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CANCER PREVENTION INITIATIVE: AN INTELLIGENT APPROACH FOR THYROID CANCER TYPE DIAGNOSTICS

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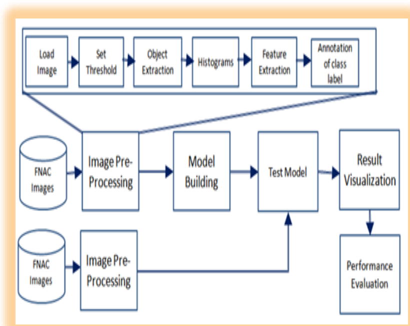
Graphical abstract



Abstract

In recent, medical Image mining has witnessed to be one of the emerging fields of machine learning. Particularly; the classification problem of DICOM (Digital Imaging and Communications in Medicine) images has become a prominent challenge. Thyroid cancer must be detected as earlier as possible; a little delay would extremely be proved hazards for human health and may be resulted into the most fatal threat to human life. Infect in-depth study of physical components of cells of FNAB (Fine needle aspiration Biopsy) would help to refine the results and provide more precise decisions about the potential occurrences of cancer, this paper proposes a system, so called 'TCTD' (Thyroid Cancer Type Diagnostics), which aims to assist the doctors during their diagnostic process conducted for thyroid follicular carcinoma and its sub-types. There are five main steps of our methodology. In first step image pre-processing techniques are used. In the second step; we use ensemble methods, such as Multi-SVM to build decision model and to analyze the frequencies between the variables. In third, fourth and fifth steps, model testing, result visualization and performance evaluation are performed by using precision, recall and f-measure estimations. The measured classification accuracy of proposed system is about 98.50% using 10 K-fold cross validation.

Keywords: Image mining, FNAB, cancer diagnosis and prognosis, ensemble methods, medical support system

1.0 INTRODUCTION

In recent years, medical image mining has proved to be one of the well-recognized research areas. Machine learning and AI based techniques have brought significant change and molded traditional medical diagnostic methods into automated computer based decision support systems such like, diagnosis of various malignant diseases of breast, lung, and thyroid and so on. Specifically; diagnosis and prognosis of thyroid cancer types using DICOM (Digital Imaging and Communications in Medicine) images of FNAB (Fine needle aspiration Biopsy) is one of the prominent problems, which deals with the micro-architectural structures of human cells and tissues. The thyroid cancer is divided into three distinct categories, for example well-differentiated, un-differentiated and benign cancers. It is very difficult to differentiate the involvement of mimic features of multiple thyroid cancers, so called thyroid cancer variants such like thyroid papillary carcinoma, lung papillary carcinoma and insular carcinoma have confused features, it is difficult to differentiate them in small cell papillary carcinoma, therefore; papillary carcinoma is a unique problem and due to the evidences of mimic features, it is very hard to decide about the confirmation of FC and PTC, thus there are maximum potential chances for misdiagnosis. Cancer can occur in any part of the body and it is identified as uncontrolled growth of cells, because cancer grows rapidly and brings the un-manageable state, where it becomes difficult to treat. Most importantly; every cancer type is treated with dissimilar therapies. Using FNAC (Fine needle aspiration cytology) and biopsy images, in recent past various research approaches have been seen to predict the diagnosis of cancers, such as [1-6]. These AI based systems are offering very nice solutions for extracting the hidden knowledge from the very large DICOM datasets; but most of them consider thyroid cancer classification as binary class problem and uses cell segmentation at the abstract level, our approach is considering classification problem of thyroid cancer types as multiclass classification problem and our study is focusing on in-depth study of physical components of human cell and tissues because in-depth segmentation of cells would help to refine the results. Thus in-order to assist the doctors during the diagnostic process of thyroid cancer and to provide more precise decisions about the potential occurrences of cancer this paper proposes a system, so called 'TCTD' (Thyroid Cancer Types Diagnostics), which offers well-structured approach to extract the deepest knowledge of human cells / tissues, along with the consideration of the nuclei, chromatin components of cells for the prediction of thyroid cancer. This approach also focuses on all the micro-architectural components (features) such as cancerous 'Cells', 'Cytoplasm', 'Nucleus' and others. We used a real world image dataset of FNAC and biopsy images collected from Cytological & Pathological department of Shaheed Muhtarma Be Nazir Bhutto Medical University (SMBBMU), Pakistan. The methodology of our proposed approach comprises on five-steps. In first step, we pre-process raw data (FNAB images). This step comprises on several sub-steps, such as load image, set-threshold, object extraction, histograms, feature extraction and annotation of class label, i.e. a doctor has to load required image in the system and selects the suspicious cancerous cell and he / she segment the desired cells with user supplied threshold. In second step, a multiclass-based decision tree model is constructed using SVM mechanism. In third, fourth and fifth steps, model testing, result visualization and performance evaluation are done through, precision, recall and f-measure techniques. 200 observations were chosen to build a decision model and measured classification accuracy of our proposed system is about 98.50% with 10 k-fold cross validation.

This paper is organized in following. In the section 2, related works is described. In section 3, background information is presented. In section 4, proposed methodology is discussed, such as, Image pre-processing techniques and ensemble methods. In section 5, discussion have been presented and in section 6, conclusion has been discussed.

2.0 RELATED WORKS

Our approach basically deals with predictive modelling in medical domain, which specifically offers a solution for thyroid cancer type diagnostics. Various related research approaches have been seen in past years.

A system [7] was proposed for the diagnosis of thyroid cancer using ultrasound images. The kernel SVM machine learning technique was used to find out the malignant and benign patterns of thyroid cancer. The reported classification accuracy of the system was measured about 97.5%. Ultrasound images visualize the disease at abstract level; our system 'TCTD' focus on in-depth level of cell segmentation to predict the well-differentiated cancers such follicular carcinoma and its variants.

A system [8] was proposed for the diagnosis of thyroid cancer, which used ultrasound images. The feature extraction was performed using 'ROI (Region of interest)'. 78 features were extracted to decide about the existence and nonexistence of thyroid cancer. Six number of 'SMV (Support Vector Machine)' were used to find out cancer patterns and the recorded classification accuracy of the system was about 78.00%. evidences of malignant lesions in any part of human body is a point of interest for clinical practitioners, but the final diagnosis of cancer type can only be proved by cytologists after conducting the FNAC and FNAB. Our proposed system provides assistance to doctors, while confirming the cancer type as stated previously.

A system [9] namely, AgNORs was proposed for the diagnosis and prognosis of cancer using cyto-pathological images (Thyroid FNAC images). A cyto-pathological camera or digital microscope was used for the acquisition of images, the Otsu threshold and segmentation technique was used to extract the normal and cancerous nuclei, whereas their medical partner was satisfied with the results about 90%.

A system [1], namely, WMC, was proposed for the diagnosis and prognosis of thyroid cancer using the images of FNAC. Two different machine learning techniques were used, i.e. 'SVM' and 'Multi-scale edge detection'. The comparison was shown and the accuracies were reported as 91% and 89% respectively. Likewise, this approach also employs the concept of cell segmentation at the abstract level, whereas, we propose in-depth level of cell segmentation would refine the results in a structured way.

A comparative study of two AI based techniques [2, 10] was proposed for the diagnosis of thyroid cancer based on FNAC Image. The Image segmentation, object detection and statistical features extraction techniques were used, such as, 'DWT (Discrete Wavelet form)', 'GLCM (gray level co-occurrences matrix)'and 'Gabber filter methods'. Three machine learning techniques were used for the classification, such as 'k-NN, ENN (Elman Neural Network) and SVM'. The classification accuracies of applied techniques were shown as 60.00%, 93.33% and 90.00% respectively.

A system [3] was proposed for the diagnosis and prognosis of thyroid cancer using FNAC images. A set of 67 numbers of features were extracted by using the 'chi-squire' statistical method. The C.45 algorithm was used classifier building. The measured classification accuracy was shown as 98%. The approach is actually based on the binary classification, i.e. malignant and non-malignant, whereas, the thyroid cancer would only be treated properly by knowing the proper stage and type of cancer.

A system [4] was proposed for the diagnosis of breast cancer identification. The 'Kohonen self-organizing map neural network' was used to extract the disease variables in breast cancer dataset. The system is also based on binary classification problem, whereas, thyroid cancer classification is a multiclass classification problem.

A system [5] was proposed for the diagnosis of breast cancer using FNAC image. 92 features were extracted for the data mining using MLP (Multi-layer Perception), PNN (Probabilistic Neural Network), LVQ (Linear vector Quantization) and SVM (Support Vector Machine).

A comparative study of two AI based algorithm [11] was conducted for the diagnosis and prognosis of thyroid cancer using cytological and ultrasound images. The 'SMV' and 'Bayesian' machine learning techniques were used and their measured classification accuracy was 93.3% and 98.8% respectively. We consider FNAB thyroid cancer problem as a multi-class classification problem because it consist upon several number of distinct class label attributes such Follicular carcinoma and its variants as stated above. Moreover, with respect to image pre-processing techniques, most of the proposed systems consider the cell segmentation at the abstract level, whereas, we contribute that in-depth level of cell study (micro-architectural components of human cell) would refine the results because cancer is a state of un-controlled growth of cells and in this state cells are mostly found with varying shapes, sizes, behaviors and etc. AI based techniques would assist the doctors during the diagnostic process to avoid the misdiagnosis of cancer. The measured classification accuracy of our proposed system is about 98.50%.

3.0 BACKGROUND

The cancer is the most dangerous disease worldwide; a considerable number of humans being are dying due to the various kinds of cancers, such as (ca. breast, ca. lung, ca. liver, ca. thyroid and other cancers). In this paper, thyroid cancer is focused. Thyroid gland is a butterfly shaped organ, located at the front and middle of neck. It is responsible to control the nerves system, metabolism and enhancing the performance of other human organs i.e. brain, heart and other organs. As per recommendations by the medical experts, only systematic diagnosis of the thyroid cancer at a right time would save the precious lives of the human beings. Traditionally, the evidence of thyroid cancer is found by observing the images of thyroid scan, C.T, MRI, X-Ray, Ultrasound and etc, whereas final diagnosis is confirmed by conducting FNAC and biopsy procedures. [Figure 1] clearly shows the difference between normal and cancerous Cells. In normal cell, all components are present as per their distribution such as nucleus, cytoplasm, chromatin and other micro-architectural parts, whereas in cancerous cells, the rest of components may vary in sizes, shapes and distribution of materials. Cancer cells are always seen with irregular components with respect to shape, size, structure and etc. For example, in one tissue of a particular organ, the distribution of chromatin is approximately equal in normal cells, while in cancer cells, the unbalanced distribution of chromatin is seen.

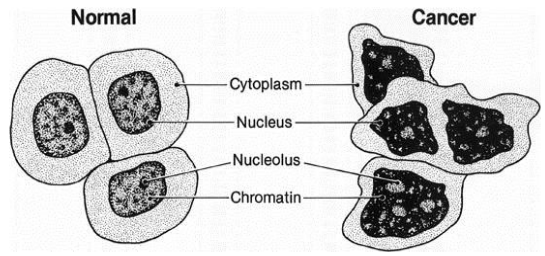


Figure 1 Group of normal cell verses cancerous cell

3.1 Thyroid FNAB

The FNAB (Fine Needle Aspiration Biopsy) is a technique to investigate a cancer type, traditionally; physician or surgeon takes sample from suspicious nodular masses using the fine needle disposable syringe [Figure 2].

Figure 2 FNAB procedure

The sample contains blood, pus, tissues, cells and other malicious material. This material is sent to the cytologist to perform cytological operations to find out the diagnosis of thyroid nodular enlargement. The cytologist spread the sample material on a FNAB glass slide and uses the staining material like fluorine. The function of the fluorine is to create visibility of cancerous material under the microscopic examination. A little fault of equipment, staining material or any mishandling of human would make the misdiagnosis. As the sample is comprised on blood cells, pus cells, different tissues and various kinds of cancerous material therefore, a very careful experiment is done by the doctor with the sport of micro-scope. One of cancer type is diagnosed according to its features. A single cell comprises on several components, i.e. IC, TCP, Mi-F, Ma-F, NCR, NA, Co, NG, Cro and CI (Cytoplasmic Inclusion).Advance digital microscopes are used by the cytologists for the purpose of image acquisition.

3.2 Our Dataset

Dataset consist upon 10 attributes Such as, IC (Increased Cellularity), TCP (Thin Collide presence), Mi-F (Micro follicular), Ma-F (Macro-follicular), NCR (Nuclear Cytoplasm Ration), NA (Nuclear atypia), Co (chromatin), NG (Nuclear groves), Cro (crowding (i.e. irregular arrangement of follicular cells in groups)) and class label attribute. The class label attribute consist upon, FC (follicular carcinoma), AC (Adeno carcinoma), FTC (Follicular Tissue carcinoma) and Normal FNAB.

4.0 METHODOLOGY

The proposed methodology of our system comprises upon five steps; Figure 3 depicts overall methodology of our approach. In first step, an image pre-processing step, which is a complex step, thus it comprises of various inner sub-steps, such as load image, set-threshold, object extraction, histograms, feature extraction and annotation of class label. In load image, we extract FNAC or biopsy images from DICOM dataset received from department of pathology, SMBBMU, Pakistan. In second sub-step, set-threshold, doctor crops suspicious cell or tissue from the infinite set of cells and segment it through user defined threshold. Details of set-threshold are given in [section 4.2]. In third sub-step, object extraction, doctor clicks on the button object extraction and our system extracts all components of the cell as a set of individual object. Thus, every component of cell becomes visualized separately on the screen. Further details are given in [section 4.3]. In fourth and fifth sub-steps histograms are used to generate textures of extracted objects, while feature extraction is used to extract and save the textures of cell objects in database. In the sixth sub-step, annotation of class label is to be performed by the doctor; class labels (done as per cell features) are underlined with each object extracted. Actually, class label data is also extracted from database. At the same time physician(s) is also involved to verify the assigned labels to particular objects. In the second step, model building, the system builds a model based on ensemble methods, such as, defined in [section 4.5]. In third step, test model, developed predictive model is tested with new extracted observation from the DICOM dataset. In the fourth and fifth steps, result visualization and performance evaluation, the model is evaluated by the confusion matrix, precision, recall and F-score, which is more discussed in [section 4.6]. Initially, the model was built on 200 observations and Multi-SVM was used to build decision model with .Net framework and measured accuracy of our approach was recorded as 98.5% with 10 k-fold cross validation.

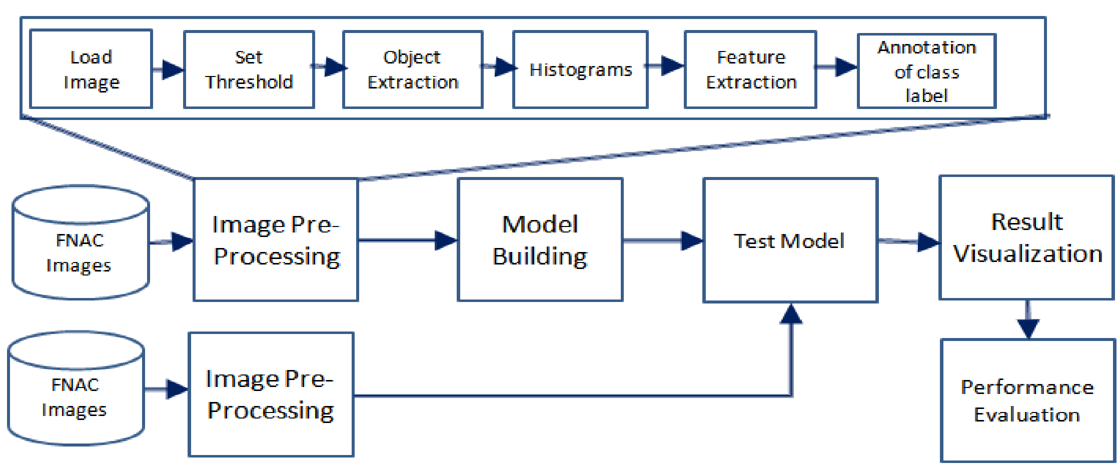


Figure 3 TCTD - Thyroid Cancer types diagnostics workflow

4.1 Image Pre-Processing

Image pre-processing stage is comprised upon the five sub-steps. In first sub-step, the image is to be loaded into the proposed system; an image threshold segmentation algorithm is applied in second sub-step. Thirdly, the object extraction, fourthly, histogram algorithms were used to extract the all possible textures and features as stated in [section 4.2, 4.5 & 4.6]. Let suppose, a raw FNAB image is containing the several number of pixels, which are represented by R and it is containing number of x and y locations as expressed in equation 1.

$$R = x_1y_1 + x_2y_2 ....x_ny_n = \sum_{k=1}^{n} xkyk \qquad (1)$$

where x_1 is the intensity of the pixel, who's exactly located at the k^{th} position

4.2 Threshold Method

DICOM images of FNAB consist upon several numbers of micro-architectural objects. In-order to reduce the noise from these images we applied histogram based segmentation algorithm. Moreover the threshold is a user supplied value that is used as initial guess. The initial guess is very suitable for fast conversion. Finally these objects of image are converted into grey scale or binary for further process.

Consider that, the first order derivate at a particular point x of one dimension is an initial guess for approximation, where the f (x) expending the function $f\,(x + d_x)$ using the trailer series and $d_x = 1$. The image of two variables, f (x, y) are dealt with the consistency of partial variables. The partial derivatives along with two spatial axes are derived by using these functions such as $\frac{dy}{dx}$ with one variable. So suppose an image $f = (x, y)$ is a collection of dark objects in a light background, in such a way that object and background pixels have gray levels grouped into two dominant modes. One obvious way to extract the objects from the background is to select a threshold 'T' that separates these modes. Then any point (x, y) for which $f = (x, y) > T$ is called an object point, otherwise, the point is called a background point. The figure 4.1 elaborates the technique and the equation 2 to 7 performs the mathematical representation of the threshold mechanism. The threshold method using Taylor series can be defined as per given following mathematical notations.

$$\frac{dy}{dx} = f'(x) = f(x+1) - f(x) \qquad (2)$$

After the application of first derivative, the second derivative is required to be subtracted; either it is the background or foreground information to find out the edges of every object in a DICOM image with respect to pixel intensity.

$$\frac{d^2y}{dx^2} = \frac{df'}{dx}(x) = f'(x+1) - f'(x) \qquad (3)$$

$$= f(x+2) - f(x+1) - f(x+1) + f(x) \qquad (4)$$

$$= f(x+2) - 2f(x+1) + f(x) \qquad (5)$$

This expression is about point x+1 is an area of image where the pixel edges are existing. The second derivative is carrying the information of the point x, therefore, subtract 1 from the arguments in the expression and obtain the result.

$$\frac{d^2y}{dx^2} = f''(x) = f(x+1) = f(x-1) - 2f(x) \qquad (6)$$

The equation 7 would transform the results, where g of x and y is the key condition, if Threshold T is equal to 1 and if all the homogenous lines greater than or equal Threshold T then it is optimum condition. The edges are high intensity pixels; it is therefore all the edges will be visible in the image. As the figure 4 is shown with respect to threshold value and all edges are visible.

$$g(x,y) = \{ \begin{matrix} 1 & ifR(x,y)/>=T \\ 0^{otherwise} & \end{matrix} \qquad (7)$$

4.3 Object Extraction

In object extraction phase, the objects of cell as visualized in figure 4 and 5 were separated by using the object extraction algorithm.

$$\theta_i = \frac{1}{2}\tan^{-1}\left(\frac{2\sum_{r=0}^{height-1}\sum_{c=0}^{width-1}(r-\bar{r})(c-\bar{c})I_i(r,c)}{\sum_{r=0}^{height-1}\sum_{c=0}^{width-1}(r-\bar{r})^2 I_i(r,c) - \sum_{r=0}^{height-1}\sum_{c=0}^{width-1}(c-\bar{c})^2 I_i(r,c)}\right) \qquad (8)$$

The equation 8 is representing the process, in this picture there are nine objects, it shows that this cell is a normal cell, when we apply the classifier, it will predict this image as Normal FNAC. The object extraction is one of the essential parts of system, in this function every object will be separated from the [figure 4] and doctor can easily examine the each component of cells.

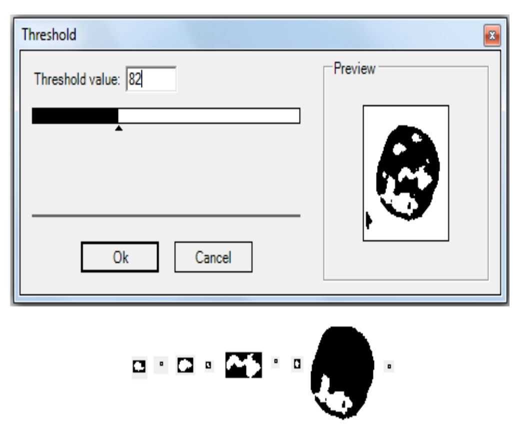


Figure 4 Set of extracted objects from cell

In addition these objects will be saved in a database automatically and doctor will assign a class label to validate the observation. In [figure 5] all the extracted objects are presented at bottom of the figure.

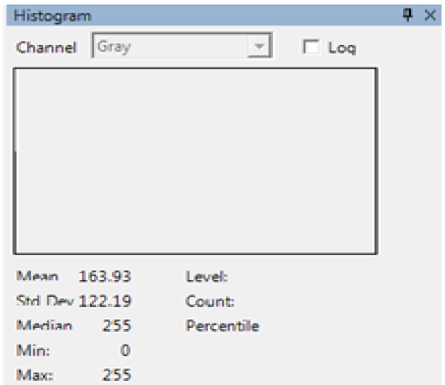


Figure 5 Histogram for measuring the intensity

4.4 Texture of objects

The histogram algorithms were used to record every careful observation of each object of the cell. The object statistical values (textures) were saved in a repository texture (Mean Values of every object) by an automated function using the database quires. The figure 6 and equation 10 is illustrated to explain the phenomena.

$$Mean = \bar{g} = \sum_{g=0}^{L-1} gP(g) = \sum_{r=0}^{height-1} \sum_{c=0}^{width-1} \frac{I(r,c)}{M} \tag{9}$$

4.5 Ensemble Methods

In machine learning the ensemble methods are used to obtain better predictive accuracy with the combination of multiple algorithms. This technique uses multiple AI based algorithms based on voting strategy, for example Decision Tree, Naïve Bayesian, SVM and Neural Networks are basically binary classifiers, but when they are used with combination they would enhance the classification accuracy. Thus; multi-class classification problems can be solved with better accuracy. The idea of ensemble methods is derived from real world examples. For example, in real life different physicians have different suggestions for making the particular diagnosis of patient. The one physician examines according to his/her experience. Actually, we would assume these opinions as the votes of doctors for a diagnosis.

It might be misdiagnosis from one physician's point of view, but majority of votes (Same opinion made by a committee of physicians) enhances the confidence level of that diagnosis and this opinion would save the patient from miss-diagnosis, so the same concept would be adopted to train the combination of classifiers, instead of single binary classifier. There are some EM techniques such as Bagging, Boosting & AdaBoost and Random Forest. In bagging a several classifiers are trained to learn the patterns of diagnosis to made, while in boosting & AdaBoost additional weight is assigned to each classifier to learn, whereas the Random Forest algorithms are used to determine the split to produces some learned decision.

4.6 Multiclass- classifier

Multiclass classification is an AI technique that is used to classify more than two class label attributes, Such as such as FC, FTC, AC and Normal. The Ensemble Methods i.e. Multi-class classifier is used to solve the problem. The multiclass classification technique uses The SVM (Support Vector Machine). The SVMs are Binary Classifier, i.e. it support two classes. But according to EM, the combination of SVMs can be used to solve the multiclass problem. There are 02 popular approaches, one is "One verses All" (OVA) and All verses All (AVA). The OVA is simple technique, where the multiples class label attributes of FNAC Cancer Disease, represented as CD. The CD classes are trained with CD binary classifiers, where the one classifier is assigned to every CD class. JD classifier is trained using the attributes of JD as a positive class; the rest of attributes would be assigned to negative class. Significantly the class JD would learn a positive value for class and vote as EM. In a result, the classifier has to predict according to voted strategy. If the CD class qualifies, one vote is to be assigned in +ve class, otherwise, the JD class is to be voted as –ve class.

Another alternate technique is "All Verses All" (AVA). In this approach each pair of classes, the classifier learns. For example, a binary classifier is used to learn for CD class

$$\frac{CD\,(CD-1)}{2} \tag{10}$$

In the 'OVA' method is represented in equation (12). Let suppose, for training data from i^{th} and j^{th}classes, run binary classification and the voting strategy.

$$Sign(w_{ij})T \bullet \Phi x + b_{ij} \tag{11}$$

If the vote is given to x in class i, then 1 is to be added to class i. Else to class j. therefore x is to be assigned to Max win class with majority of vote count. It would also be expressed as equation (13) that, "OVA" a tree algorithm, which is based on decomposition of collection for binary classifications, where the k decision functions have to assign one voted for each class

$$(wk)T \bullet \Phi x + bk, k\varepsilon y \tag{12}$$

In this way the k^{th}classifier builds a boundary line, so called 'Hyperplane'. This boundary is created to separate classes of n to k-1 other classes. Let suppose the equation (14), where the max margin of every class x is separated through a boundary line as per training data.

Class of $x = \arg\max i\{(wi)T \bullet \Phi(x) + bi\}$ (13)

The classifier should discernment between the classes, therefore in AOA; the voting count is distributed to decide that either the negative or positive class is winner. This state is also known as divide and conquer who gets the maximum number of votes will be superior one.

4.7 Performance evaluation and results

Confusion Matrix: The performance of our proposed system is 98.5% as shown in Table 1 and equation number 15 for mathematical representation.

Table 1. Confusion matrix

	FTC	FC	AC	Normal
FTC	60	0	0	2
FC	0	14	0	0
AC	0	1	61	0
Normal	0	0	0	62

The classifier classified class FTC 62 with 02 miss-classifications and 14 number of observation were classified to class FC. Moreover, the numbers of 61 observations out of 62 were classified to class AC and the numbers of 64 instances were classified by the classifier as Normal Class of FNAC dataset. A confusion matrix is a collection of correct and incorrect instances, whereas the accuracy is measure to for the performance evaluation of a system. In words, the accuracy is equal to the total number of True and false positives, divided by all true, false and positive, negative numbers. But For the multiclass problem recall or specificity are used, because individual recall values may vary from one to another class. In comparison both are the similar concepts as per equation, such as equation number 15 and equation no 18 are equal.

Precision and Recall: In literature, the precision and recall are widely used to evaluate the individual class performance. Specially, the multi-class problem is mostly evaluated by using precision as from the training perspective represented in eq. 16. Additionally, The Precision is a measure, which quantifies the hits for particular class, whereas the concept of Recall is a measure the sensitivity of a class to be predicted from a chosen dataset. The Multi-class classification problems are represented in recall, as shown in equation number 17, where the recall is equal to sensitivity which is equal to number of true positive and divided by true negative number of observations of specific class. The 100% precision rate was calculated for every class label attribute such as FTC, FC, AC and Normal.

$$Precision = \frac{Number\ of\ Tre\ Positives}{Number\ of\ True\ Positives + False\ Positives} \quad (15)$$

$$Recall = Sensitivity = \frac{True\ Positive}{False\ Positive} \quad (16)$$

As the recall measure is used for multi-class classification seniors, therefore, if we calculate the recall value for every class attribute as per results of confusion matrix and formula number 17 individually.

For example, there are four distinct classes in our class label attribute, such as, FTC, FC, AC and Normal.

- The calculated Recall values were respectively i.e. 96.77%, 100%, 98.38% and 100% for each class. Detailed results are shown in table 1.
- Specificity: The specificity is always related to Recall or sensitivity. The specificity belonging to
- True and negative rate is measure, which is generally used in two class problems where one is more interested in a particular class.

$$Sepecify = \frac{True\ Negetive}{True\ Positive + False\ Positive} \quad (17)$$

As the formula is elaborated, it is noticed that the accuracy is the same thing as the recall. It is therefore recommend to be used to measure the accuracy of a multiclass problem as well as for the binary class problem.

5.0 DISCUSSION

We used a real world dataset from SMBBMU, Pakistan. There were 25 different images of several thyroid patients examined with the complaints of thyroid nodules and goiters. All of Raw FNAC images were containing a considerable amount of cell and tissues of different thyroid cancers; however few of them were belonging to normal class of FNAB. Every cell was consisting upon many sub-objects. These objects are the behaviors and features to determine that which object is belonging to what class of thyroid cancer. At very 1st step all the FNAC or Biopsy images were converted into digital format such as JEPG by using the Digital Microscope. Then one by one image was process by the doctor (Cytologist) by using our proposed system. The doctor loaded an image to our system and cropped the most suspicious cell having the chances of thyroid cancer. In the second step he/she pressed the segmentation button and object extraction button. All of the objects were become visible on the screen and the texture of every object was recorded with its class label attribute by the doctor. Thus a training dataset of 200 observations was constructed and a decision model was constructed by using statistical and machine learning techniques such as Multiclass classifier based on Ensemble technique of OVA (one-verses-all). The classifier extracted the hidden knowledge from the dataset with 10 k-fold cross validation. For example FTC, FC and Normal classes. According to the results, which acquired on confusion matrix as shown in table

2, the classifier classified class FTC 62 with 02 miss-classifications and 14 number of observation were classified to class FC. Moreover, the numbers of 61 observations out of 62 were classified to class AC and the numbers of 64 instances were classified to Normal class. The Precision of every class was measured 100%, whereas, the Recall value of FC and Normal class was 100% and the Recall value of FTC class measured as 96.77%, meanwhile the Recall value of AC class was calculated as 98.38%. The overall classification accuracy of the system measured 98.50% with 10 k-cross validation.

Table 2 Overall performance of proposed methodology

	Total No of raw images	**No of observation / suspicious cell**	**No of extracted objects**	**No of classified cells**	**No of miss-classified cells**	**Precession (Percentage)**	**Recall** (Percentage)	**Remarks**
FTC	6	62	576	60	2	100	96.77	Table 1 is placed above to compare our system with literature
FC	6	14	126	14	0	100	100	
AC	6	62	558	61	1	100	98.38	
Normal	7	62	558	62	0	100	100	
Total	25	200	1818	197	3	100	98.50	

Table 3 Comparison of our system with literature

Approaches	Image Type	Cancer Type	Texture Yes/ No	Technique	Accuracy
1	Ultrasound Image	Thyroid Cancer	Yes	SVM	97.50 %
2	Ultrasound Image	Thyroid Cancer	Yes	SVM	78.00%
3	FNAC Images	Thyroid Cancer	No	Image Processing	Medical partner satisfied 90% %
4	FNAC Images	Thyroid Cancer	Yes	SVM	91.00 %
				Multi-scale edge detection	89.00%
5, 6	FNAC Images	Thyroid Cancer	Yes	K-NN	60.00%
				ANN	93.30%
				SVM	90.00%
7	FNAC Images	Thyroid Cancer	No	Decision Tree	98.00%
8	FNAC Images	Breast Cancer	No	KSOM NN	98.70%
9	FNAC & Ultrasound Images	Breast Cancer	Yes	MLP	92.23%
				PNN	79.47%
				LQV	97.28%
				SVM	68.80%
10	FNAC Images	Thyroid Cancer	Yes	SVM	93.30%
				Bayesian	98.80%
11	FNAC Images	Thyroid Cancer	Yes	SVM	95.00%
Our approach	FNAB Images	Thyroid Cancer	Yes	Multi-SVM	98.50%

6.0 CONCLUSION

Cancer is one of the most dangerous diseases for human beings and it is rapidly growing with the passage of time. Only timely and systematically diagnostic process would save the precious lives of humans. We developed this framework with the objective to assist the doctors while making the diagnosis of cancer types at early stage and to save the patients from misdiagnosis. We conclude that thyroid cancer problem is not a binary classification problem but it is a multi-class classification problem and in-depth level cell segmentation and object detection in image pre-process step would refine the result at more granular level instated of abstract level cell segmentation of DICOM images, i.e. FANC and biopsy. We extracted 25 raw images of FNAB and constructed 200 observations to train the classifier such as ensemble methods (multi-SVM). We employed multi-SVM set-up in .Net framework for graphical user interface because GUI more convenient to operate. Dataset was gathered from SMBBMU, Pakistan. We used recall, precision measure in performance evaluation stage. Results show that recall measure for FC and Normal class was measured at about 100%, FTC class was measured as 96.77% and AC class was calculated as 98.38%, whereas the overall classification accuracy of the system was measured at about 98.50% with 10 k-cross validation.

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