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Classification of Chronic Obstructive Pulmonary Disease (COPD) using Gabor Filter With SVM Classifier

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Abstract: In the field of medical diagnosis, early detection of COPD symptoms is difficult. The use of predictive tests leads to the treatment of COPD and also helps to identify signs of COPD early. Therefore, we present in this paper a feature extraction method for the structural representation of COPD images using the Gabor Filter. In addition, we train and evaluate COPD extracted function or category with SVM classification. The results show that the proposed method can be more accurate, more flexible, and more reliable. This approach is well adapted for early diagnosis of COPD.

Keywords: COPD Abnormalities, Classification, Gabor filter, SVM Classifier.

I. INTRODUCTION

In its early stage it's difficult to detect cancer, when the medical doctors don't note the few irregular images. The anomalies found in COPD MRIs by doctors are therefore very difficult to detect. The second opinion is therefore made important by an alternative diagnosis for medical experts. The inadequate processing and misclassification of the automated diagnostic system, on the contrary, does not consider during the diagnosis the tumors or abnormalities present at COPD. Even for ideal case imaging, due to the lack of a special injury structure and color space it is highly difficult to detect defects or tumors. This therefore includes an automated system that extracts and classifies high levels of properties to deal with the above-mentioned issues.

There are several methods available to detect the presence of tumor in COPD images. The uses of different descriptors, such as the invariant descriptor of Gabor, the descriptor for color texture, and the other descriptors for texture using local binary patterns, to represent these characteristics and to send them in for the classification processes. For classifications and extractions of lesions in COPD images a variety of feature extraction is rendered using texture descriptors. The majority of the device is however available with only one function: the texture [1]-[6], which in COPD images is not enough to detect lesions. This is a serious restriction. Therefore, the image needs to identify lesions if the feature is selected properly or structural properties can be selected correctly. The COPD structure provides data on the regional binary model [7], on the arrangement of frequencies and on the GLCM [8]. These are used to examine anomalies in a certain image.

Structural geometry analysis characterizes the basic structural knowledge that calls the gray level of a neighborhood-based pixel. The spatial relation between the pixels in the neighborhood improves the edges, angles and texture of an object. The objects are fully recognized by a human visual system that interprets the structure [9]. For characterization applications [10], however, the structural structure is commonly used.

Human visual system does not note the presence of lower-level structures in a group of pixels as they carry local structural details to describe an object. The structural analysis relies on the details needed to interpret a signal. The image element in an object or a scene is a structural representation in any digital picture. Nevertheless, the direction or location of an object cannot be predicted. In such instances, rotary invariant feature extraction is very important for the analysis of the given data set.

The co-occurrence procedure is used to define the texture in an object as a structural process. This is primarily to estimate the co-occurrence gray level matrix (GLCM) in a given direction and orientation by a pixel frequency in relation to its neighborhood. Then GLCM calculates the textural feature set on the basis of stored information [22]. In addition, it is important to extract texture functions from filters at different frequencies, measurements and orientation using a medium and standard variation of the filter responses. GLCM is also calculated to be present within a specific distance by measuring the existence of different distributed intensities. In addition, GLCM second-order statistics reflect textual information [11].

The researchers suggest in this paper a method of automated extraction of features and classification for identification of COPD as normal or abnormal. A novel extract template for structural knowledge extraction from the COPD frames is used in this method. This is achieved with Filter from Gabor. We have used few sets for practice and few sets for testing with a wide variety of features. In contrast with the current extraction and classifiers of COPD images the quality of the proposed technique is based on averaging results over several rounds.

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II. METHODS

The texture is a dataset that displays the spatial distribution of repeated intensities. For the portrayal of texture characteristics, different order of strength statistics are used. Statistical methods that assist with textural extraction are used to measure the different order of frequency statistics. In addition, structural analyzes identify structural details such as edges and angles, taking the gray rates into consideration. The texture is improved by means of a spatial connection between pixels with other structural data. The objects in the database are perceived by the human visual system through the conceptual arrangements. In order to obtain the strength responses of the COPD frames, we use Gabor CSLBP filters before structural analysis. In the third step we calculate the statistics of second order from the Gabor filter-based CSLBP correlation matrix. These functions are derived and used to train and check the classification of the SVM. Figure 1 demonstrates the operation of the whole system.

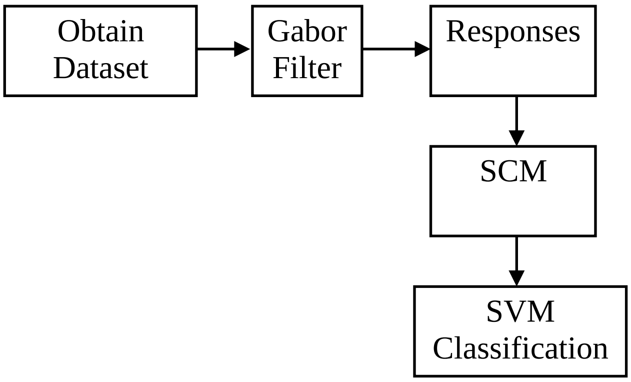

Fig. 1.Automated Classification of COPD dataset

A. Gabor Filter

The Gabor filter is derived from the convergence in the Fourier domain of complex sinuous and gaussian functions. The standard deviations govern the spatial axis x and y of the Gaussian window. The main advantage of Gabor's LBP filter is that it is able to conduct the study of spatial frequency in multi-resolution domains with its basic characteristics directivity choice and band pass design. The detection and choice of phases was based on Gabor filters as a human visual perception system.

The filter bank has 64 filters in an image with various sizes, orientations and frequencies. For the multi-resolution analysis of COPD frames, the Gabor filter properties of the band pass nature and directivity range. It is like the neural system with every filter that reflects the neuron, which is very fragile to a specific frequency. Scale, turning and illumination invariant are the features derived from the Gabor filter response.

B. Structural Co-occurrence Matrix (SCM)

In n-dimensional space, the SCM method helps to identify the similarity between the lower level structures of two separate pixels. The co-occurrence is represented in 2D histograms between the pixel structures.

The partition function generates the structural scaling used to combine pixel that are different. In addition, different partitioning values N change the structural scaling. Smooth partitions with comprehensive SCM are possible in the larger structural scale and vice versa. Try to maintain borders using the full variation, when the smoothening filter is applied, since it damages borders during mixing. In addition, during different pixel blending it reduces the loss of structural data.

Due to its computational cost, the quantizing method is considered as the primary option before using a Q partition function. This paper therefore avoids the use of the quantizing method, as the frequency variance and presence of noises is observed. As a consequence, the framework is unconnected. So, to process the pixels we use Gabor filters.

The scalar characteristics set are determined to represent the structural data saved in the form of histogram M, divided into groups, i.e. statistics, information and a divergent category.

For histogram M, the numerical community properties are structural similarity. Taking SCM into account, the correlation is defined as a statistical unit to connection the link between the structural information of histogram M.

C. Classification Model Training

The quality of different categories is contrasted with features based on learning. Such characteristics are obtained using the GLCM process for extracting the structural features. Then we use other classifiers to test the efficiency of the system proposed and it will provide more insight into structural features responding to certain classifiers. Therefore, we consider SVM as a simple classification, which is contrasted with other classification, like LDA, k-NN, NB, DT and ensemble classification. Such classifiers are classifiers based on the features derived from COPD images as regular or unusual objects.

The main idea of the SVM algorithm [12] – [21] is to divide both classes by a hyperplane as seen in the figure below because there are a number of points that fall within one of these classes. This will be achieved by optimizing the distance between each group and the separating hyperplane (from nearest points) and reducing the risk of misclassifying the samples and the test units.

III. PERFORMANCE MEASURES

The COPD data sets obtained were split specifically to allow for learning in a single set and for evaluation in another set. The partitioning of datasets is not seen as a structured SVM classification learning or test method. Since the learned template with the fixed exercise set and the fixed test set is not generalized properly. Therefore, the future data can't be successful. The proposed method uses cross-validation k-cross for the collection of training data and test data to enhance the generalization of the training model. Concrete results are obtained using a 10-cross-validation approach by training SVM classifier. This is done after the extraction of the element. The individual images are represented in a line vector after the function extraction process, and its final component is represented as a category tag. At 10-cross testing, the row vectors are randomly divided into 10 sub-sets, a single sub-set is selected for the classification training process.

The choice of random information to train and test the grade using 10-cross validation affects the quality of grade accuracy. It should be noted. The whole system is therefore iterated more than 100 times for average results.

Ultimately, the output of the SVM classifier is shown here, with the result being obtained for a single 10 cross-validation with other benchmark classifier models. The tests were performed on an Intel Core i5 processor at a frequency of 2.40 GHz using MATLAB technology.

IV. RESULTS

The classifier is further divided into normal classes and abnormal classes after collection of features from the COPD data sets. Using CSLBP, Gabor Filter is used in the proposed method to draw texture-based characteristics and to compare them to GLCM. Such features are extracted from all images of COPD diagnosis and then we train and check the SVM classifier on the same dataset.

The results are presented in Figure 2 – Figure 5, which shows the quality in 10-fold cross-validation of several classifiers in one iteration for training and testing. Classification results are created by classifying the COPD images collected with CSLBP descriptor using the Gabor Filter. From the results, it is clear that 81% reliability, 0.86 AUC, SVM classification is the highest. In the same way, the ROC evaluation of the proposed SVM classification function extraction is better than the other classifier.

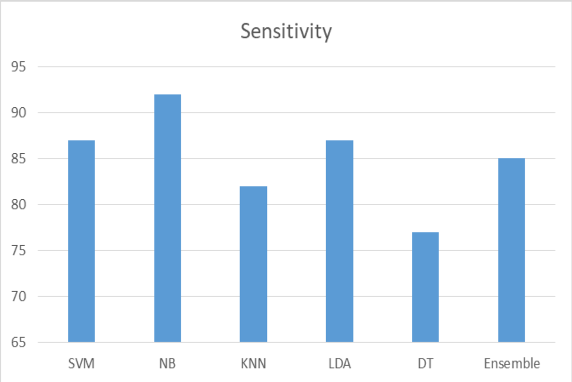

Fig. 2. Sensitivity

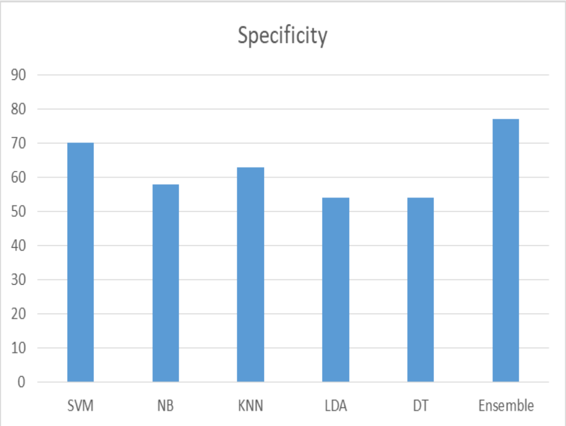

Fig. 3. Specificity

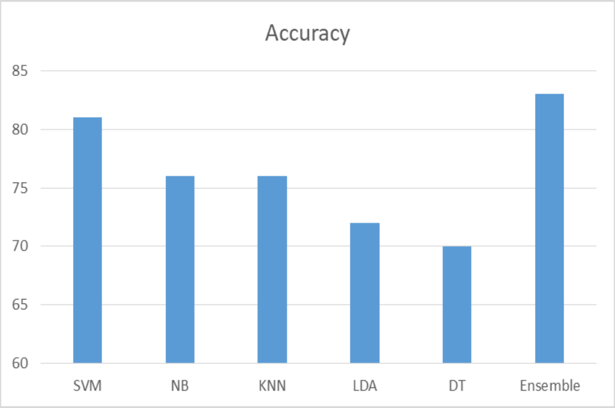

Fig. 4. Accuracy

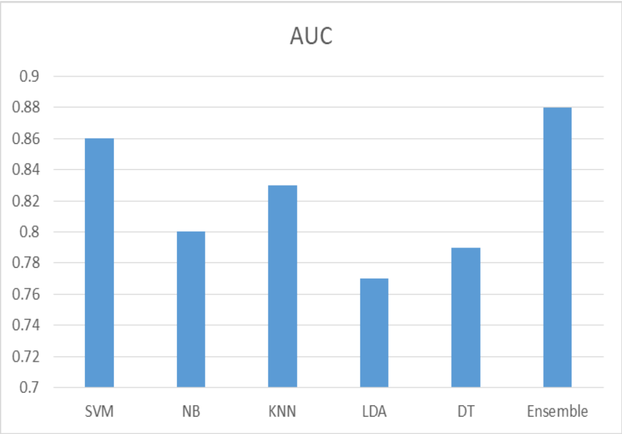

Fig. 5. Area under Curve

In the course of the experiment, we choose every time a new data subset for training and testing, which ensures that the reliability of the classification model changes each time. Therefore, the tests must be replicated over and over for definitive results. In addition, the outcomes of all of these studies were measured at 96 percent confidence interval with an error margin. The average reliability and average AUC results show that SVM works better. It is also noted that the ensemble model is almost similar to the SVM category. Nevertheless, the software sophistication of the ensemble method makes it a bad classification choice.

V. CONCLUSION

In this article we present a feature extraction technique using Gabor filter with a co-occurrence matrix for the structural representation of the affected COPD in oriented local symmetric patterns. The COPD was obtained from an online database and examined using a CSLBP Gabor Filter for anomalies or lesions. SVM is then used for the ordinary and unusual identification of the COPD data sets. The COPD structural characteristics are classified by SVM classification and findings are contrasted with other traditional classifications. The result shows that when using Gabor Filter with CSLBP extraction, the SVM is well served than other classifiers.

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