptors were used to build the ANN model (Fig. 1).

The statistical results of the MLP 12-13-1 network are shown in Table II and the predicted *RT*s values for all the essential oil compounds were given in Table III. Performance term represent the coefficients of determination, while error terms indicate a lack of data for the ANN model: root mean square error (*RMSE*), mean bias error (*MBE*), mean percentage error (*MPE*) and r^2 coefficient of determination (dimensionless).

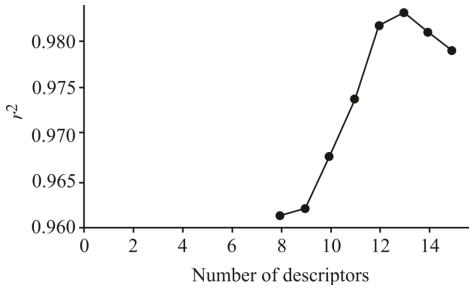

Fig. 1. The dependence of the r^2 value of the number of descriptors in the ANN model.

TABLE II. Summary of active network

Net.name	Train. perf.	Test perf.	Train. error	Test error	Train. alg.	Error funct.	Hidden act.	Output act.
MLP 12-13-1	0.983	0.945	0.001	0.005	BFGS 15	SOS	Tanh	Logistic

TABLE III. The goodness of fit tests for the developed ANN model

χ^2	*RMSE*	*MBE*	*MPE*	r^2
5.892	2.382	-0.498	16.998	0.937

The predicted RT_{pred} and *RT* values are presented in Fig. 2 confirming the good quality of the constructed ANN by showing the relationship between the predicted and experimental retention values.

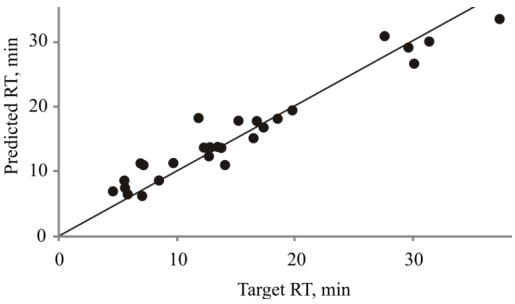

Fig. 2. Comparison of experimentally obtained RTs with ANN predicted values.

The statistical results of ANN model are listed in Tables II and III, all the results are in accordance with the criteria for a good predictive model. Obtained results reveal the reliability of the ANN models for predicting the *RT*s of essential oil compounds in *Mentha piperita*.

Molecular descriptors

2D atom type electrotopological state descriptors depict the state formalism, and were developed for further conjunction with atom classification. The classification scheme is based on the characteristics of hydride groups: 1) atomic number of an atom as element identifier; 2) a valence state designation consisting

of valence and simple connectivity delta values (for each atom together with its bonded hydrogen atoms, as in $–CH_3$ or –NH–) and 3) an aromaticity indicator.[28–30]

2D Burden modified eigenvalues (BCUT descriptors) are an extension of the Burden eigenvalues and consider 3 classes of matrices whose diagonal elements correspond to: atomic charge related values, atomic polarizability related values and atomic H bond abilities. A variety of definitions have been used for the off diagonal terms and both 2D and 3D approaches are considered. The highest and lowest eigenvalues of these matrices have been shown to be discriminating descriptors.[23–26,31,32]

Antifungal activity of the essential oil

Using the broth microdilution method, the essential oil of mint showed antifungal activity against all tested isolates of mold. The minimal inhibitory concentration (*MIC*) of tested oil against isolates of mold was in the range of 0.2–1.7 μl/ml. The minimal fungicidal concentration (*MFC*) was in the range of 1.7–454.5 μl/ml (Table IV).

TABLE IV. Minimal inhibitory concentration (*MIC*) and minimal fungicidal concentration (*MFC*) of essential oil of mint against tested isolates of mold

Isolate	*MIC*, μl/ml	*MFC*, μl/ml
Alternaria alternata	0.4	1.7
Aspergillus flavus	1.7	227.2
Aspergillus fumigatus	0.8	113.6
Aspergillus niger	1.7	7.1
Aspergillus versicolor	0.4	14.2
Cladosporium cladosporioides	0.2	1.7
Fusarium proliferatum	1.7	3.5
Fusarium sporotrichioides	0.8	1.7
Penicillium aurantiogriseum	0.8	454.5
Penicillium expansum	0.4	1.7
Penicillium oxalicum	0.8	56.8

According to the literature on the mint antifungal activity,[33] *MIC* and *MFC* values for the isolates of *A. niger*, *A. flavus*, *A. fumigatus* and *Mucor* sp. were 1 μg/ml, and for *F. oxysporum* 0.5 μg/ml. Mousavi and Raftos[34] quoted that mint essential oil had acted inhibitory against *P. expansum*, and *MIC* and *MFC* values were 0.03 and 0.085 mg/ml. In accordance with the claims of Ferdes and Ungureanu[35], mint essential oil has shown a strong antifungal effect, and at the concentration of 20 μl the inhibition of *A. niger* was occurring, while growing of *Fusarium oxisporum*, *Monascus purpureus* and *Penicillium hirsutum* has been reduced by approximately 70 %.

Mahboubi and Kazempour[36] quoted that mint essential oil, applied by broth microdilution method, has shown antifungal activity against *A. niger*, *A. parasiti-*

cus and *A. flavus*, and recorded that *MIC* and *MFC* values were 0.5/1; 1/1 and 1/2 µl/ml, respectively. Soković *et al*.[37] state that *Mentha piperita* essential oil has shown an antifungal effect towards *A. alternata*, *A. ochraceus*, *A. flavus*, *C. cladosporioides*, *P. ochrochloron*, *Phomopsis helianthi*, *Trichosporon mentagrophytes*, *Trichophyton tonsurans* and *Microsporon gypseum*, whereas the *MIC* values were in the interval from 1.5 to 3.0 µl/ml. Similar results were published by Desam *et al.*,[38] whereby *Mentha piperita* essential oil has shown an antifungal effect towards *Cladosporium herbarum*, while the *MIC* value was 1.50±0.16 µg/ml.

As shown in numerous research papers, the antifungal effect of essential oils depends on the components which are present in oil, their mutual ratio, geographical and seasonal origin, also on the solubility of specific components of oil in water.[37,39–41] Mint and 1,8-cineole are components in mint oil which are responsible for antifungal activities.[42] In line with the claims of Desam *et al*.[38] the major components of the mint essential oil from Saudi Arabi were menthol (36.02 %), menthone (24.56 %), menthyl acetate (8.95 %) and menthofuran (6.88 %). Results are similar compared with essential oil from Serbia[43] that include menthol (37.40 %), menthyl acetate (17.37 %), menthone (12.70 %), and menthofuran (6.82 %) as major components. Also, essential oil from Burkina Faso include menthol (39.3 %), menthone (25.2 %), menthofuran (6.8 %) and menthyl acetate (6.7 %)[44] as major componenets. The oils from Columbia[45] and Brazil[46] are differenet. Roldán *et al*.[45] quoted isomenthol (7.23 %), isomenthone (26.15 %), pulegone (44.54 %) and chrysanthenone (8.07 %) as major components but Sartoratto *et al*.[46] quoted as major components 3-octanol (10.1 %), linalool (51.0 %), terpin-4-ol (8.00 %) and carvone (23.42 %). Furthermore, other results from Brazil[47] include menthol (42.32 %), menthyl acetate (35.01 %), menthofuran (4.56 %), menthone (4.05 %) and 1,8cineole (5.56 %) as major components.

By analyzing the obtained results, the causality of antifungal activity and the mint essential oil chemical structure of mint essential oil could be noticed. Based on the analysis the components of mint essential oil belong to the groups of: monoterpenes, alcohol derivates of monoterpenes, ketones, sesquiterpenes, acetates and sesquiterpene oxides (Table I). The components: alpha-pinene, sabinene, beta-pinene, myrcene, *o*-cymene, limonene, 1,8-cineole, *trans*-sabinene hydrate, linalool, isopulegol, menthone and isomenthone are monoterpenes. Monoterpenes contain 10 C atoms in their structure, *i.e.*, 2 isoprene units. Intermolecular forces in organic compounds consist of dipole-dipole interactions and van der Waals forces. In non-polar or low polar compounds van der Waals forces are present. Van der Waals forces are very weak; therefore, the melting point of non-polar compounds is lower in comparison to the polar compounds. The compounds such as isomenthol, menthol, neo-isomenthol and alpha-terpineol belong to the group of alcohol or hydroxyderivates of monoterpenes. Hydroxyderivates are compounds which contain one or more OH groups in the molecule, bounded

with carbohydrate residue. Menthol is a saturated alcohol derivate of *p*-methane. Menthol is present in mint oil in the free state or as an ester. Alcohol derivates of monoterpenes have different physical characteristics then monoterpenes due to the presence of the polar OH group. The hydrogen atom acts as a bridge between the two molecules, whereas it's bonded with one atom of oxygen by covalent bonds, and with the other oxygen atom in a second molecule by dipole–dipole bonds. The hydrogen bond is a type of strong dipole-dipole interaction. Higher energy is necessary in order to break hydrogen bonds thus the melting point and the evaporation point is higher. Carvone molecule contains carbonyl group as a functional group. Polar carbonyl group enables dipole-dipole interactions. Likewise, the presence of acetate groups in methyl acetate increases the activity of the component itself. The components alpha-cubebene, *trans*-caryophyllene, alpha--humulene, beta-farnesene and D-germacrene belongs to the group of sesquiterpenes. Sesquiterpenes contain 15 carbon atoms in their structure, whereas, they occur by the coupling of three isoprene units. Sesquiterpenes have a higher molecular weight in comparison to monoterpenes.

The presence of the functional group, aromatic core, type of intermolecular bond, as well as the size and the structure of molecules affect the quantity of energy necessary for chemical reactions of component dissociation, *i.e.*, the evaporation speed. Considering the fact that organic reactions are time reactions, the component dissociation speed in the mixture is measured by the retention time. Longer period of extraction is necessary for the less evaporative fractions in comparison to more evaporative fractions.

CONCLUSION

The QSRR models for estimating the RTs were developed, for a series of 30 compounds in *Mentha piperita* essential oil, by employing the ANN modelling approach. The results demonstrated that the ANN model was adequate in predicting the *RT*s of the essential oil compounds in *Mentha piperita* essential oil. A suitable model with high statistical quality and low prediction errors was derived.

The essential oil of *Mentha piperita* showed antifungal activity against all mold isolates tested. The oil exhibited very high antifungal activity owing to the high content of menthol (39.9 %). Menthol is well known antifungal compound. The most powerful antifungal activity of mint was observed in *C. cladosporioides. P. aurantiogriseum* showed the lowest sensitivity of *MFC* value 454.5 μl/ml.

Obtained results of the mint essential oil antifungal activities could be of significant value in the improvement of antifungal protection – the damage reduction caused by molds activities in food and in the replacement of synthetic preservatives and fungicides in the products of natural origin.

SUPPLEMENTARY MATERIAL

Additional data are available electronically at the pages of journal website: http://www.shd.org.rs/JSCS/, or from the corresponding author on request.

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ИЗВОД

ХЕМИЈСКА СТРУКТУРА КОМПОНЕНТИ И АНТИФУНГАЛНА АКТИВНОСТ ЕТАРСКОГ УЉА МЕНТЕ

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Циљ ових истраживања био је да се испита хемијски састав и структура компоненти етарског уља менте и антифунгална активност уља менте на одабране изолате плесни. GC/MS анализом у етарског уља менте идентификовано је 27 компоненти. Најзаступљеније компоненте биле су ментол (39,9 %), ментон (23,51 %), ментил-ацетат (7,29 %), 1,8-цинеол (5,96 %), изоментон (5,24 %), изоментол (3,17 %), *транс*-кариофилен (2,88 %), лимонен (2,14 %), пулегон (1,38 %), *β*-пинен (1,14 %) и пиперитон (1,03 %). Анализа квантитативног односа структуре молекула једињења и ретенционог времена (*quantitative structure–retention relationship* – QSRR) коришћена је за предвиђање времена задржавања (*RT*) једињења из есенцијалног уља *Mentha piperita* добијених GC/MS анализом, коришћењем дванаест молекуларних дескриптора одабраних генетским алгоритмом. Изабрани дескриптори коришћени су као улазне променљиве вештачке неуронске мреже за формирање QSRR модела за предикцију *RT*. Коефицијент детерминације достигао је вредност 0,983, током циклуса тренинга, што указује да се овај модел може успешно користити за предвиђање вредности RT за једињења из есенцијалног уља *Mentha piperita*. Етарско уље менте показало је антифунгалну активност према свим тестираним изолатима, при чему су вредности минималне концентрације инхибиције (*MIC*) биле у опсегу 0,2-1,7 μl/ml, а вредности минималне фунгицидне концентрације (*MFC*) од 1,7 до 454,5 μl/ml. Најслабија антифунгална активност примећена је код *C. cladosporioides* (*MIC* = 0,2 μl/ml и *MFC* = 1,7 μl/ml). *P. aurantiogriseum* је показао најмању осетљивост према етарском уљу менте (*MIC* = 0,8 μl/ml и *MFC* = 454,5 μl/ml).

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REFERENCES

1. L. da Cruz Cabral, V. Fernandez Pinto, A. Patriarca, *Int. J. Food Microbiol*. **166** (2013) 1 (https://doi.org/10.1016/j.ijfoodmicro.2013.05.026)
2. M. Raccach, *J Food Saf*. **6** (1984) 141 (https://doi.org/10.1111/j.1745-4565.1984.tb00479.x)
3. M. V. Piletić, B. Lj. Milić, *Organic Chemistry,* Tehnološki fakultet, Novi Sad 1989 (in Serbian)

4. A. Kedia, B. Prakash, P. K. Mishra, N. K. Dubey,*Int. J. Food Microbiol*. **1**–**7** (2014) 168 (https://doi.org/10.1016/j.ijfoodmicro.2013.10.008)
5. B. Ruiz, X. Flotats, *Waste Manage.* **34** (2014) 2063 (https://doi.org/10.1016/j.wasman.2014.06.026)
6. R. S. Farag, Z. Y. Daw, S. H. Abo-Raya, *J. Food Sci.* **54** (1989) 74 (https://doi.org/10.1111/j.1365-2621.1989.tb08571.x)
7. H. J. D. Dorman, S. G. Deans, *J. Appl. Microbiol*. **88** (2000) 308 (https://onlinelibrary.wiley.com/doi/epdf/10.1046/j.1365-2672.2000.00969.x)
8. R. Naigre, P. Kalck, C. Roques, I. Roux, G. Michel, *Planta Med.* **62** (1996) 275 (https://doi.org/10.1055/s-2006-957877)
9. N. Mimica-Dukić, S. Kujundžić, M. Soković, M. Couladis, *Phytother. Res*. **17** (2003) 368 (https://doi.org/10.1002/ptr.1159)
10. R. P. Adams, *Identification of essential oil components by gas chromatography / mass spectroscopy*, Allured Publishing Corporation, Carol Stream, IL, 1995
11. PaDel-Descriptor database (http://www.yapcwsoft.com/dd/padeldescriptor) (accessed: 10 May, 2019)
12. C. W. Yap, *J. Comput. Chem.* **32** (2011) 1466 (https://doi.org/10.1002/jcc.21707)
13. HeuristicLab, https://dev.heuristiclab.com/trac.fcgi/ (accessed: 10 May, 2019)
14. D. E. Goldberg, *Genetic algorithms in search, optimisation and machine learning*, Addison-Wesley, Boston, MA, 1989 (ISBN:0201157675)
15. R. Leardi, R. Boggia, M. Terrile, *J. Chemom*. **6** (1992) 267 (https://doi.org/10.1002/cem.1180060506)
16. Statistica 10 software, version 10, StatSoft, Inc. Statistica, data analysis software system
17. X. Hu, Q. Weng, *Remote Sens. Environ*. **113** (2009) 2089 (https://doi.org/10.1016/j.rse.2009.05.014)
18. A. R. Samson, S. E. Hoekstra, C. J. Frisvad, *Introduction to Food-and Airborne Fungi*, Centraal bureau voor Schimmelcultures, Utrecht, 2004
19. R. A. Samson, J. C. Frisvad, *Penicillium subgenus Penicillium: new taxonomic shemes, mycotoctins and other extrolites*, CentaalbureauvoorSchimmelcultures, Utrecht, 2004
20. J. I. Pitt, A. D. Hocking, *Fungi and Food Spoilage*, Springer Science–Business Media, New York, 2009
21. S. Ahmad, M. M. Gromiha, *J. Comput. Chem*. **24** (2003) 1313 (https://doi.org/10.1002/jcc.10298)
22. J. Aires-de-Sousa, M. C. Hemmer, J. Gasteiger, *Anal. Chem*. **74** (2002) 80 (https://pdfs.semanticscholar.org/3426/a10327d8e3c6478e42f425d15e8cc1e88738.pdf)
23. R. Todeschini, V. Consonni, *Molecular descriptors for chemoinformatics*, Wiley VCH, Weinheim, 2009 (ISBN: 978-3-527-31852-0)
24. R. S. Pearlman, K. M. Smith, *J. Chem. Inf. Comput. Sci*. **39** (1999) 28 (https://doi.org/10.1021/ci980137x)
25. F. R. Burden, *J. Chem. Inf. Comput. Sci*. **29** (1989) 225 (https://doi.org/10.1021/ci00063a011)
26. F. R. Burden, *Quant. Struct. Act. Relat.***16** (1997) 309 (https://onlinelibrary.wiley.com/doi/pdf/10.1002/qsar.19970160406)
27. Y. K. Kang, M. S. Jhon, *Theor. Chim. Acta* **61** (1982) 41 (https://link.springer.com/article/10.1007/BF00573863)
28. L. H. Hall, L. B. Kier, *J. Chem. Inf. Comput. Sci*. **35** (1995) 1039 (https://doi.org/10.1021/ci00028a014)

29. R. Liu, H. Sun, S.S. So, *J. Chem. Inf. Comput. Sci*. **41** (2001) 1623 (https://doi.org/10.1021/ci010290i)
30. P. Gramatica, M. Corradi, V. Consonni, *Chemosphere* **41** (2000) 763 (https://doi.org/10.1016/S0045-6535(99)00463-4)
31. R. S. Pearlman, K. M. Smith, in *Drug Design Ligand-Protein Interactions and Molecular Similarity,* H. Kubinyi, G. Folkers, Y. C. Martin, Eds., Kluwer Academic Publishers, Dordrecht, 1998, p. 339 (https://doi.org/10.1007/0-306-46857-3)
32. R. Benigni, L. Passerini, A. Pino, A. Giuliani, *Quant. Struct. Act. Relat*. **18** (1999) 449 (https://www.academia.edu/13982599/The_information_content_of_the_eigenvalues_from_modified_adjacency_matrices_large_scale_and_small_scale_correlations)
33. M. Kazemi, H. Rostami, S. Shafiei, *J Plant Sci*. **7** (2012) 55 (https://doi.org/10.3923/jps.2012.55.66)
34. S. M. Mousavi, D. Raftos, *J. Sci. Res*. **11** (2012) 156 (https://www.researchgate.net/publication/267784697)
35. M. Ferdes, C. Ungureanu, *UPB Scientific Bull., B* **74** (2012) 87 (https://www.scientificbulletin.upb.ro/rev_docs_arhiva/fullf25_103172.pdf)
36. M. Mahboubi, N. Kazempour, *SJST* **36** (2014) 83 (https://pdfs.semanticscholar.org/ad3a/51e3af76d8ab60fec44046a5184c67d49208.pdf) (accessed: 10 May, 2019)
37. M. D. Soković, J. Vukojević, P. D. Marin, D. D. Brkić, V. Vajs, L. J. L. D. van Griensven, *Molecules* **14** (2009) 238 (https://doi.org/10.3390/molecules14010238)
38. N. R. Desam, A. J. Al-Rajab, S. Mukul, M. M. Mylabathula, R. R. Gowkanapalli, M. Albratty, *J. King. Saud. Univ. Sci*. **31** (2019) 528 (http://dx.doi.org/10.1016/j.jksus.2017.07.013)
39. X. Xianfei, C. Xiaoqiang, Z. Shunying, Z. Guolin, *Food Chem*. **100** (2007) 1312 (https://doi.org/10.1016/j.foodchem.2005.12.011)
40. A. K. Tyagi, A. Malik, *Food Control* **22** (2011) 1707 (https://doi.org/10.1016/j.foodcont.2011.04.002)
41. M. Nikolić, J. Glamočlija, A. Ćirić, T. Marković, D. Marković, T. Perić, M. Soković, *Lek. Sirov*. **33** (2013) 63 (in Serbian)
42. G. S. Griffin, L. J. Markham, N. D. Leach, *J. Essent. Oil Res*. **12** (2000) 149 (https://doi.org/10.1080/10412905.2000.9699509)
43. M. Soković, P. D. Marin, D. Brkić, J. L. D. Leo, *Food Global Sci. Books* **1** (2007)
44. I. H. Bassolé, A. Lamien-Meda, B. Bayala, S. Tirogo, C. Franz, J. Novak, R. C. Nebié, M. H. Dicko, *Molecules* **15** (2010) 7825 (https://doi.org/10.3390/molecules15117825)
45. L. P. Roldán, G. J. Díaz, J. M. Duringer, *Rev. Colomb. Cienc. Pecu*. **23** (2010) 451 (print version ISSN 0120-0690; on-line version ISSN 2256-2958)
46. A. Sartoratto, A. L. M. Machado, C. Delarmelina, G. M. Figueira,M. K. T. Duarte,V. L. G. Rehder, *Braz. J. Microbiol*. **35** (2004) 275 (https://doi.org/10.1590/S1517-83822004000300001)
47. J. Scavroni, C. S. F. Boaro, M. O. M. Marques,L. C. Ferreira, *Braz. J. Plant Physiol*. **17** (2005) 345 (https://doi.org/10.1590/S1677-04202005000400002).