THYROID ULTRASOUND IMAGE CLASSIFICATION USING IMPROVED LBP WITH HYBRID SUPPORT VECTOR MACHINE

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ABSTRACT

Medical imaging is one among the significant fields in image processing, since manual diagnosis is more cumbersome and consumes lot of time in comparison with computerized techniques. Due to technological progress, a variety of methods have evolved for the detection of several diseases affecting the human body. Different Imaging technologies such as MRI (Magnetic Resonance Imaging), X-rays, Computed Tomography, Optical Coherence Tomography and Ultrasound (US) exist. Thyroid nodules are anomalous lumps originating inside the thyroid gland that may indicate multiple ailments. In the system available, the techniques face challenges with the classification and segmentation accuracy and therefore the overall effectiveness is minimized considerably. In order to get over the above stated problems, in the newly introduced system, improved Local Binary Pattern (ILBP) with Support Vector Machine (SVM) is proposed. The preprocessing is carried out employing adaptive weighted median filter. It improves the blurred image and eliminates the noise with efficiency. In order to enhance the accuracy of segmentation, Localized Region based Active Contour is suggested. For the extraction of the essential features, improved Local Binary Pattern (LBP) is presented in US images. It is utilized or extracting the significant feature information on the basis of the features that are efficiently extracted. The classification accuracy is measured with the help of the hybrid SVM algorithm. The result of the experimentation shows that newly introduced ILBP-SVM technique yields much greater accuracy, precision, recall and f-measure values for the thyroid image dataset given.

Key words: Thyroid image, feature extraction, ILBP, Hybrid SVM, classification
1. INTRODUCTION

Ultrasonography has become the most widely used modality for detecting and diagnosing thyroid cancer, for its better reveal ability and distinction between benign and malignant nodules in pathological features. With the rapid development of medical imaging technology, computer aided diagnosis (CAD) assists to solve the subjective diagnosing problem in current method, which highly depends on personal experience. Determining the risk of cancer in a nodule can be a more difficult concept, and the approach involves medical, rational, economic, and cultural considerations. It should be remembered that in dealing with a thyroid nodule, the evidence with regard to outcome, including the prevention of death, and morbidity, from thyroid cancer, is sparse [1].

The natural course of a micro cancer or small cancer is not known. They are both frequent findings in postmortem examinations that seem to have caused no morbidity to those who died from natural or other causes. Therefore neither common sense nor evidence supports the assumption that the health of a population or of an individual benefits from an overly aggressive approach to early or small cancers. For example; in the commonest cancer, papillary thyroid cancer (PTC), there is no evidence that treatment in the earliest stage offers a significant benefit compared with treatment at a slightly later point, when the increase in size of a suspicious nodule has provided evidence that the lesion is dynamically growing [2].

In other words, while the patient may have a risk of cancer, indeed even in the presence of cancer, it is important to avoid causing undue fear to patients, and harm from invasive or unnecessary investigations. The appropriate timing of the assessment for a suspect follicular thyroid cancer (FTC) is equally unclear but is complicated by the fact that undue delay may lead to a scenario where distant metastases have become established from early haematogenous spread [3]. For the less common medullary thyroid cancer (MTC) there is overwhelming evidence that early detection and treatment results in an improved outcome. For anaplastic thyroid cancer (ATC) only early treatment provides a chance of survival.

Thyroid ultrasound technology can ensure that you get a lot of information about thyroid nodule before the operation. Through the ultrasound images, we can locate the position of the thyroid nodule, measure the size, and decide whether an operation is needed or not. In ultrasound images, in addition to the echo characteristics, nodules in degree, there are some other ultrasound characteristics which can also be acted as a judgment indicator which shows possibility of nodular malignant, such as the shape and contour of nodules. The exact boundary detection of ultrasound images will provide accuracy position for pierce, but it exists a granular pattern which called spots in the ultrasound images because of the impact of imaging principle [4]. In addition, the properties of echo, shadow, and reflection of ultrasonic will degrade the image quality. This image quality degradation caused by the nature of ultrasonic image makes it difficult to recognize its edges accurately even for an experienced physician. Especially it is very difficult to complete the nodules and tracheal of nodules positioning area of the regional segmentation.

Ultrasonography is a diagnostic imaging technique used to visualize subcutaneous body structures and internal organs for possible pathology.
or lesions [5]. Modern medical ultrasonography presents a unique set of advantages including real-time data acquisition, low cost, absence of any side effects and high resolution imaging. Thus, ultrasonography has become an invaluable tool for non invasive medical examinations, and is considered one of the most accurate methods for the diagnosis and follows up of different pathologies in a variety of tissues and organs including breast, prostate and thyroid gland.

Medical image classification can play an vital role in diagnostic and teaching purposes in medicine. For these reasons different imaging modalities are used. There are many classifications created for medical images using both grey-scale and color medical images. The best way is to find the texture of the images and have the analysis. Texture classification is an image processing method by which different regions of an image are identified based on texture properties [6].

Classification is one of the most important decision making techniques in many real world problem. Classification of data is very important role to diagnosis of diseases in medical science. This research work focus specially features selection technique to develop computationally efficient model. The texture features are used to train the classifiers such as Support Vector Machine (SVM), K Nearest Neighbor (KNN) and Bayesian. The best predictive value and efficiently identifies the percentage of the non-cancerous or cancerous people. Image classification of thyroid nodule is done in order to eliminate operator dependency and to improve the diagnostic accuracy [7].

2. RELATED WORK

Dong et al (2007) introduced a new impulse detector, which is based on the differences between the current pixel and its neighbors aligned with four main directions. Then, we combine it with the weighted median filter to get a new directional weighted median (DWM) filter. Extensive simulations show that the proposed filter not only can provide better performance of suppressing impulse with high noise level, but can preserve more detail features, even thin lines. As extended to restoring corrupted color images, this filter also performs very well.

Selvathi et al (2011) developed the automatic system to segment the thyroid gland in ultrasound images using wavelet transform and Support Vector Machine with polynomial kernel. The goal of thyroid gland segmentation is to accurately estimate the volume of the thyroid hormone from the segmented area by which the abnormal symptoms of thyroid gland can be detected. The preprocessing steps such as Adaptive Weighted Median Filter (AWMF), morphological operations and gray level compensation of the thyroid region are used. These steps were to enhance the ultrasound image by reducing the speckles. After preprocessing, the statistical features such as mean and variance are extracted in spatial domain and wavelet transformed domain. The features are used to train the SVM and this trained SVM segments the thyroid region based on pixel classification. The results are compared with the ground truth images obtained from the radiologist and the performance measure such as accuracy is evaluated.

Lankton et al (2008) discussed a natural framework that allows any region-based
segmentation energy to be re-formulated in a local way. It considers local rather than global image statistics and evolves a contour based on local information. Localized contours are capable of segmenting objects with heterogeneous feature profiles that would be difficult to capture correctly using a standard global method. The presented technique is versatile enough to be used with any global region-based active contour energy and instill in it the benefits of localization. It describes this framework and demonstrates the localization of three well-known energies in order to illustrate how this framework can be applied to any energy. It then compares each localized energy to its global counterpart to show the improvements that can be achieved. Next, an in-depth study of the behaviors of these energies in response to the degree of localization is given. Finally, we show results on challenging images to illustrate the robust and accurate segmentations that are possible with this new class of active contour models.

Tzotso et al (2006) presented to evaluate SVMs for effectiveness and prospects for object-based image classification as a modern computational intelligence method. An SVM approach for multi-class classification was followed, based on primitive image objects produced by a multi-resolution segmentation algorithm. The segmentation algorithm produced primitive objects of variable sizes and shapes. Then, a feature selection step took place in order to provide the features for classification which involved spectral, texture and shape information. Contextual information was not used. Following the feature selection step, a module integrating an SVM classifier and the segmentation algorithm was developed in C++ and based on XML technology for feature representation. For training the SVM, sample image objects, derived from the segmentation procedure were used. The SVM procedure produced the final object classification results which were compared to the Nearest Neighbor classifier results, of the eCognition software, and were found satisfactory. The SVM approach seems very promising for object based image analysis and future work will focus on the integration SVM classifiers with rule-based classifiers.

Romero et al (2016) introduces the use of single layer and deep convolutional networks for remote sensing data analysis. Direct application to multi- and hyper-spectral imagery of supervised (shallow or deep) convolutional networks is very challenging given the high input data dimensionality and the relatively small amount of available labeled data. Therefore, we propose the use of greedy layer-wise unsupervised pre-training coupled with a highly efficient algorithm for unsupervised learning of sparse features. The algorithm is rooted on sparse representations and enforces both population and lifetime sparsity of the extracted features, simultaneously. The algorithm clearly outperforms standard Principal Component Analysis (PCA) and its kernel counterpart (kPCA), as well as current state-of-the-art algorithms of aerial classification, while being extremely computationally efficient at learning representations of data. Results show that single layer convolutional networks can extract powerful discriminative features only when the receptive field accounts for neighboring pixels, and are preferred when the classification requires high resolution and detailed results.

3. PROPOSED METHODOLOGY

In this research the fig 1 shows the overall block diagram of the proposed system.
3.1 Preprocessing using adaptive weighted median filter

In this section, the input image is resized using nearest-neighbor interpolation which is simpler way. In nearest-neighbor interpolation if replace every pixel with multiple pixels of the same colors, the resulting image is larger than the original, and preserves all the original detail. For decreasing image size it is going to remove multiple pixels from same colors, the resulting image is smaller than original image. The Fig 1 shows the overall block diagram of the proposed system.

![Diagram](image)

**Fig 1 Overall block diagram of the proposed system**

After determining the noise and size of filtering window, the image is divided into noise points and non-noise points. For the non-noise points, their gray values are reserved and kept from filtering, but the noise points are removed with a new weighted median filter [13]. In this research, a more effective method is introduced in seeking weighted coefficient mentioned above. It removes the noise before filtering to avoid the negative impact of noise on calculating the filtering value and get the best filtering result. This section adopts the following classical weight function when calculating the weighted coefficient.

\[
y(x) = \frac{1}{e^{\frac{1}{x}}}
\]  

(1)

Here \(x\) denotes the difference value between the gray value of pixel of filtering window and the central value of non-noise points. It is easy to know this function corresponds to the condition of selecting weight. Assuming pixel point \((m, n)\) \(m \leq n\) to be noise point, \(FW_{m,n}\) to be the filtering window size, the process of calculating the weighted coefficients is as follows:

1. Calculate the central pixel value of non-noise points in the filtering window.

\[
\text{Median} (FW_{m,n}) = Median(\{ f(m+s, n+t) \})  \quad (2)
\]

Here \(s,t \in [-l, l]\) and pixel point \((m+s, n+t)\) is the non-noise point in the filtering window.

2. Calculate the sum of the weighted coefficients of the non-noise points \((m+s, n+t)\)

\[
\text{sum} = \frac{1}{l} \sum_{s=-l}^{l} \frac{1}{\text{Median} (FW_{m,n} - f(m+s,n+t))}  \quad (3)
\]

3. Calculate the weighted coefficient of the pixel point \((m+s, n+t)\)
Finally, conduct weighted median filtering to the centre pixel point \((m, n)\) within filtering window, the corresponding grey value after noise points are filtered is

\[
g_{m,n} = \frac{\text{Median}\{PW_{m,n} \sim f(m+s,n+t)\} \times \text{weight}\}}{m+s,n+t}
\]

Then the output result of the filter is got and used to replace the gray value \(f(m, n)\) of a noise point \((m, n)\) by the following rules:

- If the inequality \(\text{Min} P_{m \times N} < g_{m,n} < \text{Max}(P_{m \times N})\) is true, then \(f(m, n)\) is equal to \(g(m, n)\)
- Else if \(n\) is equal to 1, then \(f(m, n)\) is equal to \(f(m-1, 1)\) otherwise, \(f(m, n)\) is equal to \(f(m, n-1)\)

Step (2) ensures that the output value \(g(m, n)\) of filter could not produce new noise points when the weighted central value \(f(m, n)\) is equal to \(\text{Min}(P_{m \times N})\) or \(\text{Max}(P_{m \times N})\). So the value \(f(m, n)\) is replaced by the value \(f(m, n-1)\) and the value \(f(m, 1)\) of a line by the value \(f(m-1, 1)\).

### 3.2 Localized Region based Active Contour for segmentation

The segmentation method which is widely used in the clinical application of ultrasound imaging systems is based on the localized region based active contour method. Although the implement method of localized region based active contour segmentation is convenient and simple, inevitably, the speckle noise and texture in the ultrasound image.

It allow the foreground and background to be described in terms of smaller local regions, removing the assumption that the foreground and background regions can be represented with global statistics. The analysis of local regions leads to the construction of a family of local energies at each point along the curve. In order to optimize these local energies, each point is considered separately, and moves to minimize (or maximize) the energy computed in its own local region. To compute these local energies, local neighborhoods are split into local interior and local exterior by the evolving curve. The energy optimization is then done by fitting a model to each local region.

Let \(I\) denote a given image defined on the domain \(\Omega\) and \(C\) be a closed contour represented as the zero level set of a signed distance function \(\phi\), i.e., \(\Omega = \{x | \phi(x) = 0\}\). It specifies the interior of by the following approximation of the smoothed function:

\[
\phi(x) = \begin{cases} 
1, & \phi(x) < -\epsilon \\
0, & \phi(x) < \epsilon \\
\frac{1}{2} \left( 1 + \frac{\phi}{\epsilon} + \frac{1}{\pi} \sin \frac{n\phi}{\epsilon} \right), & \text{otherwise} 
\end{cases}
\]

Similarly, the exterior of is defined as \(1 - \phi(x)\)

To specify the area just around the curve, we will use the derivative of \(\phi(x)\), a smoothed version of the delta

\[
\phi(x) = \begin{cases} 
1, & \phi(x) = 0 \\
0, & \phi(x) < \epsilon \\
\frac{1}{2\epsilon} \left( 1 + \cos \frac{n\phi}{\epsilon} \right), & \text{otherwise} 
\end{cases}
\]

### 3.3 Improved Local Binary Pattern (ILBP) for Feature Extraction
In this research, Improved Local Binary Patterns (ILBP) is introduced which is efficient gray-scale texture descriptor. It is invariant to illumination changes since it is defined by the relationship of a pixel with its neighbors, thus can identify successfully the microstructures in an image. The basic LBP is defined for a pixel $p_c$ as

$$LBP_{p_c} = \sum_{k=1}^{P} I_p - I_{p_c} \cdot 2^k \quad (8)$$

Where $I(p)$ denotes the intensity of a pixel $p$, and $P$ is the total number of pixels in the chosen neighborhood of the center pixel $p_c$. The function $I$ is a simple thresholding function in the form

$$I(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{otherwise} \end{cases} \quad (9)$$

It obtains a binary pattern of $P$ bits for each pixel. By varying this number $P$ and the radius of the circular neighborhood one can obtain LBP at different resolutions. In this work, it uses the uniform LBP on a neighborhood of radius. Improved LBP is grouped according to the number of 0/1 transitions that they contain, and the patterns containing more than 2 transitions are assigned the same identity. So, for each pixel in a region of interest it assigns a value from 0 to 58, and obtains a 59 bin histogram for that region.

In order to extract more relevant information in all patterns, and meanwhile keep the resulting feature vector compact, it used an improved local binary pattern operator, denoted here as ILBP$P_R$. It assigns every uniform pattern to a separate label, ranging from 0 to $P(P-1)+1$. In other words, the ILBP code is equivalent to the LBP code if it is uniform.

In this research, Improved LBP (ILBP) is proposed to enhance the feature extraction performance. The oriented mean and standard deviation of the local absolute difference are taken into account in order to make the matching more robust against local spatial structure changes. To minimize the variations of the mean and standard deviation of the directional differences, a scheme that minimizes the directional difference along different orientations adding the parameter $w$.

This research includes the standard deviation information not in the matching method but in the descriptor algorithm, and it is called ALBPS on that account. Furthermore, whereas a $1 \times 1$ matching technique is used by scheme uses the TSVM in order to classify a descriptor. This is a huge advantage for obtaining most useful features from the thyroid images. The standard deviation $\sigma$ is obtained using given below equation

$$\sigma_p = \sqrt{\frac{1}{N\cdot M} \sum_{i=1}^{N} \sum_{j=1}^{M} (g_{c, i, j} - \mu_p)^2} / (M \cdot N) \quad (10)$$

Where $N$ and $M$ are the numbers of rows and columns respectively $g_{c, i, j}$ is the centre pixel at position $(i, j), g_{c}(i, j)$ is the neighborhood of $g_{c}(i, j)$ lying along the orientation $2\pi n/P$ with the radius $R$ and $\mu_p$ is the oriented mean obtained using the following:

$$\mu_p = \sum_{i=1}^{N} \sum_{j=1}^{M} g_{c, i, j} / (M \cdot N) \quad (11)$$

The entropy is calculated to measure the more informative features from the given thyroid images. It represented by

$$LBP_{image} = \sum_{i=1}^{P} \log p(i) \quad (12)$$
The difference between the total image feature extraction information from \( n \) occurrences and the Entropy equation, only thing that changed in the place of \( n \). Therefore, entropy is the average amount of information in a certain event. The thyroid image entropy in a neighborhood of one location \( \sigma \in \Sigma \) is \( H(\sigma) = H(i) + H(b) \), where \( i \in I \) and \( b \in B \) are the corresponding locations in I, B, respectively. Since B is essentially noise, the entropy \( H(b) \) is the classical entropy. The local entropy in the ideal image is a ridge entropy: it is a measure of the torsion and continuity of ridges. Thus the ILBP is used to produce complete representation of image feature extraction information of the images.

\[
 \text{ILBP}_{p,R} = \sum_{p=1}^{P} s \ g_p - g_c \ 2^p + \text{LBPMage} \quad (13)
\]

Where \( g_p \) is gray values of pixels regularly spaced on circle and \( g_c \) is the gray value of the center pixel by neighborhood size \( P \) and the radius \( R \). It is improved by \( \text{LBPFinger} \).

The ILBP one matches pairs of corresponding minutiae in ridges and valleys, thus obtaining also their precise location. Minutiae matched in this way are called validated. Invalid minutiae are reanalyzed in a third recursion: they can either be discarded as spurious minutiae or yield some useful additional information.

### 3.4 Classification using SVM algorithm

In this research, hybrid SVM is proposed to improve the classification performance. SVM belongs to the class of supervised learning algorithms in which the learning machine is given a set of examples (or inputs) with the associated labels (or output values). Like in decision trees, the examples are in the form of attribute vectors, so that the input space is a subset of \( \mathbb{R}^n \). SVM is a classifier that searches for a hyperplane with the largest margin, which is why it is known as maximum margin classifier. SVMs create a hyperplane that separates two classes (this can be extended to multi class problems). While doing so, SVM algorithm tries to achieve maximum separation between the classes. Separating the classes with a large margin minimizes a bound on the expected generalization error. By “minimum generalization error”, it means that when new examples (data points with unknown class values) arrive for classification, the chance of making error in the prediction (of the class to which it belongs) based on the learned classifier (hyperplane) should be minimum. Intuitively, such a classifier is one which achieves maximum separation-margin between the classes. The two planes parallel to the plane are called bounding planes. The distance between these bounding planes is called margin. By SVM “learning”, i.e. finding hyperplane which maximizes this margin. The points (in the dataset) falling on the bounding planes are called the support vectors. SVM has greater advantages over other classifiers since they are independent of the dimensionality of the feature space. Use of quadratic programming in SVM has an edge over other classifier which gives only local minima whereas SVM provides global minima. But at the same time SVM also has a limitation of not considering spatial autocorrelation while classifying the data. SVM was designed initially as binary classifier i.e. it classifies the data into two classes but researchers have extended its boundaries to be a multi-class classifier. SVM was first introduced as a training algorithm that automatically tunes the capacity of the classification function maximizing the margin between the training patterns and the decision boundary. This algorithm operates with large class of decision functions that
are linear in their parameters but not restricted to linear dependences in the input components. For the computational considerations, SVM works well on the two important practical considerations of classification algorithms i.e. speed and convergence.

Training dataset (D)

To reduce the error minimization we can use given below formula

\[ \Phi \ w = \frac{1}{2} ||w||^2 \] (14)

Estimating function

\[ F(x) = \sum_{i=1}^{n} \alpha_i y_i k(x_i, y_i) + b \] (15)

Algorithm procedure

Given thyroid image dataset D=(x1, y1),……,(xn, yn), C // x and y – labeled samples and C-class

Initialize vector v=0, b=0; class) // v-vector and b-bias

Train an initial SVM and learn the model

For each \( x_i \in X \) do // xi is a vector containing features describing example i

Classify \( x_i \) using \( f(x_i) \)

If \( y_i \ f(x_i) < 1 \) // prediction class label

Find \( w', b' \) for known data // \( w', b' \) for new features

Add \( x_i \) to known data

Minimize the error function using (14) and estimate using (15)

If the prediction is wrong then retrain

Repeat

End

Recognize the images

4. EXPERIMENTAL RESULT

In this research, thyroid USG images are obtained bitmap format (bmp.). It consists of 25 cystic and 14 solid thyroid USG images. In this research, the existing methods are such as histogram and Multilayer perceptron (MLP) and proposed method of ILBP-SVM is evaluated for given thyroid image dataset.

4.1 Accuracy

Accuracy is defined as the complete correctness of the model and is evaluated as the total actual classification parameters \( (T_p + T_n) \) which is classified by the sum of the classification parameters \( (T_p + T_n + F_p + F_n) \). The accuracy is computed as like:

\[ \text{Accuracy} = \frac{T_p + T_n}{(T_p + T_n + F_p + F_n)} \]

\( T_p \) - True Positive

\( T_n \) - True Negative

\( F_p \) - False Positive

\( F_n \) - False Negative
Where $T_P$ is known as the amount of correct predictions that an instance is negative, $T_n$ is called the amount of incorrect predictions that an instance is positive, $F_p$ is known as the amount of incorrect of predictions that an instance negative, and $F_n$ is known the amount of correct predictions that an instance is positive.

**Fig 2 Accuracy**

From the above Fig 2, the graph demonstrates that the accuracy metric comparison for the methods. It can be said that the proposed approach provides higher accuracy when compared with the other histogram and MLP approaches. In x-axis the methods are considered and in y-axis the accuracy is considered. The experimental result confirms that the proposed ILBP-SVM algorithm gives greater accuracy value than the histogram and MLP methods.

**4.2 Precision**

Precision is explained as the ratio of the true positives opposite to both true positives and false positives result for imposition and real features. It is distinct as given below

$$\text{Precision}(P) = \frac{T_P}{T_P + F_P}$$

**Fig 3 Precision**

From the above Fig 3, the graph demonstrates that the precision metric comparison for the methods. It can be said that the proposed approach provides higher precision when compared with the other histogram and MLP approaches. In x-axis the methods are considered and in y-axis the precision is considered. The experimental result confirms that the proposed ILBP-SVM algorithm gives greater precision value than the histogram and MLP methods.

**4.3 Recall**

Recall value is evaluated on the root of the data retrieval at true positive forecast, false negative. Normally, it can be decided as follows,

$$\text{Recall}(R) = \frac{T_R}{T_R + F_R}$$
From the above Fig 4, the graph demonstrates that the recall metric comparison for the methods. It can be said that the proposed approach provides higher recall when compared with the other histogram and MLP approaches. In x-axis the methods are considered and in y-axis the recall is considered. The experimental result confirms that the proposed ILBP-SVM algorithm gives greater recall value than the histogram and MLP methods.

4.4 F-measure

It is a measure of an accuracy of the test. It consider both the precision \( p \) and the recall \( r \) of the test to compute the score

From the above Fig 5, the graph demonstrates that the F-measure metric comparison for the methods. It can be said that the proposed approach provides higher F-measure when compared with the other histogram and MLP approaches. In x-axis the methods are considered and in y-axis the F-measure is considered. The experimental result confirms that the proposed ILBP-SVM algorithm gives greater F-measure value than the histogram and MLP methods.

5. CONCLUSION

Ultrasound imaging is widely used to inspect the nodules in thyroid images. In this research, ILBP-SVM is proposed to improve the thyroid image classification results. The preprocessing is performed using adaptive weighted median filter. It improves the classification accuracy. ILBP is used to extract the important features from the given US images. SVM is applied to increase the thyroid classification accuracy. The result concludes that the proposed method proves superior accuracy, precision, recall and f-measure rather than histogram and MLP methods.

REFERENCES


