Classification of Honeybee Infestation by *Varroa Destructor* using Gas Sensor Array

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Abstract: Infestation of bee colony with *Varroa destructor* proceeds exponentially. It is important to detect the disease at its very early stage. However, the distinction of later infestation stages is also practical. We proposed to apply gas sensor array measurements of beehive air as the source of information which may be useful for this kind of assessment. Honeybee infestation was classified into three categories: 'low', 'medium' and 'high', two categories: 'low' and 'medium to high', and another two categories: 'high' and 'medium to low'. Responses of gas sensor array to beehive air were used as the input data of the classifier, which was trained to distinguish the categories. The results of the analysis demonstrated that category 'low' was determined most effectively, with an error rate of about 10%. Category 'high' was most difficult to determine. In this case the lowest error rate was about 20%. Based on our analysis, the approach based on binary classification was favoured and SVM outperformed ensemble of classification trees. It was found, that first several minutes of gas sensors exposure to beehive air were sufficient to attain effective classification. The presented method of varroosis determination, based on beehive air sensing with gas sensors is innovative and has high potential of application in beekeeping.

1 INTRODUCTION

Bees are critically important for the environment and to the economy. They play a vital role in the environment by pollinating both wild flowers and many crops. Honey bees also provide honey and other apiculture products such as pollen, wax, propolis and royal jelly. Unfortunately, the population of these insects is decreasing at an alarming rate throughout the world. This phenomenon is still poorly understood (EPILOBEE, 2016). Probably, it is caused by the combined effect of interrelated factors, e.g. shifting flowering seasons due to climate change, reduced floral diversity, use of pesticides, habitat loss, lack of genetic diversity, insect parasites and harmful microorganisms.

The best source of highly reliable information about the condition of bee colony, events that may require the beekeeper's action and environmental conditions affecting the colony health is beehive monitoring. It can be based on regular inspection or measurements of the appropriate parameters (Sperandio et al., 2019). The first approach requires a great experience. It is time-intensive and subject to observer error. Hence, the measurement strategy is preferred. In practice, beehive monitoring is focused on the continuous, automatic determination of temperature, air humidity and gas content, analysis of sound and vibration of a beehive, counting of outgoing and incoming bees, video observation, weighing the colony (Cecchi et al., 2019; Kviesis, 2015). The data

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can be provided in real time and used for individual bee colony maintenance.

Substantial information about honeybee colony is included in the chemical composition of air inside the hive. Usually, this gas is a mixture of compounds emitted by the bees themselves (e.g. pheromones, other chemicals released to repel pests and predators, metabolites, etc.), substances originating from hive stores (e.g. honey, nectar, larvae, sealed brood, beeswax, pollen, beebread and propolis), and volatile compounds from hives construction materials (wood, paint, plastic, etc.). The beehive atmosphere also contains compounds which come from vehicles, farms, industries, and households located in the hive vicinity.

The combination of gaseous mixture inside the hive is unique. Sometimes bee diseases can influence the indoor air of a hive. For example, foulbrood has a characteristic odor, and experienced beekeepers, with a good sense of smell, can detect the disease upon opening a hive. It is known, that the notorious varroa mites can change their surface chemicals to match the development stage of their hosts. It is interesting to know if, despite this, the information about infestation is included in the chemical composition of the air surrounding bees inside the hive. Potentially, changes of the chemical properties of the indoor air could be the basis for detection of varroosis (Szczurek et al. 2019a; Szczurek et al. 2019b). This most destructive disease of honey bees worldwide is caused by a *Varroa destructor* (*V.d.*).

Generally speaking, the determination of the chemical indicators of varroosis can be based on the detection of specific volatile chemicals, qualitative and quantitative gas analysis and qualitative classification of indoor air. Today, there are a number of well-established methods which are capable of detecting the specific chemical species or analysing the complex gaseous mixture. They offer very good detection limit, accuracy, sensitivity and repeatability. Unfortunately, the available methods and instruments are expensive and require trained, experienced personnel. In practice, they are beyond the reach of average users - beekeepers.

In this situation, the measurement instruments based on gas sensors offer wider usefulness and applicability. Chemiresistors are especially promising in this field of application (Yunusa et al., 2014). These devices present high sensitivity, detection at the level of ppm, small sizes, low cost, simplicity of their use. The serious shortcomings of the semiconductor gas sensors is poor selectivity, resulting from the sensing mechanism. For that reason, it is impossible to detect individual chemical species using a single semiconductor sensor. The measurement potential of devices based on chemiresistors may be improved by the application of the multi-sensor array, the appropriate operation mode, signal processing and data analysis. The instruments established on this idea are particularly useful for the pattern recognition.

The aim of this study is to show that the measurement instrument consisting of the sensor array and the appropriate data classification module allows to detect varroosis. The term detection in this work is understood as the action of accessing information about the rate of infestation. The effective detection can include the determination of several levels of infestation. We expected that the accuracy and sensitivity of the detection process is strongly influenced by the number of the assumed categories. The determination of this relationship can be of major importance in respect of the practical application of sensor device as bee disease detector.

The main advantages of the presented method of *Varroa destructor* classification based on gas sensing are related to its cost-effectiveness, availability and low detection limit. Continuous measurement may be accomplished and the measurement data is provided in real time. On-site detection can be performed. These features are the good basis for establishing the honey bee dieses monitoring system.

2 EXPARIMENTAL PART

2.1 Gas Sensor Device

Prototype Multisensor detector of air quality was used in the study. The construction was developed in the Laboratory of Sensor Technique and Indoor Air Quality Studies at Wroclaw University of Science and Technology, Poland. This autonomous, multifunctional and programmable device is based on gas sensors. It allows for continuous measurements of gas samples and remote access to the recorded data. The prototype was designed to operate in field conditions. For this purpose, it was fitted with solar panels, battery and the cover, which protects against the meteorological conditions. The general view of the instrument is presented in Figure 1.

The instrument was composed of several functional modules: 1) multichannel recorder of gas sensor signals MCA-8, 2) communication controller Beecom, 3) charging regulator for solar panel, Steca Solsum 6.6 , 4) gel battery, HZY EV12-33, with the nominal power 36 Ah and voltage 12V and battery level indicator, 5) photovoltaic solar panel, CL050-12P, with the nominal power 50W, 7) AC adapters and 6) casing.

The major functional unit of the device was the multichannel recorder of gas sensor signals MCA-8. It included the following gas sensors TGS832, TGS2602, TGS823, TGS826, TGS2603, and TGS2600. They were mounted in individual sensor chambers, made of aluminum. Gas sensors heaters temperature was stabilized.

The device was dedicated to operate continuously and perform measurements in the dynamic mode. A peristaltic pump was mounted inside in order to enforce the gas flow. The instrument was fitted with 8 gas inlet ports, which could be individually connected to gas sensors chambers by means of a set of valves. This solution allows for an intermittent gas sampling from 8 locations.

Figure 1: General view of the instrument based on gas sensors.

As default, the measurement data is recorded on the instrument's SD card, with the temporal resolution of 1s. Optionally, the remote data transfer could be realized using GSM (5s resolution). The operation of the gas sensor device is programmable. The user has to define the following parameters: duration of gas intake through individual inlet ports, pump operation rate as well as the power of gas sensors heaters. The program is executed from SD card. The instrument may be also operated in an interactive mode using a PC based software.

Three options of powering the device are available: mains power supply, battery and photovoltaic solar panel. The last two solutions were aimed to secure the autonomous operation of the device in field conditions.

2.2 Field Experiments

Fifteen honey bee colonies were chosen for the experiment. They belonged to three groups called A, B and C. Each group included five colonies. Groups differed in respect of the degree of *Varroa destructor* infestation. The infestation rates of individual colonies are shown in Table 1, Table 2 and Table 3.

The *Varroa destructor* infestation rates of honey bee colonies were determined using a flotation method. It involves shaking a sample of dead bees with a detergent or alcohol and then rinsing them on a sieve (COLOSS BEEBOOK, 2013; Fries et al., 1991). The infestation rate is the number of mites found in a sample of bees, divided by the number of bees and expressed as the percentage.

Table 1: Honey bee colonies which belonged to group A.

Colony	*V.d.* infestation rate
A1	0.0
A2	0.6
A3	0.0
A4	0.3
A5	0.2

Table 2: Honey bee colonies which belonged to group B.

Colony	*V.d.* infestation rate
B1	4.9
B2	4.7
B3	4.4
B4	3.8
B5	4.3

Table 3: Honey bee colonies which belonged to group C.

Colony	*V.d.* infestation rate
C1	60.3
C2	52.0
C3	11.0
C4	11.5
C5	13.0

The air of beehives occupied by bees was measured using gas senor device.

The measurement experiment lasted five days. Each day, three bee colonies, were investigated, one from group A, B and C. A single measurement of a bee colony consisted of two phases: 1) the exposure of gas sensors to beehive air (600 s), 2) the exposure of gas sensors to the regeneration air (900 s). The measurements of three individual colonies were performed in sequence. The sequence was repeated, therfore multiple measurements were done for each bee colony.

During measurements, gas sensor device was connected to beehives by means of polyethylene tubing. One inlet port was used to deliver the air sampled from one beehive. The gas sampling points were located inside hives, in their central, upper parts, between brood combs. In this location, the bee colony infestation should be most strongly reflected in the quality of beehive air, because the mite proliferates on the brood. One additional inlet port of gas sensor device was dedicated to the delivery of ambient air for sensors regeneration. Dedicated filter, filled with charcoal allowed for air preparation. Inlet ports of the device were protected by particle filters.

The experiment was run in field condidtions.

3 DATA ANALYSIS

3.1 Varroa Destructor Infestation Categories

We examined three approaches to categorization of bee colonies infestation by *V.d.*.

The first approach consisted in distinguishing three categories of infestation: 'low', 'medium' and 'high'. The range of bee colonies infestation rate, associated with individual categories, was suggested by professional beekeepers, as displayed in Table 4. The recognition between three categories of *V.d.* infestation 'low', 'medium' and 'high' with one classifier would be very attractive in a beekeeping practice.

Table 4: Categorization of bee colonies infestation by *V.d* using three categories: 'low', 'medium' and 'high'.

Category	*V.d.* infestation rate of bee colony [%]
Low	0-2
Medium	2-6
High	>6

Table 5: Categorization of honey bee colonies infestation by *V.d* using two categories: 'low' and 'medium to high'.

Category	*V.d.* infestation rate of bee colony [%]
Low	0-2
Medium to high	>2

With reference to the experimental data, the category 'low' was represented by bee colonies group A. In this group the *V.d.* infestation rate was from 0% to 0.6%, see Table 1. The category 'medium' was represented by colonies group B. In this group the *V.d.* infestation rate was from 3.8% to 4.9%, see Table 2. The category 'high' was represented by bee colonies group C. Here, the *V.d.* infestation rate was from 11% to 60.3%, see Table 3.

Table 6: Categorization of honey bee colonies infestation by *V.d* using two categories: 'high' and 'medium to low'.

Category	*V.d.* infestation rate of bee colony [%]
High	>6
Medium to low	0-6

The problem of recognition of three categories of infestation was represented by a three-class classification task.

Second approach consisted in distinguishing two categories of *V.d.* infestation , which were 'low' and 'medium to high', as shown in Table 5. This approach could be used to filter out bee colonies which are not infested or slightly infested, perhaps not yet requiring treatment, from all other infested colonies.

The third approach also consisted in distinguishing two categories of *V.d.* infestation. However, the considered categories were 'high' and 'medium to low', as shown in Table 6. This approach could be used to detect bee colonies which are severely infested, and should be subject to a radical treatment, from other less infested or even healthy colonies.

The problem of recognition of two categories of infestation was represented by a binary classification task. The distinction of two categories is less attractive for the beekeeper. However, this approach is likely to offer a trade off in terms of smaller classification error. Two-class problems may be solved using wide range of classifiers, which are not available in case of multiclass classification.

3.2 Classification

Classification was based on responses of all sensors, which were elements of gas sensor array. In order to form a feature vector, a 3 min long fragment was extracted from the signal of each gas sensor. It consisted of 180 responses recorded one after another with temporal resolution of 1s. Fragments of signals of all sensors were combined to form one feature vector.

Several feature vectors were considered in this work as the basis of classification. They included fragments associated with first, second, third, fourth etc. three minutes of gas sensor array exposure to the test gas – beehive air.

Two classifiers were applied. Ensemble of classification trees (Ren et al., 2016) and support vecor machine (SVM) (Nalepa and Kawulok, 2019). The first classifier was utilised for solving three-class as well as two-class classification problems. SVM was applied for binary problems solving, exclusively.

The performance of classification was evaluated based on confusion matrices, as shown in Table 7 and Table 8.

Table 7: Confusion matrix for two-class problem.

	Predicted cat. 1	Predicted cat. 2
True cat. 1	$n_{1,1}$	$n_{1,2}$
True cat. 2	$n_{2,1}$	$n_{2,2}$

Regarding two-class problem (see Table 7), the rate of correct classification (TC) of data representing category 1 was called TC1 rate and it was given by eq. 1.

$$\text{TC1 rate} = n_{1,1}/(n_{1,1}+n_{1,2}) \quad (1)$$

TC2 rate was determined analogically.

Table 8: Confusion matrix for three-class problem.

	Predicted cat. 1	Predicted cat. 2	Predicted cat. 3
True cat. 1	$n_{1,1}$	$n_{1,2}$	$n_{1,3}$
True cat. 2	$n_{2,1}$	$n_{2,2}$	$n_{2,3}$
True cat. 3	$n_{3,1}$	$n_{3,2}$	$n_{3,3}$

In case of three-class problem (see Table 8), the rate of correct classification of data representing category 1 was given by eq. 2.

$$\text{TC1 rate} = n_{1,1}/(n_{1,1}+n_{1,2}+n_{1,3}) \quad (2)$$

TC2 rate and TC3 rates were determined analogically.

Classification models were validated using ten-folds cross-validation procedure. It was repeated fifteen times for each classifier, when using a particular feature vector as input. The results of repeated cross-validations were averaged and standard deviation was computed. Following, confusion matrices were prepared which included the averaged results as well as the information about their spread.

4 RESULTS

4.1 Three Categories of *Varroa Destructor* Infestation: 'Low', 'Medium' and 'High'

Three categories of *V.d.* infestation: 'low', 'medium' and 'high' were recognized using one classifier, ensemble of classification trees. The classification performance was examined with respect to different fragments of gas sensors signals, utilised as the basis of classification. Figure 2 presents the results of classification in terms of True Category rates for each category.

As shown in Figure 2, three considered infestation categories were distinguished with various efficiencies. The rate of correct classifications was the best in case of category 'low' (on average, TC1 rate was from 80% to 87%). Smaller rates were associated with category 'medium' (on average TC2 rate was from 72% to 76%) and the worst results were attained in case of category 'high' (on average, TC3 rate was from 66% to 74%).

Similar results were obtained when using different fragments of gas sensors signals as the bass of classification. TC rates varied as a function of the duration of gas sensors exposure to beehive air, but no clear relationship was observed between the two. Based on the obtained results (see Figure 2), first three minutes of gas sensors exposure could be considered sufficient for collecting the informative measurement data, useful for classification.

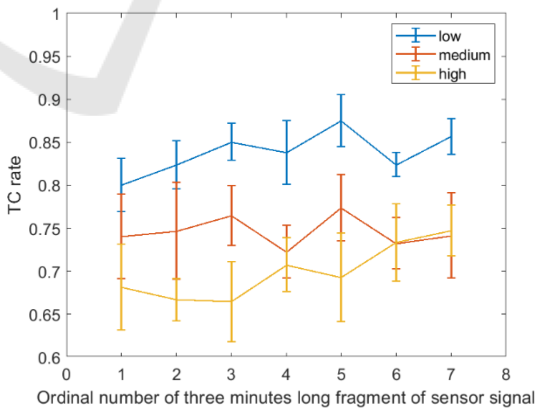

Figure 2: Results of classification for three categories of *V.d.* infestation: 'low', 'medium' and 'high'. Ensemble of classification trees was applied and various fragments of gas sensors signals recorded during exposure to beehive air were utilised as the classifier input.

Table 9 presents a confusion matrix for classification based on first three minutes of gas sensor array exposure to beehive air. As shown, misclassified data, truly belonging to class ‘low’ were mostly allocated to class ‘medium’ (12.1%) and the remaining 7.9% was assigned to class ‘high’. Majority of misclassified items, truly belonging to class ‘medium’ was recognized as members of category ‘high’ (19.8%) and only 6.2% of them were allocated to class ‘low’. In case of category ‘high’, also 24.3% of misclassified data were allocated to class ‘medium’ and only 7.6% were assigned to class ‘low’.

Table 9: Confusion matrix for recognition of three categories of *V.d.* infestation: ‘low’, ‘medium’ and ‘high’. Mean±standard deviation for 15 cross-validations are shown. Ensemble of classification trees was applied. Input data consisted of first three minutes of gas sensor array responses to beehive air.

	Predicted ‘low’	Predicted ‘medium’	Predicted ‘high’
True ‘low’	80.0±3.1	12.1±2.3	7.9±2.3
True ‘medium’	6.2±1.6	74±4.9	19.8±5.0
True ‘high’	7.6±1.9	24.3±3.9	68.1±5.0

It should be noted that regarding extreme categories ‘low’ and ‘high’, the structure of misclassified items allocation was logical. Namely, most of overlaps were between the directly neighbouring classes, ‘low’ with ‘medium’ and ‘high’ with ‘medium’. In case of category ‘medium’, the misclassified items mostly fell in the category ‘high’ and much less of them was recognized as members of category ‘low’. This asymmetry indicates considerable similarity of categories ‘medium’ and ‘high’, while category ‘low’ was more distinct than the two.

4.2 Two Categories of *Varroa Destructor* Infestation: ‘Low’ and ‘Medium to High’

Another approach consisted in determining two categories of *V.d.* infestation, namely ‘low’ and ‘medium to high’. Classification was realised using ensemble of classification trees and SVM. The results are shown in Figure 3 and Figure 4, respectively.

From the comparison of TC rates obtained when using ensemble of classification trees, infestation categories ‘low’ and ‘medium to high’ were distinguished more effectively (see Figure 3) than categories ‘low’, ’medium’ and ‘high’(see Figure 2),. TC rates associated with the recognition of categories ‘low’ and ‘medium to high’ were similar, at the level of about 83%, see Figure 5. Still, a considerable improvement could be achieved by applying another classifier. In case of using SVM, TC rate was 93% for category ‘low’ and 88% for category ‘medium to high’, see Figure 4. This result shall be recognized as very good.

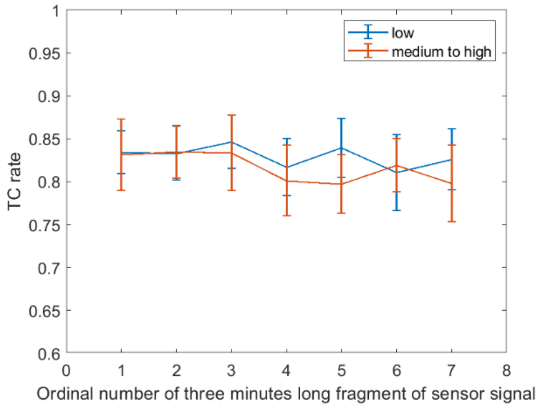

Figure 3: Results of classification for two categories of *V.d.* infestation: ‘low’ and ‘medium to high’. Ensemble of classification trees was applied and various fragments of gas sensors signals recorded during exposure to beehive air were utilised as the classifier input.

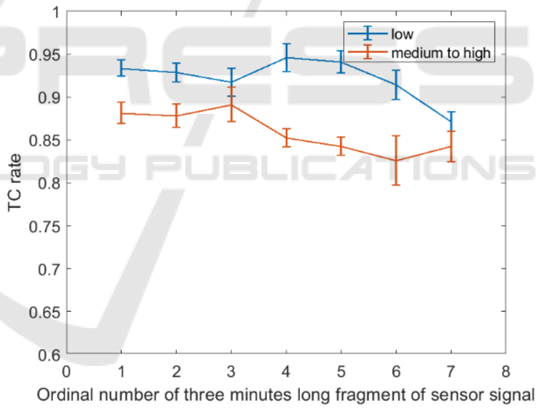

Figure 4: Results of classification for two categories of *V.d.* infestation: ‘low’ and ‘medium to high’. SVM was applied and various fragments of gas sensors signals recorded during exposure to beehive air were utilised as the classifier input.

It has to be added that the ensemble of classification trees was relatively insensitive to the fragment of gas sensor signal utilised as the source of input data. SVM favoured the information acquired during early stages of gas sensors exposure.

4.3 Two Categories of *Varroa Destructor* Infestation: 'High' and 'Medium to Low'

Additionally, the distinction of *V.d.* infestation categories 'high' and 'medium to low' was considered. Classification was based on gas sensor array measurements and it was realised using ensemble of classification trees and SVM. The results are shown in Figure 5 and Figure 6, respectively.

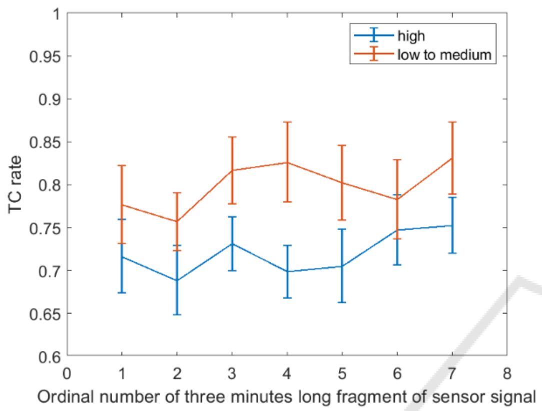

Figure 5: Results of classification for two categories of *V.d.* infestation: 'high' and 'medium to low'. Ensemble of classification trees was applied and various fragments of gas sensors signals recorded during exposure to beehive air were utilised as the classifier input.

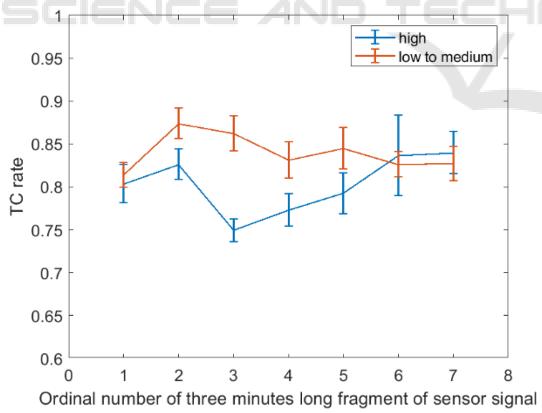

Figure 6: Results of classification when two categories of *V.d.* infestation are distinguished: 'high' and 'medium to low'. SVM was applied and various fragments of gas sensors signals recorded during exposure to beehive air were utilised as the classifier input.

From the comparison of TC rates obtained when using ensemble of classification trees, infestation categories 'high' and 'medium to low' (see Figure 5) were determined more effectively than categories 'high' and 'medium' (see Figure 2). However, the attained improvement was not substantial. True Category rate was, on average, 74% for recognition of category 'high' and 80% for category 'medium to high', see Figure 5. The change of classifier to SVM resulted in the increase of the classification performance indicators, up to the level of 80% and 84%, respectively (see Figure 6). In case of both classifiers, late fragments of gas sensor array signals were favoured as the sources of information.

5 DISCUSSION

Three approaches to classification of *V.d.* infestation of bee colonies were compared in this work. They consisted in the determination of:

1. three categories of infestation: 'low', 'medium' and 'high';
2. two categories of infestation: 'low' and 'medium to high';
3. two categories of infestation: 'high' and 'medium to low'.

The first approach was realised using ensemble of classification trees. In case of the second and third approach SVM was applied, additionally.

Ensemble of classification trees is applicable to both binary and multi class problems. Nevertheless, when using this method for binary problems (second and third approach) better results were attained, as compared with the multi class problem (first approach). Regarding binary classification tasks, further improvement was possible by applying SVM.

Clearly, the best discernible *V.d.* infestation category was 'low', no matter if binary or three class classification problem was formulated and solved. In this case, the best attained TC1 rates were at the level of 90%. This result indicates that conditions of no infestation or very weak infestation are quite clearly discernible from the conditions of medium or advanced infestation, based on gas sensor array responses.

The detection of *V.d.* infestation category 'high', was most difficult. The analysis of assignment of misclassified data, truly belonging to this category indicated a considerable overlap with the category 'medium' and vice versa. When realised in the framework of binary classification task, the detection of 'high' infestation rate was more effective. In particular, the use of SVM allowed for achieving TC1 rate about 80%.

The classification performance was examined for several fragments of gas sensors signals utilised as the sources of input data for the classifier. Clearly, the duration of gas sensors exposure to beehive air had an influence on the recognition of infestation categories. However, we have not identified any fragment which could be definitely preferred. One could notice, that the measurement data collected during first three minutes of gas sensors exposure to beehive air is a reasonable source of information about the infestation. This result justifies the measurement procedure which includes a relatively short period of gas sensors exposure to beehive air. This observation is highly beneficial from practical point of view.

6 CONCLUSIONS

The paper was dedicated to the recognition of several categories of bee colonies infestation by *Varroa destructor*, based on responses of gas sensor array to beehive air.

The results of the analysis demonstrated that first several minutes of gas sensors exposure to beehive air were sufficient to attain effective classification. Category representing 'low' infestation was determined most effectively, with an error rate of about 10%. Category 'high' was most difficult to determine. In this case the lowest error rate was about 20%. The approach based on binary classification granted higher performance as compared with three class classification. SVM outperformed ensemble of classification trees.

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