Support Vector Machine Optimized by Firefly Algorithm for Emphysema Classification in Lung Tissue CT Images

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ABSTRACT

Digital images and digital image processing facilitated significant progress in numerous areas where medicine is an important one of them. Computer-aided detection and diagnostics systems are used to assist specialists in interpretation of medical digital images. One of the important research issues is detection and classification of the chronic obstructive pulmonary disease in lung CT images. In this paper we proposed a method for emphysema classification based on texture and intensity features. Only six different characteristics of the uniform local binary pattern and intensity histogram were used as input vector for support vector machine that was used as classifier. Feature vector was significantly reduced compared to the other state-of-the-art methods while the classification accuracy was increased. On images from standard dataset global accuracy of our proposed algorithm was 98.18% compared to 95.24% and 93.9% of two other compared algorithms.

Keywords

Support vector machines, lung tissue classification, CT images, image processing, firefly algorithm, swarm intelligence

1 INTRODUCTION

Digital images and digital image processing have been proven to be of great use in medicine. Numerous sources have been used for gathering digital images of various tissues and organs, such as X rays, ultrasound, magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET). Each of these image types have good and bad characteristics, thus they are all used for different organs, diseases and anomalies. Since MRI, CT, PET and other medical devices and procedures produce a large number of images that need to be analyzed in short time, computer-aided detection and diagnosis systems (CAD) are very useful to speed up the process, highlight suspicious parts, enhance image quality for easier diagnostic, etc.

One of the extensively studied topic is detection of chronic obstructive pulmonary disease (COPD). Usual method for early stage detection of COPD is by using CT imaging which enables detection of emphysema. Example of lung slice CT image is shown in Fig. 1.

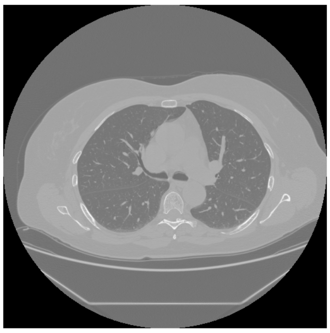


Figure 1: Lung CT slice

Emphysema stands for a long-term and progressive disease of the lungs that causes shortness of the breath. In CT images emphysemas can be recognized as regions close to the air with low attenuation values. Three different types of emphysemas can be recognized, centrilobular emphysema (CLE), paraseptal emphysema (PSE) and panlobular emphysema (PLE). Examples of normal tissue (NT), CLE and PSE are shown in Fig. 2.

In recent years different approaches were proposed for emphysema detection and classification. Some of the well known classifiers were used for labeling the types of the tissues such as k nearest neighbor [IM14], artificial neural networks [BSBY14], convolution neural

(a) NT - normal tissue (b) CLE - centrilobular emphysema (c) PSE - paraseptal emphysema

Figure 2: Examples of the normal tissue and different emphysemas

network [SSK15], [ACE+16], etc. Besides the classification method, feature selection is a very important part of the CAD system for emphysema classification, i.e. diagnosis determination. Numerous papers propose different texture features combined with the image intensity, while the other use some other features such as invariant moments, structural co-occurrence matrix and others.

In this paper, we proposed a method for emphysema lesion detection and classification. For classification support vector machine (SVM) was used and the lung tissues were described by uniform local binary pattern (LBP) and intensity histogram features. Only six different characteristics of the uniform local binary pattern and intensity histogram were used as input vector for support vector machine that was used as classifier. Feature vector was significantly reduced compared to the other state-of-the-art methods while the classification accuracy was increased.

The remainder of this paper is organized as follows. In Section 2 literature review on recent proposed methods for emphysema lesion classification are discussed. In Section 3 our proposed method is described. Experimental results along with comparison with other state-of-the-art methods are presented in Section 4. At the end, conclusion and possible further work are given in Section 5.

2 LITERATURE REVIEW

Computer-aided diagnosis systems were exhaustively studied in the recent years [TTD17]. In [DBF+13] a CAD system for breast cancer detection in mammographic images was proposed, while in [KY14] CAD for brain tumor detection in MRI images was developed. In [STT16] a method for brain MRI abnormality detection was proposed. Another computer-aided diagnosis systems from literature deal with Alzheimer's type dementia classification [RGSG+13], detection of Parkinson's disease [HAB15], cancer detection [LC15], etc. Different image processing techniques were used such as edge detection [NTT16], multilevel thresholding [Tub14], etc.

CAD for chronic obstructive pulmonary disease detection, especially emphysema, represents one of the important research topics. In general, there are two main steps in these systems: feature extraction and classification.

In [DSS15] features based on local diagonal extrema pattern (LDEP) for CT images were proposed. The relationship between central pixel and diagonal neighbors was described by using the first order local diagonal derivatives. Indexes and values of the local diagonal extremes were found and compared with the intensity of the central pixel. Features were formed based on these indexes and comparisons. Feature dimension was reduced by using only diagonal neighbors and it was shown that it represents an efficient feature descriptor.

A cascade method that combines multi-fractal features and alpha histograms descriptors was proposed in [IM15]. Multi-fractal features were useful to differentiate normal tissue and abnormalities while alpha histogram descriptor additionally improved classification accuracy. For classification naive Bayes classifier was used.

In [NERCE14] emphysema classification framework based on complex Gabor filters and local binary patterns was proposed. By combining these two features global characteristics as well as local information were described and additionally kernel Fisher analysis was used to reduce the size of feature vector. For classification *k*-nearest neighbor classifier was used and it was reported that combination of the mentioned descriptors represents effective features for emphysema classification.

Quality of a learning technique to classify emphysema based on embedded probabilistic principal component analysis (PPCA) was tested in [ZCKR+13]. The first step of the proposed method was to find the most discriminant linear space for each emphysema pattern against the remaining patterns where lung CT image patches can be embedded. PPCA model was trained for each pattern. Contribution of the mentioned paper is the ability to compute the class membership posterior probability for each emphysema pattern. Proposed method has shown competitive results against different texture-based approaches.

In [KWE14] five classes of increasing disease severity were considered. Three different methods were exploited for this multi-class classification problem. The first method used a global rankSVM for ranking, while hierarchical SVM was used for classification. Finally combination of these two classifiers was proposed and named hierarchical rankSVM. Results have shown that hierarchical approaches were computationally efficient and classification achieved accuracies were a little better in the case of hierarchical SVM.

Physician-in-the-loop feedback approach was proposed in [RRK+14] in aim to minimize ambiguity in the selected training samples. Multiple metrics for features were used and seven unoptimized support vector models were built for each of them. The training samples were classified by using these seven SVM models. Label of the region of interest was determined by majority voting.

In [YFAL16] texton-based method for classification of emphysema was proposed. Lung textures were described by the nearest-texton frequency histograms. Experiments were done for characterizing lung textures with sparse decomposition from texton dictionaries while different regularization strategies were used. Additionally, the sparsity-inducing constraints were introduced to the construction of the dictionaries. Accuracy higher than 90% was reported.

In [KI15] convolution neural network (CNN) was proposed for emphysema classification. As input for the proposed classifier raw high resolution CT images of lung were used. It was reported that promising accuracy has been achieved. Another method that uses CNN was proposed in [Pei15]. Feature extraction was done by CNN as well as classification. It was reported that for differentiation of normal tissue and one type of emphysema high accuracy was achieved.

Local binary pattern was frequently used for emphysema description. In [NKOS15] comparative study of basic LBP and two variations, completed LBP (CLBP) and local ternary pattern (LTP), was presented. Joint histogram of density and texture histogram was used as input vector for linear SVM. Histograms were calculated for regions of different sizes and the best results were 81.36%, 82.99% and 83.29% for LBP, CLBP and LTP respectively. Another method that uses LBP was proposed in [SSdB10]. Combined histogram of the LBP and intensity histogram was used as input vector for adjusted k-nearest neighbor classifier. Classification accuracy was 95.4%.

This review shows that emphysema classification systems represent an important and active research area. In this paper we try to develop faster and more accurate algorithm based on fewer features, hence appropriate for further improvements.

3 OUR PROPOSED METHOD

In this paper we propose a computer-aided system for emphysema classification. The proposed method consists two main parts, feature extraction and classification. In the past it has been proven that different types of emphysema can be well distinguished by the texture features [SSdB10], [YFAL16]. We propose rotation invariant version of local binary pattern as a texture descriptor. For better classification results these features were combined with intensity features. Appropriate features are mandatory for high classification accuracy but accuracy also depends on the quality of the classifier. In this paper we propose very successful classifier, support vector machine, optimized by fireworks swarm intelligence algorithm.

3.1 Feature extraction

Local binary patterns (LBP) are well known texture feature descriptors. Originally, LBP were proposed as an invariant measure for local structure in 3×3 neighborhoods. Different modifications were proposed later and nowadays are used as a simple but good texture descriptor. Binary patterns are obtained by thresholding circular neighbor pixels according to the central pixel. LBP value of the central pixel (x, y) is defined by the following equation:

$$LBP_{P,R} = \sum_{p=0}^{P} s(I(x_p, y_p) - I(x, y))2^P \qquad (1)$$

where P is the number of neighbor pixels at distance R that will be considered, $I(x, y)$ is the intensity of the central pixel (x, y) and function s is defined as:

$$s(k) = \begin{cases} 1 & \text{if } k \geq 0, \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

Fig. 3 represents illustration of Eqs. 1 and 2.

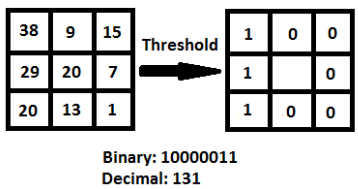


Figure 3: LBP

After obtaining the LBP which are actually binary codes, histogram is made. Size of the histogram is determined by the number of the possible binary codes which is defined by the number of considered neighbor pixels P.

One of the LBP characteristic is that it is invariant to any monotonic gray-scale transformation. As long as relative relation between pixel intensities is saved after transformations, LBP remains the same. LBP has been widely studied in the past thus numerous modifications of LBP can be found in literature. One of the highly desirable characteristic of texture descriptors is rotation invariance and various changes of LBP were proposed to achieve this. In this paper we used uniform LBP. In uniform LBP, number of the possible patterns is reduced. Instead of considering all possible patterns only those that contain less than two transitions from 0 to 1 (or 1 to 0) are used while all others are considered as the same pattern. If 8 neighbor pixels were used for forming LBP ($P = 8$, $R = 1$), the number of patterns is reduced from 2^8 =256 to 59. In this paper, uniform local binary patterns were transformed into decade numbers and normalized histogram of occurrence frequencies was made.

Besides texture descriptor, LBP histogram, normalized intensity histogram was used. In [SSdB10] joint LBP and intensity histogram were also used and it has been proven that intensity information significantly increases classification accuracy.

Histograms are usually used as input feature vectors and since intensity histogram is a 256-dimensional vector and uniform LBP histogram is 59-dimensional vector the input vector would be 315-dimensional. Larger dimension of feature vectors can make classification more difficult. Instead of using complete histograms in this paper we propose to use just some histogram characteristics. Numerous metrics are used to provide useful information based on the histogram. In this paper we used six common metrics. For each histogram, uniform LBP and intensity histogram mean (μ), standard deviation (σ), skewness, kurtosis, energy and entropy were calculated and used as input vector. If normalized histogram is annotated by p and N represents the number of histogram values then these metrics can be calculated by the following equations:

$$\mu = \sum_{i=0}^{N} i * p(i) \tag{3}$$

$$\sigma = \sqrt{\sum_{i=0}^{N} (i-\mu)^2 * p(i)} \tag{4}$$

$$\mathrm{skewness} = \frac{1}{\sigma^3} \sum_{\mathrm{i}=0}^{\mathrm{N}} (\mathrm{i}-\mu)^3 * \mathrm{p(i)} \tag{5}$$

$$\mathrm{kurtosis} = \frac{1}{\sigma^4} \sum_{\mathrm{i}=0}^{\mathrm{N}} (\mathrm{i}-\mu)^4 * \mathrm{p(i)} - 3 \tag{6}$$

$$\mathrm{energy} = \sum_{\mathrm{i}=0}^{\mathrm{N}} \mathrm{p(i)}^2 \tag{7}$$

$$\mathrm{entropy} = -\sum_{\mathrm{i}=0}^{\mathrm{N}} \mathrm{p(i)} * \log_2 \mathrm{p(i)} \tag{8}$$

By using these metrics the 12-dimensional feature vector is used (6 dimensions for the LBP histogram and 6 dimensions for the intensity histogram) instead of earlier mentioned 315-dimensional vector hence input vector for classifier is significantly reduced.

3.2 Classification

In this paper we used one of the widely used and very successful binary classifier: support vector machine (SVM). Emphysema classification represents multiclassification problem. In order to use binary classifier for multiclassification two method were proposed in literature - *one against one* and *one against all*. In this paper we used *libsvm* package for building SVM models where *one against one* method was implemented and the final decision was made by voting.

Accuracy of the SVM classification, besides depending on the chosen features, also depends on selection of the two parameters, soft margin parameter C and kernel function parameter. SVM model is defined by solving quadric optimization problem:

$$\frac{1}{2}||w||^2 + C\sum_{i=1}^{n} \varepsilon_i, \tag{9}$$

where w is normal vector to the hyperplane and ε_i are slack variables.

Kernel function is used for nonlinear SVM and Gaussian radial basis function kernel (RBF) is usually a good choice. RBF is defined by the following equation:

$$K(X_i, X_j) = \exp(-\gamma||X_i - X_j||^2). \tag{10}$$

where X_i and X_j represent two feature vectors. C is the parameter for the soft margin cost function and controls the influence of each individual instance. Kernel function is used for enabling non-linear separable data to be classified by SVM. One of the most used kernel function is RBF which has a free parameter γ. Large γ will lead to high bias and low variance model, and vice-versa.

For building an optimal SVM model, values for the pair (C, γ) need to be found. The simplest method to find a good parameter pair is to use grid search. SVM model is build for numerous pair values and the best one is chosen for SVM training. Grid search is simple but it is also computationally expensive and represents discretized search for continuous parameters. Finding the optimal parameters is a hard optimization problem and one of the methods for solving them is usage of different metaheuristics. In the last decades nature inspired algorithms, especially swarm intelligence algorithms were proposed and successfully used for such problems.

In literature different swarm intelligence algorithms were applied to finding optimal SVM parameters problem. In [BHX13] particle swarm optimization (PSO) and pattern search based memetic algorithm were used for SVM parameters tuning while in [LH15] PSO was hybridized by artificial bee colony and adjusted for

SVM optimization. Fireworks algorithm for SVM optimization was proposed in [TTB16], [TTS16].

In this paper we adjusted a novel firefly algorithm (FA) for tuning SVM parameters for emphysema classification. Firefly algorithm was proposed in [Yan09] by Yang and it is inspired by social and flashing behavior of fireflies. It has been successfully used in numerous applications [BT14a], [BT14b], [TB14]. Fireflies are attracted by their lights where attractiveness of one firefly is directly proportional to its brightness. The brightness is defined by the following equation:

$$I(X) = \begin{cases} \frac{1}{f(X)} & \text{if } f(X) > 0 \\ 1 + |f(X)| & \text{othewise.} \end{cases} \quad (11)$$

where X represents position of the firefly and f is objective function. Attractiveness β depends on the distance between fireflies:

$$\beta(r) = \frac{\beta_0}{1 + \gamma r^2} \quad (12)$$

The position of a firefly i attracted to more attractive or brighter firefly j is updated by the following equation:

$$x_i^{t+1} = x_i^t + \beta e^{\gamma r_{ij}^2}(x_j^t - x_i^t) + \alpha_t \varepsilon_i^t \quad (13)$$

where β_0 represents attractiveness at $r = 0$, α is randomization parameter, ε_i^t represents a vector of random numbers drawn from a Gaussian distribution or uniform distribution at time t, and r_{ij} is distance between two fireflies (i, j).

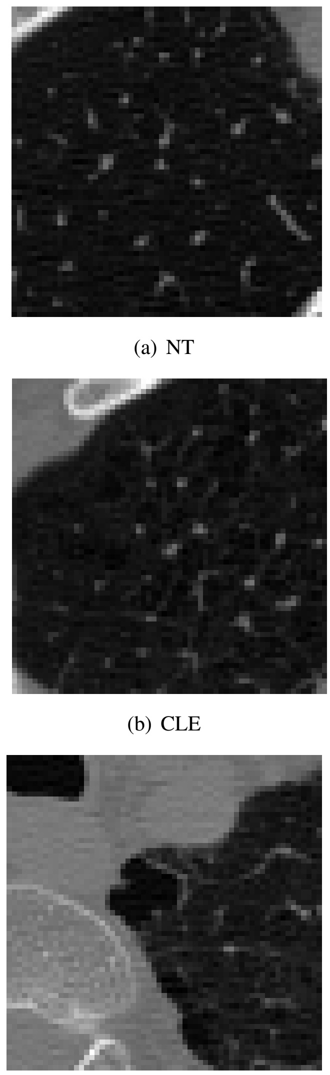
In our previous work [TMT16] we proposed FA for SVM optimization and the proposed method was tested on standard benchmark classification problems. The proposed method achieved better results comparing to the other state-of-the-art algorithms. FA algorithm was used for 2-dimensional problem, where search range for the first parameter C was set to be $[2^{-5}, 2^{15}]$ while the second parameter γ was in range $[2^{-15}, 2^{5}]$. Objective function was accuracy from 10-fold cross validation.

4 EXPERIMENTAL RESULTS

Proposed algorithm was implemented in Matlab R2016a while SVM was built by LIBSVM (Version 3.22) [CL11]. Experiments were performed on the platform with the following features: Intel ® Core$^{\text{TM}}$i7-3770K CPU at 4GHz, 8GB RAM, Windows 10 Professional OS.

Parameters for the FA were set empirically as follows: $\alpha = 0.2$, $\gamma = 0.23$ and $\beta_0 = 1$. Population size was 50, while the maximal number of iteration was set to 30. Additionally, if the accuracy did not improve in 10 consecutive iterations, algorithm stops. SVM parameters C and γ were searched in exponential space, search range for exponent for C was set to $[-10, 20]$ and the SVM model was built for $C = 2^x$ where x is parameter selected by FA, while exponent for parameter γ was searched in interval $[-20, 10]$ and similarly for SVM model $\gamma = 2^y$ was used where y was generated by FA.

For the experiments we used standard public computed tomography emphysema database [SSdB10] available for download at *image.diku.dk/emphysema_database/*. Database contains 168 manually labeled 2D regions of interest (ROI) of size 61×61, slice thickness 1.25 mm and in-plane resolution of 0.78 mm $\times$ 0.78 mm. Three different types of ROI exist in the database, normal tissue (NT), centrilobular emphysema (CLE) and paraseptal emphysema (PSE). Examples of the patches from the database are shown in Fig. 4.



(a) NT

(b) CLE

(c) PSE

Figure 4: Examples of the regions of interst (normal tissue and emphysema) from the used database

The first part is to train support vector machine model for region classification based on the patches in the used dataset. Because of the small number of patches (only 168) in the dataset, in most papers that used this dataset (including the papers that we compare with), all images were used for training. Since in this paper we proposed region based classification method with the region size of 31×31, for each patch 961 overlapping blocks were obtained (each patch size is 61×61), thus we were able to provide training set and test set based on the patches in the database. SVM model was trained with 1000 randomly chosen blocks for each class from different patches (3000 training regions in total). Test set had 1500 regions (500 from each class).

The best SVM model was for $C = 2^{18.23}$ and $\gamma = 2^{-12.36}$ where global accuracy was 98.18. In Table 1 confusion matrix of classification is presented. The rows represent true labels and in columns are labels assigned by SVM model. The results are in percents.

	NT	CLE	PSE
NT	100	0	0
CLE	0	100	0
PSE	0	5.47	94.53

Table 1: Confusion matrix for ROI classification by our proposed method (accuracies in %)

In order to prove quality of our proposed algorithm, we compared our results with two other methods. The first one was proposed in [SSdB10] where different rotation invariant LBP were used also along with the intensity histogram. Classification was done by k-nearest neighbor. Input vector for the classifier was joint LBP and intensity histogram. The second algorithm that was used for comparison was proposed in [YFAL16]. In [YFAL16] lung textures were described with sparse decomposition from texton dictionaries when different regularization were used. Sparsity was further expanded by adding constraints to the dictionaries.

In [SSdB10] global accuracy of the classifier was 95.24%. Global accuracy of patches classification by our proposed method was 98.18%. In [SSdB10] the largest error was made for classification NT class, where 93.22% was correctly classified while 6.88% was classified as PSE. Our proposed method had the lowest accuracy for classification of the PSE class - 94.53%. Instances from PSE class were classified as CLE in 5.47%. Instances of NT and CLE classes were classified with 100% accuracy. In [YFAL16] only global accuracies for different proposed methods were reported. The highest accuracy was 93.9%, while other methods achieved accuracies of 92.1%, 91.8%, 92.4% and 91.7%. All reported results in [YFAL16] were lower than the accuracy of our proposed method that achieved 98.18%. The comparison results are summarized in Table 2.

Our proposed method also achieved better results for classification patches compared to [NKOS15] where complete joint histograms of three different LBP variants and intensity were used as input for linear SVM. Reported accuracies were 81.36%, 82.99% and 83.29% while accuracy of our proposed method was 98.18%.

	THM	LBP-kNN	GFWA
NT	-	93.22	100
CLE	-	98.00	100
PSE	-	93.91	94.53
global acc.	93.9	95.24	98.18

Table 2: Comparison results of our proposed method and methods proposed in [SSdB10] and [YFAL16]

5 CONCLUSION

In this paper a method for lung tissue classification was proposed. Different lung tissues were described by simple and powerful texture features, uniform local binary patterns. Beside texture features, intensity features were used. In this paper feature vector was reduced comparing to the other state-of-the-art approaches by using histogram characteristics such as mean, standard deviation, skewness, kurtosis, energy and entropy, rather than the whole histogram. Compared to the other methods from the literature our proposed method achieved higher accuracy for classification of regions of interest provided in standard benchmark dataset. In further work feature selection can be included in the proposed algorithm and it can be additionally adjusted for CT image segmentation by introducing the fourth class that will distinguish lung tissue from the background.

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7 REFERENCES

[ACE+16] Marios Anthimopoulos, Stergios Christodoulidis, Lukas Ebner, Andreas Christe, and Stavroula Mougiakakou. Lung pattern classification for interstitial lung diseases using a deep convolutional neural network. *IEEE transactions on medical imaging*, 35(5):1207–1216, 2016.

[BHX13] Yukun Bao, Zhongyi Hu, and Tao Xiong. A PSO and pattern search based memetic algorithm for SVMs parameters optimization. *Neurocomputing*, 117:98–106, 2013.

[BSBY14] Zahra Beheshti, Siti Mariyam Hj Shamsuddin, Ebrahim Beheshti, and Siti Sophiayati Yuhaniz. Enhancement of artificial neural network learning using centripetal accelerated particle swarm optimization for medical diseases diagnosis. *Soft Computing*, 18(11):2253–2270, 2014.

[BT14a] Nebojsa Bacanin and Milan Tuba. Firefly algorithm for cardinality constrained mean-variance portfolio optimization problem with entropy diversity constraint. *The Scientific World Journal*, 2014, 2014.

[BT14b] Ivona Brajevic and Milan Tuba. Cuckoo search and firefly algorithm applied to multilevel image thresholding. In Xin-She Yang, editor, *Studies in Computational Intelligence, Cuckoo Search and Firefly Algorithm: Theory and Applications*, volume 516, pages 115–139. Springer, 2014.

[CL11] Chih-Chung Chang and Chih-Jen Lin. LIBSVM: A library for support vector machines. *ACM Transactions on Intelligent Systems and Technology*, 2(3):27:1–27:27, May 2011.

[DBF+13] C Dromain, B Boyer, R Ferre, S Canale, S Delaloge, and C Balleyguier. Computed-aided diagnosis (CAD) in the detection of breast cancer. *European journal of radiology*, 82(3):417–423, 2013.

[DSS15] S. R. Dubey, S. K. Singh, and R. K. Singh. Local diagonal extrema pattern: A new and efficient feature descriptor for CT image retrieval. *IEEE Signal Processing Letters*, 22(9):1215–1219, 2015.

[HAB15] Thomas J Hirschauer, Hojjat Adeli, and John A Buford. Computer-aided diagnosis of Parkinson's disease using enhanced probabilistic neural network. *Journal of medical systems*, 39(11):179, 2015.

[IM14] Musibau Ibrahim and Ramakrishnan Mukundan. Multi-fractal techniques for emphysema classification in lung tissue images. *International Conference on Environment, Chemistry and Biology*, 78:115–119, 2014.

[IM15] Musibau Ibrahim and Ramakrishnan Mukundan. Cascaded techniques for improving emphysema classification in computed tomography images. *Artificial Intelligence Research*, 4(2):112–118, 2015.

[KI15] E. M. Karabulut and T. Ibrikci. Emphysema discrimination from raw HRCT images by convolutional neural networks. In *9th International Conference on Electrical and Electronics Engineering (ELECO)*, pages 705–708, 2015.

[KWE14] S. Kurugol, G. R. Washko, and R. S. Estepar. Ranking and classification of monotonic emphysema patterns with a multi-class hierarchical approach. In *11th IEEE International Symposium on Biomedical Imaging (ISBI)*, pages 1031–1034, 2014.

[KY14] Dong-Hyun Kim and Soo-Young Ye. CAD for detection of brain tumor using the symmetry contribution from MR image applying unsharp mask filter. *Transactions on Electrical and Electronic Materials*, 15(4):230–234, 2014.

[LC15] Howard Lee and Yi-Ping Phoebe Chen. Image based computer aided diagnosis system for cancer detection. *Expert Systems with Applications*, 42(12):5356–5365, 2015.

[LH15] Kuan-Cheng Lin and Yi-Hsiu Hsieh. Classification of medical datasets using SVMs with hybrid evolutionary algorithms based on endocrine-based particle swarm optimization and artificial bee colony algorithms. *Journal of medical systems*, 39(10):119, 2015.

[NERCE14] Rodrigo Nava, Boris Escalante-Ramírez, Gabriel Cristóbal, and Raúl San José Estépar. Extended Gabor approach applied to classification of emphysematous patterns in computed tomography. *Medical and biological engineering and computing*, 52(4):393–403, 2014.

[NKOS15] Mizuho Nishio, Hisanobu Koyama, Yoshiharu Ohno, and Kazuro Sugimura. Classification of emphysema subtypes: Comparative assessment of local binary patterns and related texture features. *Advances in Computed Tomography*, 4(03):47–55, 2015.

[NTT16] Marina Nikolic, Eva Tuba, and Milan Tuba. Edge detection in medical ultrasound images using adjusted canny edge detection algorithm. In *24th Telecommunications Forum (TELFOR)*, pages 691–694. IEEE, 2016.

[Pei15] Xiaomin Pei. Emphysema classification using convolutional neural networks. In Honghai Liu, Naoyuki Kubota, Xiangyang Zhu, Rüdiger Dillmann, and Dalin Zhou, editors, *International Conference on Intelligent Robotics and Ap-*

plications (ICRA): Proceedings, Part I, pages 455–461. Springer International Publishing, 2015.

[RGSG+13] Javier Ramirez, JM Gorriz, Diego Salas-Gonzalez, A Romero, Miriam Lopez, Ignacio Alvarez, and Manuel Gomez-Rio. Computer-aided diagnosis of Alzheimer's type dementia combining support vector machines and discriminant set of features. *Information Sciences*, 237:59–72, 2013.

[RRK+14] Sushravya Raghunath, Srinivasan Rajagopalan, Ronald A Karwoski, Brian J Bartholmai, and Richard A Robb. Active relearning for robust supervised training of emphysema patterns. *Journal of digital imaging*, 27(4):548–555, 2014.

[SSdB10] L. Sorensen, S. B. Shaker, and M. de Bruijne. Quantitative analysis of pulmonary emphysema using local binary patterns. *IEEE Transactions on Medical Imaging*, 29(2):559–569, 2010.

[SSK15] Hayaru Shouno, Satoshi Suzuki, and Shoji Kido. A transfer learning method with deep convolutional neural network for diffuse lung disease classification. In *International Conference on Neural Information Processing*, pages 199–207. Springer, 2015.

[STT16] Aleksandar Stojak, Eva Tuba, and Milan Tuba. Framework for abnormality detection in magnetic resonance brain images. In *24th Telecommunications Forum (TELFOR)*, pages 687–690. IEEE, 2016.

[TB14] Milan Tuba and Nebojsa Bacanin. JPEG quantization tables selection by the firefly algorithm. In *International Conference on Multimedia Computing and Systems (ICMCS 2014)*, pages 153–158, April 2014.

[TMT16] Eva Tuba, Lazar Mrkela, and Milan Tuba. Support vector machine parameter tuning using firefly algorithm. In *26th International Conference Radioelektronika*, pages 413–418. IEEE, 2016.

[TTB16] Eva Tuba, Milan Tuba, and Marko Beko. Support vector machine parameters optimization by enhanced fireworks algorithm. In Ying Tan, Yuhui Shi, and Ben Niu, editors, *LNCS, Advances in Swarm Intelligence: 7th International Conference on Swarm Intelligence, Proceedings, Part I*, volume 9712, pages 526–534. Springer International Publishing, 2016.

[TTD17] Eva Tuba, Milan Tuba, and Edin Dolicanin. Adjusted fireworks algorithm applied to retinal image registration. *Studies in Informatics and Control*, 26(1):33–42, 2017.

[TTS16] Eva Tuba, Milan Tuba, and Dana Simian. Adjusted bat algorithm for tuning of support vector machine parameters. In *IEEE Congress on Evolutionary Computation (CEC)*, pages 2225–2232. IEEE, 2016.

[Tub14] Milan Tuba. Multilevel image thresholding by nature-inspired algorithms: A short review. *Computer Science Journal of Moldova*, 22(3), 2014.

[Yan09] Xin-She Yang. Firefly algorithms for multimodal optimization. *Stochastic Algorithms: Foundations and Applications, LNCS*, 5792:169–178, 2009.

[YFAL16] J. Yang, X. Feng, E. D. Angelini, and A. F. Laine. Texton and sparse representation based texture classification of lung parenchyma in CT images. In *38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 1276–1279, 2016.

[ZCKR+13] T. Zulueta-Coarasa, S. Kurugol, J. C. Ross, G. G. Washko, and R. San Jose Estepar. Emphysema classification based on embedded probabilistic PCA. In *35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 3969–3972, 2013.