Classification of Postural Profiles among Mouth-breathing Children by Learning Vector Quantization

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Summary
Background: Mouth breathing is a chronic syndrome that may bring about postural changes. Finding characteristic patterns of changes occurring in the complex musculoskeletal system of mouth-breathing children has been a challenge. Learning vector quantization (LVQ) is an artificial neural network model that can be applied for this purpose.

Objectives: The aim of the present study was to apply LVQ to determine the characteristic postural profiles shown by mouth-breathing children, in order to further understand abnormal posture among mouth breathers.

Methods: Postural training data on 52 children (30 mouth breathers and 22 nose breathers) and postural validation data on 32 children (22 mouth breathers and 10 nose breathers) were used. The performance of LVQ and other classification models was compared in relation to self-organizing maps, back-propagation applied to multilayer perceptrons, Bayesian networks, naive Bayes, J48 decision trees, k*, and k-nearest-neighbor classifiers. Classifier accuracy was assessed by means of leave-one-out cross-validation, area under ROC curve (AUC), and inter-rater agreement (Kappa statistics).

Results: By using the LVQ model, five postural profiles for mouth-breathing children could be determined. LVQ showed satisfactory results for mouth-breathing and nose-breathing classification: sensitivity and specificity rates of 0.90 and 0.95, respectively, when using the training dataset, and 0.95 and 0.90, respectively, when using the validation dataset.

Conclusions: The five postural profiles for mouth-breathing children suggested by LVQ were incorporated into application software for classifying the severity of mouth breathers’ abnormal posture.

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1. Introduction

Breathing is the first vital function developed at birth. It becomes the most important body function and, as such, should be cared for. Chronic mouth breathing is associated with pediatric allergy-related and otorhinological complaints [1]. Narrowing of the pharynx has been reported to be associated with forward extension of the neck in order to attempt to straighten the pharyngeal tube and thereby improve the reduced airflow through it [2].

The skull, mandible, cervical portion of the spine and upper airways can be regarded as a system in which its parts are positioned in a close interrelationship. Mouth breathing is a physiological abnormality of the correct respiratory process that causes postural changes because of the abnormal, interrelated performance of the muscles in each of the parts of this system [3]. The main characteristics reported in studies on the posture of mouth-breathing children have been forward projection of head and shoulders, lordosis, protruding scapulas, frontal depression of the thorax, and protruding abdomen [4, 5]. The change to normal spinal curvature caused by mouth breathing does not resolve on its own when its etiological factors are eliminated [6].

The musculoskeletal system associated with human body posture is complex and includes a large number of musculoskeletal body structures. Since it is an integrated control system, changes involving one biomechanical unit of this system can lead to adjustments to other nearby or distant units within the system [7, 8].

The skeletal muscles work synergically. Along the vertebral column, for instance, they are arranged in a chain system [9], and the intrinsic complexity of the musculoskeletal systems may result in nonlinear mechanical relationships. For example, a study by Yi [10] was unable to show any linear relationship between excursion of the diaphragm muscle and spinal curvature behavior, although clinical practice suggested that a relationship existed between these biomedical variables.

Nonlinear relationships and large numbers of variables are characteristic of modern mathematical modeling in biomedici-
The use of traditional statistical methods is sometimes ineffective for describing the relationship between variables representing biomedical events. Such methods may therefore be rendered ineffective for presenting findings when biomedical datasets are analyzed [12]. The ineffectiveness of traditional statistical modeling is particularly critical when investigating patterns and determining categories from biomedical datasets.

In order to overcome the limitation of traditional statistics, a number of mathematical techniques based on parametric and nonparametric statistics have been devised, such as pattern recognition and clustering [13, 14]. However, artificial neural networks (ANNs), a non-traditional data analysis tool, have become a popular method for analyzing biomedical data [15–18].

An ANN is a system of interconnected units that process information by performing simple computations in parallel on a weighted basis and receiving feedback from other units [19]. ANNs can be applied as a semi-parametric tool to analyze sets of semi-parametric data [20]. They have become widely used in biomedical applications because they are generic tools for obtaining nonlinear maps that correlate sets of entry variables and sets of output variables [21]. In a previous study [22], we succeeded in determining different patterns of changes to the natural standing posture caused by mouth breathing among children, by using an unsupervised learning ANN model known as a self-organizing map (SOM) [23]. This model showed that different etiological factors involved in mouth breathing were associated with different postural profiles among mouth-breathing children.

Encouraged by the success of the above-mentioned study, and acknowledging that multidisciplinary treatment of mouth breathing (in particular concerning postural rehabilitation) is sometimes difficult to implement, software to support healthcare professionals in determining postural abnormalities among mouth-breathing children needs to be developed. Our proposal was to apply another ANN model, named learning vector quantization (LVQ) [23]. Unlike the SOM learning algorithm (competitive learning), LVQ uses supervised learning. This strategy is important in relation to classification and feature extraction when using clustering techniques [24].

2. Objectives

The present investigation aimed to apply LVQ to determine postural pattern categories among mouth-breathing children, for incorporation into application software for healthcare professionals. This software would also incorporate expert advice on the need for physiotherapeutic treatment for abnormal posture. Thus, it might be possible to use such software as a decision-making support tool that would both save unnecessary referral to orthopedic specialists and emphasize the cases of critical need for such referral.

3. Methods

This study was partitioned into two main tasks. First, LVQ was applied and validated to determine postural profiles among mouth-breathing children. Within this stage, we also proposed a software routine for automatically indicating postural changes. In the second stage, the results achieved using LVQ for automatic classification of mouth breathers and nose breathers were compared with the following other pattern classifiers [25]: SOM, back-propagation applied to multilayer perceptrons (BP) [19], Bayesian networks (BN) [26], naïve Bayes (NB) [27], decision trees (J48) [28], k* [29], k-nearest-neighbor classifiers (KNN) [30], and support vector machines (SVM) [31]. The present study was approved by the institutional ethics committee, under procedural number 0997/05.

3.1 Dataset

The study data included the variables used for postural assessments on 84 children (52 mouth breathers and 32 nose breathers). Table 1 shows the subject composition of each dataset (named DS1 and DS2) used in this study. DS1 and DS2 subjects were randomly included in the applicable databases.

Inclusion criteria: age 5 to 12 years, mouth breathing and free and informed consent form signed by guardian.

Exclusion criteria: craniofacial malformations, musculoskeletal disease, orthopedic traumas, respiratory diseases and neurological diseases.

3.1.1 Clinical and Otorhinolaryngological Examination

All participants underwent anamnesis and otorhinolaryngological clinical examination in order to define the nose and mouth-breather groups. The otorhinolaryngological clinical examination consisted of:

1. Anterior rhinoscopy: in order to detect the presence of obstructive factors, such as hypertrophy of inferior nasal turbinates.
2. Oroscopy: to assess oral cavity abnormalities. The degree of palatine tonsil hypertrophy was defined in accordance with criteria published by Brodsky [32].
3. Otoscopy: presence of tympanic membrane retraction and/or liquid level in middle ear.
4. Nasofibroscopy: carried out in order to assess the nasal cavities, septal displacement, turbinate hypertrophy and nasopharynx; to determine the degree of pharyngeal tonsil hypertrophy in relation to the right and left choanal spaces; and to measure the palatine tonsils that cause pharyngeal constriction.

The criteria for allergic rhinitis were the presence of symptoms such as coryza, nasal obstruction and sneezing, by means of a positive prick test. We included patients with both allergic and non-allergic rhinitis [9].

The clinical examination was of fundamental importance for identifying the obstructive factor and for enabling appropriate treatment. However, the definition of
“mouth breather” was based on clinical assessment.

Thus, children were defined as mouth breathers if they exhibited mouth breathing during consultation, with confirmation from their guardian that they had been predominantly breathing through the mouth for the previous six months, in addition to at least one of the following findings: skeletal crossbite, high-arched palate, anterior open bite, shortened upper and protruding lower lips or lips that did not seal. Children were defined as nose breathers (controls) if the signs and symptoms described above were absent [10].

### 3.1.2 Variables

Table 2 shows the variables used for postural assessment. DS2 included an extra variable showing the need for physiotherapeutic intervention among mouth-breathing patients. This variable also indicated the class of postural changes occurring among the mouth breathers investigated.

Figure 1 shows points and angles that were used as references for assessing posture, described as follows: a) Cervical lordosis: tragus of the ear, acromion and C7, such that the acromion was the apex of the angle. The larger this angle was, the further forward the position of the head and the lower the degree of cervical lordosis was.

b) Thoracic kyphosis: L1, acromion and T7, with an angle drawn from the acromion to L1 and from L1 to T7, such that L1 was the apex of the angle. The larger this angle was, the greater the degree of thoracic kyphosis was.

c) Lumbar lordosis was measured using an angle drawn between three anatomical points: L1, anterior superior iliac spine (ASIS) and the greater trochanters, such that ASIS was the apex of the angle. Here, the smaller the angle was, the greater the degree of lumbar lordosis was.

d) Position of the pelvis: an angle was drawn between three anatomical points: ASIS, the midpoint of the knee joint on the lateral face and the greater trochanters, such that the midpoint of the joint line was the apex of the angle. The greater the angle was, the further forward the pelvic tilt position was.

All subjects underwent postural assessment with the aid of photographs taken in left lateral view, thereby ensuring that the spinal curvatures were visible in sagittal profile.

Postural analysis was carried out using the SAPO (Software for Postural Analysis) postural analysis package (http://sapo.incubadora.fapesp.br). The analysis on the photographs consisted of the following steps: opening the photograph, zooming to 40%, calibrating the image based on the plumb-line and marking the anatomical points on the photograph.

Figure 2 shows the distribution charts for the variables of thoracic kyphosis, cervical lordosis, lumbar lordosis and pelvis positioning.

In addition, Student’s t-test [33] was performed to compare postural variables between mouth breathers and nose breathers. The means for these two groups were found to be significantly different (p < 0.05), as shown in Table 3.

### 3.2 Learning Vector Quantization

In addition to performing dimension reduction, thereby enabling representation of the relevant characteristics of the input

![Fig. 1 Points and angles used in postural assessment: a) cervical lordosis, b) thoracic kyphosis, c) lumbar lordosis and d) pelvis positioning. Available at http://sapo.incubadora.fapesp.br](http://sapo.incubadora.fapesp.br)
pattern (the main SOM property), LVQ also uses class information to make slight changes to the weight of each neuron in the grid, in order to improve the classifier decision [23]. Because of this characteristic, studies have reported that the performance of LVQ in relation to pattern recognition and feature extraction has been significant within the field of biomedicine [34, 39].

Specifically, LVQ uses a competitive learning rule. In this type of learning, the neurons are placed in a grid that is usually one- or two-dimensional. Maps with greater numbers of dimensions are possible but not as common, because visualizing them becomes problematic [19, 35]. For this reason, approaches involving models with other dimensions were rejected and the present study standardized on two-dimensional maps alone. The neurons were connected to adjacent neurons through a neighborhood relationship, thus dictating the map structure. The neurons on the map could be arranged in rectangular or hexagonal shapes [23].

3.2.1 Neighborhood Function

The neighborhood function determines how strongly the neurons are connected to each other. A Gaussian function is generally used to implement the neighborhood function [23]:

\[ h_{c,i}(t) = \exp\left(-\frac{\|c - i\|^2}{2\sigma^2(t)}\right), \]  

where \(c\) is the vector position of the neuron \(c\) and \(i\) is the vector position of the winning neuron \(i\). The calculation for the winning neuron is shown in Formula 3. The parameter \(\sigma^2(t)\) is the standard deviation of the neighborhood function [12].

The standard deviation of the neighborhood function \(\sigma^2(t)\) decreases with the number of steps \(t\) [23]. One popular choice for the dependence of \(\sigma\) on the discrete time \(t\) is the exponential decay given by the following (19):

\[ \sigma(t) = \sigma_0 \exp\left(-\frac{t}{\tau_1}\right), \]  

where \(\tau_1\) is a time constant.

In addition to the Gaussian function, a rectangular function, a Gaussian function with a cut-off or an Epanechnikov function can also be used as neighborhood functions for LVQ [23].
3.2.2 Training

At each training step, a sample $x$ is chosen at random from the entry pattern, and its similarity is calculated with all the neurons on the map, triggered by $m_i$ in function (3). The best-matching unit (BMU), also known as the winning neuron [12], is the unit in which the weight of the grid vector has greatest similarity with sample $x$ of the entry vector. The similarity is usually defined by the smallest value of the Euclidian distance between the vector $x$ and all the neurons of the grid, represented by the formula [12, 23]:

$$\|x - m_i\| = \min_{i} \|x - m_i\|.$$  \hspace{1cm} (3)

After determining the BMU, the vector values of the SOM neurons are updated. The values for the BMU and its topological neighborhoods move close to the vector for the entry pattern of the entry space. Specifically for the LVQ, there are different rates for updating the neuron weights. If sample $x$ from the entry pattern corresponds to the same neuron class (determined when initializing the LVQ grid), the updating rate is given by the following [23]:

$$m_i(t + 1) = m_i + \eta(t) * h_{cin}(t)[x(t) - m_i(t)],$$  \hspace{1cm} (4)

where $t$ is the time, $\eta(t)$ is the learning rate and $h_{cin}(t)$ is the neighborhood function around the winning neuron $c$.

Likewise, if sample $x$ from the entry pattern does not correspond to the same neuron class, the updating rate is given by the following [23]:

$$m_i(t + 1) = m_i - \eta(t) * h_{cin}(t)[x(t) - m_i(t)].$$  \hspace{1cm} (5)

This updating rule leads to topological ranking of the character maps in the entry space, in the sense that neurons in the same category will tend to have vectors of similar synaptic weight [12].

Specifically, the learning parameter $\eta(t)$ is a variable in time that corresponds to the case of stochastic approximation. In particular, it should start with a value $\eta_0$ and then gradually decrease with increasing time $n$. This requirement can be satisfied by choosing an exponential decay for $\eta(t)$, as shown in the following [12]:

$$\sigma(t) = \sigma_0 \exp \left(-\frac{t}{\tau_2}\right),$$  \hspace{1cm} (6)

where $\tau_2$ is a time constant.

3.2.3 Classification Process

After adjusting the neuron weights (done during the training stage), classification of a new sample will take place when it is presented to LVQ. A BMU is indicated as represented in Formula 3. Specificity and sensitivity are calculated according to the classification of the neuron (mouth breathing or not) and the classification of the sample that has been presented.

3.3 Leave-one-out

Given a sample with $n$ cases or sets of variables, the leave-one-out algorithm (LOO) consists of using $n - 1$ sets of variables to train the ANN model, with the $n$-th case held out to test the model. This process is repeated $n$ times until each of the $n$ sets of the sample has been used to test the model [36].

3.4 ROC Curve

The ROC curve correlates sensitivity with the complement of specificity attained by any pattern recognition tool for different ranges of values assumed by one or more of the variables/parameters analyzed. In ANN applications, it is used to determine the classifier showing the best performance [37]. The performance of each classifier is measured by computing the area under the curve (AUC) plotted for each classifier. Larger AUCs will determine classifiers with better performance [37].

One critical point when using ROC curves to compare performances is to determine the range of inputs to be analyzed. In this study, each LOO iterative step was proposed as a range for comparison.

3.5 Inter-rater Agreement (Kappa Statistics)

The inter-rater agreement (Kappa statistics) [39] is used to evaluate the agreement level between two classifications on ordinal or nominal scales. The agreement is quantified by the weighted Kappa (WK), which in this study was calculated using a 95% confidence interval. The WK values are presented in Table 4 [39]. The aim in using WK values was to identify the agreement level between the classifiers studied and the gold standard.

3.6 Software

The SOM Toolbox version 2.0 [40] package was used to implement SOM and LVQ neural models and the Neural Networks Toolbox® version 4.0.1 (MathWorks Inc., Natick, MA, USA) was used to implement the perceptron and BP models. Both software packages allow implementation of ANN algorithms through Matlab® version 7.0 (MathWorks Inc., Natick, MA, USA). After performing several tests with different parameters, the final configurations of the SOM Toolbox and ANN Toolbox for ANN models and DS1 that attained best accuracy were:


<table>
<thead>
<tr>
<th>WK value</th>
<th>Agreement strength</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 0.20</td>
<td>poor</td>
</tr>
<tr>
<td>0.21–0.40</td>
<td>fair</td>
</tr>
<tr>
<td>0.41–0.60</td>
<td>moderate</td>
</tr>
<tr>
<td>0.61–0.80</td>
<td>good</td>
</tr>
<tr>
<td>0.81–1.00</td>
<td>very good</td>
</tr>
</tbody>
</table>

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Neighborhood function: Gaussian. Running length: 100. Learning rate: 0.001.

Visual Basic 6.0© (Microsoft Corporation) was used to implement a classifier for mouth-breathing children's posture, and Microsoft Access® 2002 (Microsoft Corporation) was used to create a databank for the data from the present study.

In addition, the Weka program version 3.5.2 [26] was used to implement pattern recognition models. Several tests were performed using different parameters in data mining models, and the final configurations with the best accuracy can be accessed at http://telemedicina6.unifesp.br/projeto/methods.html. Furthermore, Kappa was performed using MedCalc®, version 10.4.8.0 (MedCalc Software, Mariakerke, Belgium).

4. Results

4.1 Postural Profile Determination among Mouth-breathing Children

4.1.1 LVQ Training

As the LVQ model allowed visualization of its neural topology, the labeling of the neurons in the LVQ neural structure was performed using DS1. This labeling reflected the largest number of neuron activations by data referring to either nose-breathing or mouth-breathing children during the training of the ANN model.

Figure 3a shows the neuron identification after training: neurons 1, 4 and 7 were characteristically activated by data from nose breathers and neurons 2, 3, 5, 6, 8 and 9 by data from mouth breathers. This labeling reflected the largest number of neuron activations by data referring to either nose-breathing or mouth-breathing children during the training of the ANN model. LVQ attained specificity of 0.95, sensitivity of 0.90 and AUC of 0.92 for the classification of mouth-breathing children.

Figure 4a shows the LVQ topology for DS2 mouth-breathing children who were prescribed spinal rehabilitation treatment. By comparing the two topological patterns and the numbers of


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children with the same diagnosis associated with activation of one neuron, the following classes or postural profiles were established (Fig. 4c):

- **Class A**: mouth-breathing children with critical postural problems needing spinal rehabilitation care (associated with neurons 8 and 9).
- **Class B**: mouth-breathing children with moderate changes to normal posture (associated with neurons 5 and 6).
- **Class C**: mouth-breathing children with posture slightly affected (associated with neurons 2 and 3).

Two other classes were also proposed:

- **Class D and E**: nose breathers with slightly altered posture (associated with neurons 1, 4 and 7).

4.2 LVQ Accuracy Comparison

LVQ accuracy was compared with that of other pattern classification algorithms: SOM, BR, BN, NB, J48, k*, KNN and SVM. DS1 was used as the input pattern and LOO was the validation technique applied. Sensitivity, specificity and AUC and their 95% confidence intervals attained are shown in Table 5.

Kappa statistics were applied to obtain the agreement level between the classifier models and the gold standard. For this test, we used DS1 and LOO. The WK values for each classifier are shown in Table 6.

5. Discussion

One important feature of LVQ and SOM is that, unlike other classifiers, the neural topology (neighboring neurons) allows the developer to have a view of the classification inside a map and help prompt new patterns (Figs. 3 and 4). Although the LVQ specificity rate was lower than in BN and NB models, it should be noted that...

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**Table 5** Mean specificity, sensitivity and area under ROC curve (AUC) attained by each classifier studied, calculated using leave-one-out cross-validation and dataset 1

<table>
<thead>
<tr>
<th>Classifiers</th>
<th>Specificity</th>
<th>CI Specificity</th>
<th>Sensitivity</th>
<th>CI Sensitivity</th>
<th>AUC</th>
<th>CI AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>BN</td>
<td>1</td>
<td>1</td>
<td>0.9</td>
<td>0.78–1.01</td>
<td>0.94</td>
<td>0.87–1.00</td>
</tr>
<tr>
<td>NB</td>
<td>1</td>
<td>1</td>
<td>0.9</td>
<td>0.78–1.01</td>
<td>0.94</td>
<td>0.87–1.00</td>
</tr>
<tr>
<td>LVQ</td>
<td>0.95</td>
<td>0.86–1.04</td>
<td>0.9</td>
<td>0.78–1.01</td>
<td>0.92</td>
<td>0.84–0.99</td>
</tr>
<tr>
<td>KNN</td>
<td>0.95</td>
<td>0.86–1.04</td>
<td>0.9</td>
<td>0.78–1.01</td>
<td>0.92</td>
<td>0.84–0.99</td>
</tr>
<tr>
<td>SVM</td>
<td>0.95</td>
<td>0.86–1.04</td>
<td>0.9</td>
<td>0.78–1.01</td>
<td>0.92</td>
<td>0.84–0.99</td>
</tr>
<tr>
<td>SOM</td>
<td>0.95</td>
<td>0.86–1.04</td>
<td>0.87</td>
<td>0.73–0.99</td>
<td>0.91</td>
<td>0.82–0.98</td>
</tr>
<tr>
<td>BP</td>
<td>0.91</td>
<td>0.77–1.03</td>
<td>0.9</td>
<td>0.78–1.01</td>
<td>0.9</td>
<td>0.79–0.97</td>
</tr>
<tr>
<td>J48</td>
<td>0.86</td>
<td>0.70–1.01</td>
<td>0.9</td>
<td>0.78–1.01</td>
<td>0.88</td>
<td>0.79–0.97</td>
</tr>
<tr>
<td>k*</td>
<td>0.86</td>
<td>0.70–1.01</td>
<td>0.87</td>
<td>0.73–0.99</td>
<td>0.86</td>
<td>0.76–0.96</td>
</tr>
</tbody>
</table>
the LVQ sensitivity rate was the same as the
BN and NB rates, as seen in ▶Table 5.
Moreover, the WK values presented in
▶Table 6 did not reveal any difference in
agreement strength (WK > 0.81, ▶Table 4)
between the LVQ and Bayesian approaches.
We can thus say not only that LVQ helped in
discovering new categories but also that
this RNA model showed important results
in relation to the task of pattern recogni-
tion.

In addition, the results shown in ▶Ta-
ble 5 suggest that SOM presents lower accu-
rac}y for postural classification, compared
with the LVQ model. Moreover, although
tests with SOM were carried out to deter-
mine profiles for mouth-breathing chil-
dren, the feature extraction for this ANN
model was worse than that of LVQ. SOM
showed problems while separating relevant
postural profiles, and some SOM artificial
neurons could not correctly indicate either
nose breathers/mouth breathers or visual
clusters. Some studies [34, 41] have re-
ported that SOM shows difficulties in clas-
sifying biomedical data. In this ongoing
work, the ANN model presented the same
behavior. Furthermore, we can show that
LVQ boosted the feature extraction because
of the supervised learning.

As configured in the present study, LVQ
showed specificity and sensitivity rates of
0.90 and 0.95, respectively, for recognizing
mouth-breathing children by using pos-
tural parameters in the model validation.
However, some remarks regarding posture
need to be made:

● As seen in ▶Figure 3c, LVQ classified
one mouth-breathing child as a nose-
breathing child. This was a case of a
mouth breather who was declared by a
specialist as having no problems with his
spine.

● Conversely, ▶Figure 3b shows a nose
breather classified as a mouth-breathing
child. However, this child was classi-
fied as needing no spinal rehabilitation
(class C).

The above events may constitute evidence
that some nose-breathing and mouth-
breathing children share the same postural
profile, which could be either characteristic
of normal spinal curvature or character-
istic of slight abnormality of the spine.

Use of the LOO cross-validation algo-
rithm for the first phase has been reported
to be a good choice when working with
fairly small number of attributes [19, 41],
as in the dataset used in the present study.

Furthermore, exploratory use of k-fold
(fivefold and tenfold) [36] cross-validation
algorithms was also performed. This
yielded sensitivity and specificity rates
lower than those attained with LOO. Two
reasons may account for the lower rates of
k-fold sensitivity and specificity obtained
with k-fold cross-validation in this study:
a) the higher rates attained with LOO may
de be due to its intrinsic rounding up of the
final neuron weight vector during the
validation procedure; and b) there may be
intrinsic variability of sensitivity and
specificity rates in k-fold cross-validation,
linked to the variable randomization ob-
tained in each instance of data sampling,
on each occasion when a k-fold test is carried
out.

Finally, the present study showed that
most mouth-breathing children had a
characteristic type of posture, and that de-
termination of postural categories was pos-
sible through the use of LVQ. Identification
of such patterns enabled development of
an automatic postural classification tool
that would potentially be useful for pos-
tural treatment among mouth-breathing
children. However, because the database
was small, it needs to be determined
whether the results shown by LVQ might
present any problems of overfitting. Thus,
进一步 studies could determine the effec-
tiveness of the present tool in relation to
two main approaches:

First, there could be an assessment com-
paring the classification of the level of pos-
tural abnormality provided by the system
with the classification made by the medical
treatment provider.

Second, there could be an assessment of
the effectiveness of postural rehabilitation
compliance among mouth-breathing pa-
tients. We believe that a tool that can sup-
port health providers’ decisions would be
able to provide more information and
guidance to mouth-breathing patients not
only regarding their treatment for nasal
obstruction but also their postural rehabili-
tation therapy, thereby reinforcing a multi-
disciplinary approach towards treating
mouth-breathing children. This approach
can be guided by the children’s compliance
with postural rehabilitation therapy before
and after the implementation of this tool
in multidisciplinary centers caring for
mouth-breathing children.

6. Conclusion
By using the LVQ model, it was possible
to determine postural patterns among
mouth-breathing children. The LVQ model
showed satisfactory performance in terms
of sensitivity and specificity (0.90 and 0.95,
respectively). Five postural categories for
mouth-breathing children were deter-
mined and incorporated into application
software for classifying the severity of
mouth breathers’ abnormal posture.

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Souza.

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