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Comparison of Performance on the Different Classifiers of the Locating Protected Projection (LPP) Dimension Reduction Method Based LBP Features

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ABSTRACT

İmage cells have taken with Light Microscope help. The local binary pattern (LBP) features have obtained for original images. High-dimensional of these LBP features is reduced to lower-dimensional with Locality Preserving Projections (LPP). These low dimensional data are classified by the Random Forest (RF), Naive Bayes (NB), and Artificial Neural Networks (ANN) classifiers. The classification results are compared with previous studies. The performance achieved with the ANN classifier is higher than the RF and NB classifiers. Moreover, feature vector size used in ANN classifier is a lower than feature vector size used in RF and NB classifiers. The success rates achieved with the ANN, RF, and NB classifiers is respectively 96.29%, 74.44%,and 70.00% according to LPP Method.

Keywords: local binary pattern features, lpp, random forest, Artificial Neural Networks, Naive Bayes

1. INTRODUCTION

Gastric cancer is a type of cancer that occurs in the Gastric tissue and gastric wall. According to studies conducted by the Ministry of Health in our country, gastric cancer was identified as the second most common cancer type. Endoscopy is the most important factor in the early diagnosis of this disease. Endoscopic examination of the endometrium and biopsy specimens are taken and diagnosed as pathological examinations. It is seen that half of the people who have this disease are late in the diagnosis and doctors can not apply any treatment [1]. The most common sites of this disease in the world are distant countries such as Japan and China. Japan, the number of people with Gastric cancer accounts for about 30% of other cancer diseases. In the Americas, the number of Gastric cancer people increases every year [2,3]. According to research conducted worldwide, 26% of males and 11% of females have Gastric cancer. Gastric cancer is located in the third place after lung and breast cancer in women and second place after lung cancer in males. According to the number of new Gastric cancer caught is estimated to be around 30 thousand a year [4]. S. Yoshihiro and colleagues [5] studied Gastric cancer by developing computer-based systems that can predict the risk factor. In the system developed, endoscopy images were taken from patients carrying H. pylori bacteria. 15 parameters were used to classify the gastric mucosa with 3 parameters on the back panel. The classification data were processed by Bayesian theorem and outputs were obtained. This study is the source for the treatment of patients who are at risk of gastric cancers or patients who have to undergo endoscopy. D.Ahmadzadeh [6] developed a cancer diagnosis system by using KDM (decision support machine) and local pattern algorithm methods for

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Gastric cancer diagnosis. By using the feature identification, feature extraction and noise reduction steps in the system they have developed the results of estimation of 91,8% of 55 randomly selected samples were found. The common feature of both systems used in the study is that it is a system that helps the doctor in time and material sense. Akbari et al. [7] developed a Gastric cancer diagnosis system by using infrared ultra-spectral imaging method. This study was performed by selecting patients with gastric cancer. Spectral features were extracted from cancerous and normal tissues and compared with this, KDM method was used to determine the detection of cancerous regions by spectral diagram It was performed. High performance was obtained from the system by using HFD and Log transformation in the direction of the obtained data. In the study performed, 25 patients with indole cancer were detected in 30 patients and 83,3119% of the obtained system was mathematically successful. Is a type of cancer that, when diagnosed late, leads the patient to death [8]. Gastric cancer usually begins with ulcer and gastritis complaints. Cancer can affect lymph nodes and other peripheral organs [9].

Theory and Method of the article are explained in Section 2. Section 3 explains the Experiment results of the article. Section 4 describes the conclusions of the article.

It is the main purpose of this article to support with computer programs to early detection of stomach cancer by using histopathology images. The contribution of this article is that the RF, ANN, and NB classifiers are based on the LBP feature selection and the LPP size reduction method. The data is supplied to the RF, ANN, and NB classifiers input supported by the LBP feature account method and the LPP size reduction method. Until today, it is not comparised of performance on the different classifiers of the locating protected projection (LPP) dimension reduction method based LBP features.

1. THEORY AND METHOD

The steps of this article is shown in Figure. 1.

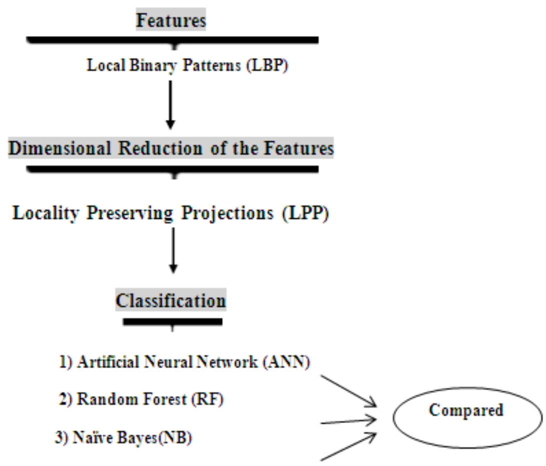

Figure. 1. Steps for classification of normal, benign, and malign gastric cancer images

In this article has been used the Local Binary Patterns (LBP) features. The dimensions of these properties were reduced to lower dimensions by the Locality Preserving Projections (LPP) method. These low dimensional features have been classified by Random Forest (RF), Naive Bayes (NB), and Artificial Neural Networks (ANN) methods.

1.1. Local Bınary Patterns (LBP) Features

LBP code is combine eight binary numbers or zero binary code for the center pixel. As a threshold the value of a center pixel is LBP operator [9]. If the value is lower than the center pixel, A neighboring pixel has a lower rank [10]. That pixel is assigned one, otherwise it becomes zero. LBP operators are in different sizes. The middle pixel was made with radius L. This middle pixel value has been compared with points on the edge of chamber. Interpolation is required to get the values of any sampling points of any number of pixels in the environment and any radius [9]. The notation (K, L) represents the neighborhood. The coordinates of the neighbors are (x_k, y_k) and the coordinates of the pixel in the middle are (x_c, y_c) [9].

$$x_k = x_c + \mathrm{L}\cos\left(\frac{2\pi p}{K}\right) (1)$$

$$y_{k=}y_c + L\sin\left(\frac{2\pi p}{K}\right) \quad (2)$$

The gray values of neighbors is p_k, and the gray value of the middle pixel is p_c. Based on this, M texture adjacent to the local pixel (x_c, y_c) can be expressed as:

$$M = m(p_c\,, p_0 - p_c, \ldots\ldots, p_{k-1})(3)$$

k = 0, ..., k - 1

It is also possible to define the texture in another way when the values of these points are obtained. The middle pixel's value and differences can be expressed as:

$$M = m(p_c, p_0 - p_c, \ldots\ldots, p_{k-1} - p_c) \quad (4)$$

$$M \approx (p_0 - p_c, \ldots\ldots, p_{k-1} - p_c) \; (5)$$

Textural properties in original distribution in the Equation 3 are conserved in the common disparity. Because, an image that does not deal with the M (p_c) total brightness value does not provide useful information for tissue analysis.

$$M \approx (r(p_0 - p_c), \ldots, s(p_{k-1} - p_c) \quad (6)$$

$$r(x) = \begin{cases} 1, x \geq 0 \\ 0x < 0 \end{cases}$$

Each r ($p_k - p_c$) values in the Equation (7) are multiplied with 2^k. and These binomial weights are summed. LBP for pixel (x_c, y_c) are obtained as

$$LBP_{K.L}(x_c, y_c) = \sum_{k=0}^{k-1} r(p_k - p_c)2^k \quad (7)$$

1.2. Locality Preserving Projections (LPP) Dimension Reduction

LPP [11-14] is a linear method that attempts to preserve the knowledge of local neighborhood in an ideal way. In this method, a data set of d dimensional n starts with the creation of a neighborhood graph G consisting of n nodes for $X = \lfloor x_1, x_2, \ldots x_n \rfloor$. The i x data instance corresponds to i. When constructing the neighborhood graph, ε-neighborhood or k-neighborhood of a data sample is used. Put an edge that connects the nodes of neighboring data samples. Using the generated neighborhood graph, a symmetric NxN weight matrix W is found. W_{ij} can be found in two different ways:

1) If x_i ve x_j are interconnected in the neighborhood graph ($t \; \varepsilon R$):

$$W_{ij} = e^{-\frac{\|x_i - x_j\|^2}{t}} (8)$$

2) If x_i ve x_j are interconnected in the neighborhood graph:

$$W_{ij} = 1 \; (9)$$

After these operations, the following generalized eigenvalue problem is solved:

$$XKX^T a = \lambda XLX^T a \; (10)$$

The L matrix [11-14] is called the laplacian matrix and has the form $K = L - W$. L matrix is a diagonal matrix and each diagonal element is equal to the sum of each column of W weight matrix:

$$L_{ii} = \sum_j W_{ij} \quad (11)$$

1.3. Random Forest (RF) Classifier

RF is a collection of tree type classifiers. In the RF method, tree-type classifiers are used in the $\{h(x, \theta_K)r = 1, \ldots\}$ type. where, x is the input data; θ_K represents the random vector. The RF method uses the Gini index. Gini measurements determine the cleavage position having the smallest Gini index [15,16]. Two parameters defined by the user are required to produce a tree with the RF classifier. These parameters, m is the number of variables used in each node. and N is the number of trees that will be developed to determine the best division. The starting m value is randomly selected by the user [15,16]. The next m's are increased or decreased according to the generalized fault. The generalized error data helps to understand the classification accuracy. K displacement new training data is generated from K training data. The $h(x, K_r)$ classifier is constructed using the new training data set. Only voting with this classifier occurs for each x, y in the training data. K_r does not contain the x and y. Pick a random sample (pixel) for a given K training dataset and belong to class P_i this pixel. According to this situation, the Gini index is expressed as follows.

$$\sum \sum_{j \neq i} (f(P_i, K)/|K|)(f(P_j, K)/|K|) \; (12)$$

Here, K is the training data set, Pi is the class to which a randomly selected pixel belongs, $f(P_i, K)/|K|)$ indicates the possibility of belonging. to the Pi class of the selected example.

Gini index measures the class homogeneity. While as the GINI index decreases, class homogeneity increases, as the GINI index increases, class heterogeneity increases. That branch is successful when a lower-node GINI index is less than the upper-node GINI index. When the GINI index reaches zero, that is, when a class is left in each node, tree branching ends. When all N trees are produced, the pixel class is determined based on the prediction results obtained from N trees [15-16].

1.4. Artifical Neural Network (ANN) Classifier

In this article, ann classifier is used to compare the effect of the lpp size reduction method on the random forest classifier. The used ann model is a backpropagation algorithm. Back propagation artificial neural networks consist of 2 basic stages; These are forward feed and back propagation. Forward feed is the stage which input data is given to the network. The outputs obtained at the end of this stage are entered into the error function and the weights are changed by propagating the errors backwards. The gradient approximation method is used to minimize the error function and thus the total error. Since the neural network starts with random initial weights, the results after training vary somewhat each time the sample is run. To avoid this change, the random value is set to produce the same results each time [17]. In this article, this random value is chosen as 1000. The number of hidden layers in the a feed-forward network established for stomach cancer recognition is designated as 38.

1.5. Naive Bayes (NB) Classifier

The Naive Bayes classifier is a probabilistic classifier based on the Bayes theorem and based on independent assumptions. Bayes' theorem is a classifier method that refers to a random variant, showing the relationship between conditional probabilities and marginal probabilities [18].

$$P(X \backslash Y) = \frac{P(Y \backslash A)P(X)}{P(Y)} \quad (13)$$

In Equation (13), $P(X \backslash Y)$ is the probability of occurrence of the X event in the case of Y event. $P(Y \backslash A)$ is the likelihood of the Y event occurring when the X event occurs. $P(X)$ and $P(Y)$ are the prior probabilities of X and Y events [20]. A classification operation consists of many attributes and a target variable.

$$p(T \backslash K_1 \ldots\ldots K_k) = \frac{P(T)p(K_1 \ldots\ldots K_n \backslash T)}{p(K_1 \ldots\ldots K_n)} \quad (14)$$

T represents the given target and K properties. Naive bayes classifier is generally the product of all conditional probabilities [18,19].

3. EXPERIMENTAL RESULTS

Normal (n), benign (b), and malign (m) gastric image cells have been taken from faculty of Medicine the Fırat University with Light Microscope help. The size of these images is 2592x1944. Total number of images are 180 which be 60 n, 60 b, and 60 m. 90 of these 180 images were used for testing purposes and 90 were used for training purposes. The Local Binary Patterns (LBP) features have been obtained for normal, benign, and malign original images. High-dimensional of these LBP feature vectors is reduced to lower-dimensional with Locality Preserving Projections (LPP). These low-dimensional data is 36x180. These low-dimensional data are classified as normal benign and malign by Random Forest (RF) classification. 60 LBP feature values were primarily calculated with the LBP property calculator for each image. Thus, a data size of 60 * 180 was obtained. İmages data in the these 60 * 180 size have been used the 60 * 90 for training purposes and 60 * 90 for test purposes. The 60 feature values of these quantities used for training and testing have been reduced to 36 properties by the LPP size reduction method. The these data in the size of 36*90 have been used for training and testing purposes. 36*90 data have been used for training purposes. 36*90 data have been used for test purposes. In summary, the training data set contains 60 feature vectors for 90 different groups. These feature vectors is reduced to lower-dimensional with LPP. During the training process, 36 feature vectors are given to RF. 3 output which be n, b, and m were obtained.

In Table 1, the LBP_Train value has been obtained by calculating the LBP properties of all 90 original training images. The obtained LBP_Train size is 60*90. In the same way, in Table 1, the LBP_Test value has been obtained by calculating the LBP properties of all 90 original test images. The obtained LBP_Test size is 60*90. The LBP_LPP_TrainData value in the Table 1 has been obtained by applying the LPP size reduction method to the LBP_Train values. In Table 1, the obtained for LBP_LPP_RFTestData size is 36*90. The LBP_LPP_RFTestData value has been obtained by applying the LPP size reduction method to the LBP_Test values for RF classifier. The obtained for LBP_LPP_ANNTestData size is 10*90. The LBP_LPP_ANNTestData value has been obtained by applying the LPP size reduction method to the LBP_Test values for ANN classifier. The obtained for LBP_LPP_NBTestData size is 10*90. The LBP_LPP_NBTestData value has been obtained by applying the LPP size reduction method to the LBP_Test values for NB classifier.

In Table 1, TrainGT is a class number that represents 30 n, 30 b, and 30 m images used for training images. TestGT is a class number that represents 30 n, 30 b, and 30 m images used for test images.

Table 1. Testing and training parameters in the RF, ANN, and NB classifiers for gastric cancer images

Parameters of the gastric cancer images	Parameters Dimensional		
LBP_Train	60*90		
LBP_Test	60*90		
LBP_LPP_RFTrainData	36*90		
LBP_LPP_RFTest Data	36*90		
LBP_LPP_ANNTrainData	10*90		
LBP_LPP_ANNTrainData	10*90		
LBP_LPP_NBTrainData	10*90		
LBP_LPP_NBTrainData	10*90		
TrainGT	1*30	2*30	3*30
TestGT	1*30	2*30	3*30
Hidden Layer of ANN	38		
Random Value of ANN	1000		
LBP_LPP_RF Accuracy74.44%			
LBP_LPP_ANN Accuracy 96.29%			
LBP_LPP_NB Accuracy70.00%			

In Table 2, LDA is linear discriminant analysis method. In Table 2, HOG_LDA_ANN [21] accuracy rate has been found as 88,9 %. LBP_LPP_ANN [21] accuracy rate has been found as 85,56 % for selected 30 feature. LBP_LPP_ANN accuracy rate has been found as 96.29 % for selected 10 feature. Method LBP_LPP_RF accuracy Rate has been found as 74.44%. Method LBP_LPP_NB accuracy rate has been found as 70.00%.

Table 2. Comparison of Different Results

Compared	
Method	Accuracy
LBP_LPP_RF74.44% (36 Features)	
HOG_LDA_ANN[21]	88.9% (180Features)
LBP_LPP_ANN[21]	85.56% (30 Features)
LBP_LPP_ANN	96.29% (10 Features)
LBP_LPP_NB	70.00% (10 Features)

4. CONCLUSION

Until today, there have been many studies in the field of health [20-33]. However, there are many patients who can not be diagnosed the early cancer. For this reason, computerized methods are still needed for early cancer diagnosis. In this article, it is aimed to developed a new computer aided approach based on lpp size reduction for early diagnosis. The innovation of this article is comparied of performance on the different classifiers of the locating protected projection (LPP) dimension reduction Method Based LBP Features. n, b, and m gastric image cells have taken from faculty of Medicine the Fırat University with Light Microscope help. Total number of gastric images are 180 which be 60 n, 60 b, and 60 m. 90 of these 180 gastric images were used for testing purposes and 90 were used for training purposes. The local binary pattern (LBP) features have obtained for original images. High-dimensional of these LBP features is reduced to lower-dimensional with Locality Preserving Projections (LPP). These low dimensional data are classified by the Random Forest (RF), Naive Bayes (NB), and Artificial Neural Networks (ANN) classifiers. The classification results are compared with previous studies. The Local Binary Patterns (LBP) features have obtained for n, b, and m original Gastric images. The size of these LBP feature vectors is 60x180. High-dimensional of these LBP feature vectors is reduced to lower-dimensional with Locality Preserving Projections (LPP). These low-dimensional data is 36x180 for RF, 10X180 for ANN, and 10x180 for NB. These low-dimensional data are classified as n, b, and m by RF, ANN, and NB classifiers. The success rates achieved with the LBP_LPP_ANN, LBP_LPP_RF, and LBP_LPP_NB classifiers is respectively 96.29%, 74.44%,and 70.00% according to LPP Method. The success performance achieved with the ANN classifier is

higher than the RF and NB classifiers. Moreover, feature vector size used in ANN classifier is a lower than feature vector size used in RF and NB classifiers.
In future studies, an analysis will be performed by applying different feature extraction methods to different cancer images.

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REFERENCES

[1] Ural, Berkan, et al. "Gastric Cancer Regional Detection System," *Journal of medical systems,* vol. 40, no. 1, pp. 31, 2016.

[2] Hirayama, Akiyoshi, et al. "Quantitative metabolome profiling of colon and Gastric cancer microenvironment by capillary electrophoresis time-of-flight mass spectrometry," *Cancer research,* vol.69, no. 11, pp. 4918-4925, 2009.

[3] Brenner, Hermann, Dietrich Rothenbacher, and Volker Arndt. "Epidemiology of Gastric cancer," *Cancer Epidemiology: Modifiable Factors*, pp. 467-477, 2009.

[4] Fujioka, Naoko, et al. "Discrimination between normal and malignant human gastric tissues by Fourier transform infrared spectroscopy," *Cancer Detection and Prevention*, vol. 28, no.1, pp.32-36, 2004.

[5] Sasaki, Yoshihiro, et al. "Computer-aided estimation for the risk of development of gastric cancer by image processing," *Artificial Intelligence in Theory and Practice III, pp.* 197-204, 2010.

[6] Ahmadzadeh, D., Fiuzy, M., Haddadnia, J. "Gastric Cancer Diagnosis by Using a Combination of Image Processing Algorithms, Local Binary Pattern Algorithm and Support Vector Machine," *Journal of Basic and Applied ScientificResearch*, vol. 3, no. 2, pp. 243-251, 2013.

[7] Akbari, Hamed, et al. "Cancer detection using infrared hyperspectral imaging." *Cancer science, vol.* 102, no. 4, pp. 852-857, 2011.

[8] Tannapfel, Andrea, et al. "Expression of the p53 homologues p63 and p73 in multiple simultaneous gastric cancer." *The Journal of pathology*, vol. 195, no. 2, pp. 163-170, 2001.

[9] Malkapurkar, AnaghaV, Rupali Patil, and Sachin Murarka. "A new technique for LBP method to improve face recognition." *International Journal of Emerging Technology and Advanced Engineering, vol.* 1, no.1, pp. 67-71, 2011.

[10] T. Ojala, M. Pietik¨ainen and D. Harwood, "A comparative study of texture measures with classification based on feature distributions" *Pattern Recognition*, vol. 29, 1996.

[11] He, Xiaofei, and Partha Niyogi. "Locality preserving projections," *Advances in neural information processing systems*, pp. 153-160, 2004.

[12] Yildiz, Eray, and Yusuf Sevim. "Comparison of linear dimensionality reduction methods on classification methods." *Electrical, Electronics and Biomedical Engineering (ELECO), National Conference on*. IEEE, 2016.

[13] Wang, Z., & He, B. "Locality perserving projections algorithm for hyperspectral image dimensionality reduction," *In Geoinformatics, 2011 19th International Conference on*, pp. 1-4, IEEE, 2011.

[14] Jin, Xin, et al. "Locality preserving projection on source code metrics for improved software maintainability, " *Advances in Artificial Intelligence*, pp. 877-886, 2006.

[15] Pal, Mahesh. "Random forest classifier for remote sensing classification." *International Journal of Remote Sensing*, vol. 26, no. 1, pp. 217-222, 2005.

[16] Korkmaz, Sevcan Aytaç, and Hamidullah Binol. "Analysis of Molecular Structure Images by using ANN, RF, LBP, HOG, and Size Reduction Methods for early Stomach

Cancer Detection."*Journal of Molecular Structure* (2017).

[17] http://www.atasoyweb.net/Geri-Yayilimli-Yapay-Sinir-Aglari. 25.12.2017.

[18] McCallum, Andrew, and Kamal Nigam. "A comparison of event models for naive bayes text classification." *AAAI-98 workshop on learning for text categorization*, Vol. 752, pp. 41-48, 1998.

[18] McCallum, Andrew, and Kamal Nigam. "A comparison of event models for naive bayes text classification." *AAAI-98 workshop on learning for text categorization*, Vol. 752, pp. 41-48, 1998.

[19] Yongkui, S., Pengrui, L., Ying, W., Jingyu, Z., & Meijie, L. "The Prediction of the Caving Degree of Coal Seam Roof Based on the Naive Bayes Classifier," *Electronic Journal of Geotechnical Engineering,* vol. 19, no. Z2, 2014.

[20] Korkmaz, Sevcan Aytac, et al. "Diagnosis of Breast Cancer Nano-Biomechanics Images Taken from Atomic Force Microscope," *Journal of Nanoelectronics and Optoelectronics, vol.*11, no. 4, pp. 551-559, 2016.

[21] Korkmaz, Sevcan Aytaç, et al. "A expert system for stomach cancer images with artificial neural network by using HOG features and linear discriminant analysis: HOG_LDA_ANN." *Intelligent Systems and Informatics (SISY), 2017 IEEE 15th International Symposium on*. IEEE, pp. 327-332, 2017.

[22] Korkmaz, Sevcan Aytaç, et al. "Recognition of the stomach cancer images with probabilistic HOG feature vector histograms by using HOG features," *Intelligent Systems and Informatics (SISY), 2017 IEEE 15th International Symposium on*. IEEE, pp. 339-342, 2017.

[23] Korkmaz, Sevcan Aytac, Mehmet Fatih Korkmaz, and Mustafa Poyraz. "Diagnosis of breast cancer in light microscopic and mammographic images textures using relative entropy via kernel estimation." *Medical & biological engineering & computing*, pp. 1-13, 2015.

[24] Korkmaz, S. A., & Korkmaz, M. F. " A new method based cancer detection in mammogram textures by finding feature weights and using Kullback–Leibler measure with kernel estimation," *Optik-International Journal for Light and Electron Optics, vol.* 126, no. 20, pp. 2576-2583, 2015.

[25] Korkmaz, S. Aytac, and M. Poyraz. "A New Method Based for Diagnosis of Breast Cancer Cells from Microscopic Images: DWEE—JHT." *Journal of medical systems*, vol. 38, no. 9, pp.1-9, 2014.

[26] Korkmaz, Sevcan Aytac, and Mustafa Poyraz. "Least Square Support Vector Machine and Minumum Redundacy Maximum Relavance for Diagnosis of Breast Cancer from Breast Microscopic Images." *Procedia-Social and Behavioral Sciences* vol. 174, pp. 4026-4031, 2015.

[27] KORKMAZ, Sevcan AYTAÇ. "DETECTING CELLS USING IMAGE SEGMENTATION OF THE CERVICAL CANCER IMAGES TAKEN FROM SCANNING ELECTRON MICROSCOPE." *The Online Journal of Science and Technology-October*, vol. 7, no.4, 2017.

[28] Korkmaz, Sevcan Aytaç, et al. "New methods based on mRMR_LSSVM and mRMR_KNN for diagnosis of breast cancer from microscopic and mammography images of some patients." *International Journal of Biomedical Engineering and Technology*, vol.19, no. 2, pp. 105-117, 2015.

[29] Korkmaz, Sevcan Aytaç, and Haluk Eren. "Cancer detection in mammograms estimating feature weights via Kullback-Leibler measure." *Image and Signal Processing (CISP), 2013 6th International Congress on.* Vol. 2., IEEE, 2013.

[30] Sengur, Abdulkadir, and Ibrahim Turkoglu. "A hybrid method based on artificial immune system and fuzzy k-NN algorithm for diagnosis of heart valve diseases." *Expert Systems with Applications, vol.* 35, no. 3, pp. 1011-1020, 2008.

[31] Şengür, Abdülkadir, İbrahim Türkoğlu, and M. Cevdet İnce. "ENDOSKOPİK GÖRÜNTÜLERİN DEĞERLENDİRİLMESİNDE GÖRÜNTÜ İŞLEME TEMELLİ AKILLI BİR KARAR DESTEK SİSTEMİ." *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi, vol.*15, no.1, pp, 33-42, 2009.

[32] Özçift, Akın, and Arif Gülten. "Genetic algorithm wrapped Bayesian network feature selection applied to differential diagnosis of erythemato-squamous diseases." *Digital Signal Processing* vol.23, no.1, pp. 230-237, 2013.

[33] Güler, Inan, et al. "Classification of aorta doppler signals using variable coded-hierarchical genetic fuzzy system." *Expert Systems with Applications, vol.* 26, no. 3, pp. 321-333, 2004.