Ultrasound Image Classification for Down Syndrome During First Trimester Using Haralick Features

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Abstract — Down syndrome or Trisomy 21 is a genetic disorder which causes mental disability to the baby during the gestation period. Ultrasound scan, a noninvasive test which includes ultrasound fetal image scan for the Nuchal Translucency measurement (NT). This work proposes a method to detect and classify the down syndrome images for Nuchal translucency from ultrasound scan images using Gray Level Co-occurrence Matrix (GLCM). Fourteen GLCM features are used for feature extraction. The features are classified using Support Vector Machine (SVM) classifier for normal NT and abnormal NT image. The high performance and classification rate of 94.4% is obtained using SVM classifier with Polynomial Kernel function.

Keyword - Down syndrome, Trisomy, Nuchal Translucency, Chromosomal Abnormalities, Gray Level Co-occurrence Matrix(GLCM), Support Vector Machine (SVM)

I. INTRODUCTION

Down syndrome or Trisomy 21 is a chromosomal disorder which causes birth defects and mental retardation. Chromosomal disorders are detected using invasive and non invasive testing. Ultrasound scan which is a non invasive test and an improved methodology to identify pregnancies at increased risk of chromosomal abnormalities and Down Syndrome. At 11–13^{+6} weeks, all major chromosomal defects are associated with increased NT thickness [1][2]. In trisomies 21, 18 and 13 the pattern of increase in NT is similar and the average NT in these defects is about 2.5 mm above the normal median for crown-rump length. Nuchal translucency is an accumulation of fluid at the back of fetus neck during the first trimester. NT increases from 10 to 13 $^{+6}$ weeks of gestation period. The fluid tends to disappear after this period. [3].Detection and classification of normal and abnormal NT images are performed by sonographers. The depth and thickness of NT is measured using ultrasound, which has greater risk cardiac defects, physical disabilities and other genetic conditions. Trisomy 21 screening can also be performed using NT and biochemical markers which includes pregnancy-associated plasma protein-A (PAPP-A) and the beta subunit of human chorionic gonadotrophin (free β-hCG) resulting in an 82-87% of detection rate [4].

In singleton pregnancies many research papers are presented for Down syndrome detection using Nuchal translucency. S. Nirmala and V. Palanisamy [5] proposed Blob analysis for detecting chromosomal abnormalities for Nuchal Translucency measurement. Yinhui Deng et al. [6] proposed a hierarchical structural model for the computerized recognition of the NT region. Lai Khin Wee et al. [7] projected multilayer feed forward Neural Network and Bidirectional Iterations forward propagations method NT identification and analysis of fetal chromosomal anomalies. Spencer K et al.[8] assessed the down syndrome screening for trisomy21 by Nuchal Translucency (NT) using the multiples of the median (MoM) . Nina Mahale et al.[9] study was to establish distribution of median values of NT thickness with crown rump length(CRL) using linear regression method.

In section 2 preliminary methodologies and preprocessing filters for Down syndrome image for NT are discussed. Section 3 includes proposed GLCM methodology for feature extraction followed by Experimental results and discussions. Finally conclusions are presented in section 5.

II. METHODOLOGY AND MATERIALS

The preliminary methodology and formulae are presented here, which are needed in the remaining section of the work. The preprocessing of ultrasound scan images are preprocessed using Lee and Frost Filter. Adaptive non linear speckle reducing filter Lee and Frost is used to decrease the speckle noise in ultrasound images and preserves edges.

A.Lee Filter

Lee filter gives the enhanced performance in despeckling the ultrasound image. Transducer introduces it includes superfluous noise while capturing the image. Hence the image is corrupted with noise. Quite a lot of de-noising techniques exist for noise removal, which includes adaptive nonlinear speckle reducing filter. Lee Filter[10][11], an adaptive filter is used for noise reduction which preserves the edges. The Lee filter formula is

$$img(i,j) = I_m + N*(C_p - I_m) \tag{1}$$

where I_m is the mean intensity of the filter window

$$W = \frac{\sigma^2}{(\sigma^2 + \rho^2)} \tag{2}$$

where σ^2 is the variance of the pixel values within the filter window and is calculated as

$$\sigma^2 = \frac{1}{N}\left[\sum_{j=0}^{N-1}(x_i)^2\right] \tag{3}$$

x_j -Pixel value within filter window at indices j

N - is the size of the window

M - is the size of the image

y_i -Value of each pixel in the image

$$\rho^2 = \left[\frac{1}{m}\sum_{i=0}^{\mu-1}(y_i)^2\right] \tag{4}$$

B. Frost Filter

Frost filter act like a median filter , Damping factor K is choosen in such a way the homogenous areas approaches 0 and the value of m approaches 1. Frost filter [11] maintains a balance between averaging and the all-pass filter. Balance is achieved by forming and exponentially shaped filter kernel that can vary from basic average filter to an identity filter on adaptive basis. Results variation occurs due to the coefficients. In case of high coefficient variation the sharp features are preserved without averaging

a) $$a^2 = s^2 / z^2 \tag{5}$$

b) $$[m(t)] = e^{-Ka^2[t]} \tag{6}$$

c) $$y(t) = \frac{\sum_i m(t_i)x(t_i)}{\sum_i [m(t_i)]} \tag{7}$$

s^2 and z^2 are for Image variance and mean, t and $m(t)$ represents pixel coordinate and weight factor. Equation (5) is substituted in equation (6) to get $m(t)$ value and $y(t)$ is obtained by substituting equation (6).The constant k is for controlling the Damping rate. $x(t)$ and $y(t)$ represents Original pixel value in the point t and replacing pixel value for the point t respectively.

C. Grey Level Co-occurrence Matrix

Grey-Level Co-occurrence Matrix texture measurements were proposed by Haralick in the 1970s.The GLCM is also called the grey tone spatial dependency matrix. GLCM is used for second order texture calculations, which calculates the neighboring pixels in the image. It includes only 16 data cells and GLCM computation can be carried out in four directions $\delta = 0°$, $\delta = 45°$, $\delta = 90°$, $\delta = 135°$.The probability $p(i,j)$ represents that two pixels with a specified separation have grey levels i and j. GLCM of an image is calculated using a displacement vector d which is defined by its radius δ and orientation θ. Eight choices for angle are used which includes 0°, 45°, 90°, 135°, 180°, 225°, 270° or 315°.Each and every pixel has neighboring pixels to choose the angle θ. GLCM is dimensioned to the number of gray levels G and stores the co-occurrence probabilities g_{ij}

D. SVM Classifier

The extracted features from GLCM are classified using SVM classifier with kernel function. Classification involves both training phase and testing phase for ultrasound images.SVM is a popular machine learning technique which controls complexity. Support Vector Machines are supervised learning models which are used for medical image classification for both normal and abnormal images. Support Vector Machine was proposed by Vapnik. SVM constructs a linear hyperplane which separate two sets of data . The maximum margin that separates the hyperplane between the two classes is given by 2/||w||.

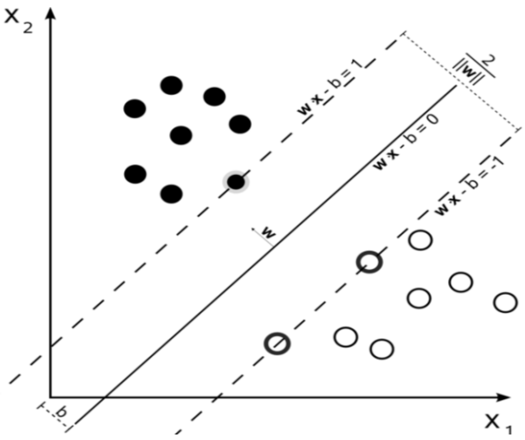

Fig. 1. SVM classification with separating margin between the two classes

Given training data D, a set of point of the form $D=(x_i, y_i)$ for i = 1...n, $y_i \in \{-1,1\}, x_i \in R^d$ where y_i is either -1 or 1 indicating to which the point belongs. The decision boundary should classify all points correctly. The training data are linearly separable therefore exists two hyperplane which separates the two classes. The two hyper plane maximizes the distance which separates the margin between two classes. The linear function takes the form

$$w.x_i + b \geq 1 \quad if \ y_i = +1 \tag{8}$$

$$w.x_i + b \leq 1 \quad if \ y_i = -1 \tag{9}$$

$$y_i(w.x_i + b) \geq 1 \quad for\ all\ i \tag{10}$$

Where w is the weight vector normal to the hyper plane. The SVM classifier uses the Kernel function for linearly separable data points which maps the low dimensional data to high dimensional space .The most common Kernel functions are RBF, Linear , Polynomial and Quadratic.

E. Classification using Kernel Function

SVM kernel functions are defined as $k(x_{i,} x_j) = \phi(x_i)\phi(x_j)$ where $\phi(x)$ maps the vector *x* to some other Euclidean space. The kernel function for the NT image classification includes

1) Linear Kernel : simplest kernel function which is represented by inner product plus an constant C

$$k(x, y) = x^T.y + c \tag{11}$$

2) Polynomial Kernel : When all the training data is normalized polynomial kernels are well suited

$$k(x, y) = (\alpha x^T.y + c)^d \tag{12}$$

d = Polynomial degree

3) RBF kernel : Gaussian kernel is an example of RBF kernel

$$k(x, y) = \exp\left(\frac{\|x - y\|^2}{2\sigma^2}\right) \tag{13}$$

$\sigma =$ Standard deviation

4) Quadratic kernel : $$k(x, y) = 1 - \frac{\|x - y\|^2}{\|x - y\|^2 + C} \tag{14}$$

III. PROPOSED GLCM FEATURE EXTRACTION METHOD

The proposed system consists of four phases which includes, preprocessing, and feature extraction, classification and performance analysis. Feature extraction is performed from the preprocessed image. The fig.2 Architecture diagram represents the process involved for NT image classification.

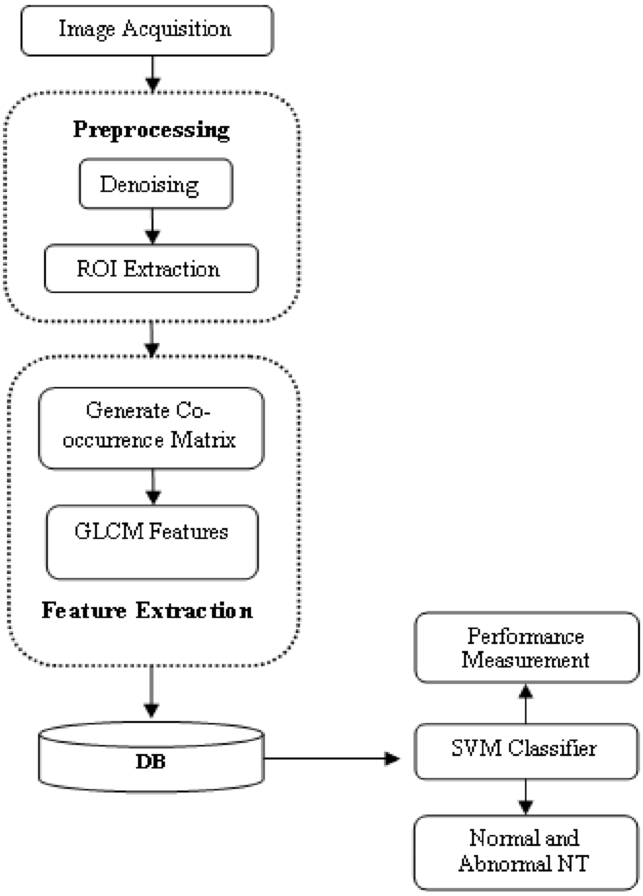

Fig. 2. Architecture Diagram for NT Image Classification

The above diagram represents the flow for NT image classification. Sonography is the operator reliant imaging technique. Medical ultrasound imaging is done using ultrasonic waves in 3 to 20 MHz range. Ultrasound is the preferred imaging modality for the diagnosis and monitoring of pregnant women and their babies[12]. An ultrasound scan in pregnancy is an unproblematic method that uses high frequency echo waves to generate a two-dimensional black and white image. Ultrasound probe, transducer is used to acquire the fetal images. Medical Ultrasound is performed mainly by a pulse-echo approach with a B-mode which is brightness mode . The caliper must be placed correctly to obtain the NT. The image acquisition is the process of obtaining ultrasound scan images from sonographers. The fig.3 below shows the Normal and abnormal NT ultrasound scan images.

Fig. 3. Normal and Ultrasound scan image for normal and abnormal NT

The image contains speckle noise , removed by denoising using Lee filter and Frost filter which is discussed in section 2. After preprocessing the ROI for NT is obtained. The normal and abnormal images of known datasets are used for training and unknown images for testing phase respectively. The images are preprocessed by despeckling using Lee and Frost filters and extracting Region of Interest(ROI).The Feature extraction is performed using GLCM by generating grey level co-occurrence matrix on both normal and abnormal images of NT. SVM classifier finally classifies the images for normal and abnormal NT using Kernel function.

A . GLCM Feature Extraction

GLCM is a mathematical method used for the statistical texture analysis. GLCM texture measurement is proposed by Haralick with different fourteen textural features. GLCM computation can be carried out in four directions $\delta = 0°$, $\delta = 45°$, $\delta = 90°$, $\delta = 135°$ .In the proposed work $\delta = 0°$ is used for feature extraction. The work is implemented by using all the fourteen textural features of GLCM, which includes Angular second moment, Contrast, Correlation, Sum of squares, Inverse Difference Moment, sum of average, Sum variance, Sum Entropy, Difference Variance, Difference entropy, Information measures of correlation, maximal correlation coefficient.

The original data set is reduced by certain features measurement. GLCM extracts statistical texture features. Number of operations required to compute any one of these features is propositional to the number of resolution cells in the image. In GLCM Co-occurring pairs obtained by choosing θ equal to 0° would be similar to those obtained by choosing θ equal to 180°. For GLCM dimension determination Gray value of the pixel and gray levels are important The textural features summarize the relative frequency distribution describes how frequently one gray tone will appear in a particular spatial relationship to another gray tone on the image. The following equations define these textural features [13][14]. Fourteen Haralick features are used for feature extraction

$p(i, j) = (i, j)^{th}$ entry in a normalized gray tone spatial dependencies

$p_x(i)$ =ith entry in marginal probability matrix obtained by summing rows $p(i, j) = \sum_{j=1}^{N_g} p(i, j)$ (15)

N_g - Number of distinct gray level in the quantized image

$\sum_i$ and $\sum_j$ $\sum_{i=1}^{N_g} and \sum_{j=1}^{N_g}$ respectively

$$p_y(j) = \sum_{i=1}^{N_g} p(i, j) \tag{16}$$

$$p_{x+y}(k) = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i, j) \tag{17}$$

where $i + j = k = 2,3....N_g$

$$p_{x-y}(k) = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i, j) \tag{18}$$

where $|i - j| = k$ =k=2,3,... $N_g - 1$

The Haralick textual Features are as follows

1) Angular Second Moment(ASM) :Angular second moment is also known as Energy is low when all elements in the GLCM are close to either 0 or 1 and high when the GLCM has equal values or pixels are similar which is calculated using,

$$f1 = \sum_i \sum_j \{p(i, j)\} \tag{19}$$

2) Entropy: Entropy measures the complexity or disorder of the image. Complex textures tend to have high entropy. Entropy is strongly and inversely correlated to energy

$$f2 = -\sum_i \sum_j p(i, j)log(p(i, j)) \tag{20}$$

3) Contrast: Contrast measures the spatial frequency of an image. It is the difference between highest and the lowest values of contiguous set of pixels

$$f3 = \sum_i \sum_j (i - j)^2 p(i, j) \tag{21}$$

4) Variance: Variance is also as sum of squares, where μ is the mean of p (i, j)

$$f4 = \sum_i \sum_j (i-\mu)^2 p(i,j) \quad (22)$$

5) Correlation: Correlation features is a measure of gray tone linear dependencies in the image

$$f5 = \frac{\sum_i \sum_j (ij)p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (23)$$

Where μ_x, μ_y, σ_x and σ_y are the means and standard deviations of p_x and p_y

6) Homogeneity: This statistics is also called a Inverse Difference moment. It measures the image homogeneity and assumes larger values for smaller gray tone differences in pair elements. It has maximum value when all the elements in the image are same

$$f6 = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j) \quad (24)$$

The rest of the textural features used in the feature extraction includes sum of average, sum of entropy, sum of variance, Difference variance, Difference Entropy, maximum Correlation coefficient, Information measures of correlation are secondary and derived from those features which are listed above.

IV. Experimental Results And Discussion

The experimental results of NT image classification are conducted on 100 images. The experiments are carried out on Intel core i5 processor and 3GB RAM. All the implementation performed using MATLAB. The preprocessing is performed in two ways, by using Lee filter and Frost filter. The ultrasound image dataset consists of 32 normal NT and 39 abnormal NT down syndrome images. The confusion matrix is known as contingency or error table, which used to measure the classification accuracy for ultrasound NT down syndrome images. ROC graphs observe the performance of classifiers. A ROC graph is a plot with the false positive rate on the *X* axis and the true positive rate on the *Y* axis. Sensitivity and specificity is computed by True positive (TP), False positive (FP), False Negative (FN) and True Negative (TN). Sensitivity, Specificity and Accuracy are calculated by the following

$$Sensitivity = \frac{TP}{TP + FN} \quad (25)$$

$$Specificity = \frac{TN}{TN + FP} \quad (26)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (27)$$

A. Confusion Matrix

The classified groups of images are represented as diagonal elements of the confusion matrix. The sensitivity is the actual positive cases which are correctly classified. The specificity is the actual negative cases which are correctly classified. In fig. 4 the confusion matrix for sensitivity and specificity for NT images are 93.8 % and 94.9 % respectively.

TABLE I . CONFUSION MATRIX FOR NT IMAGE CLASSIFICATION

Confusion Matrix		Predicted		
		Positive	Negative	
Actual	Positive	30 (TP)	10 (FP)	Positive Predicted Value
	Negative	2 (FN)	29 (TN)	Negative Predicted Value
		Sensitivity	Specificity	
		93.8%	94.9%	

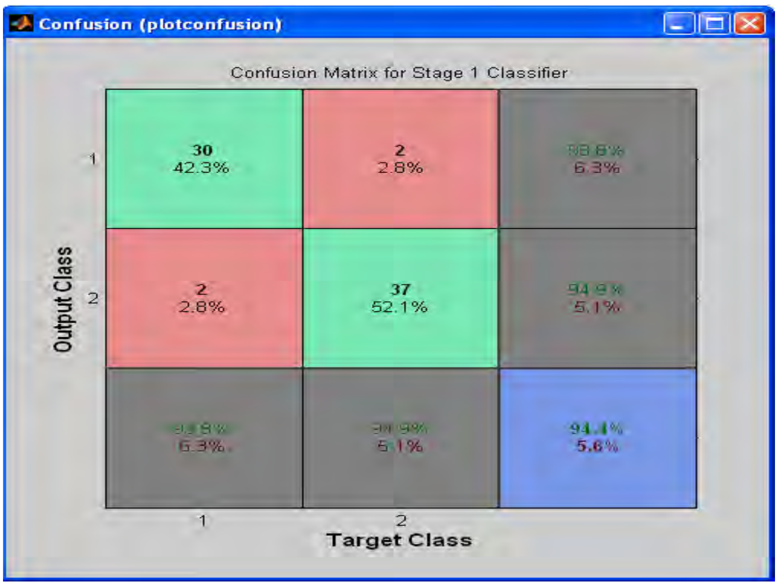

Fig. 4. Confusion Matrix

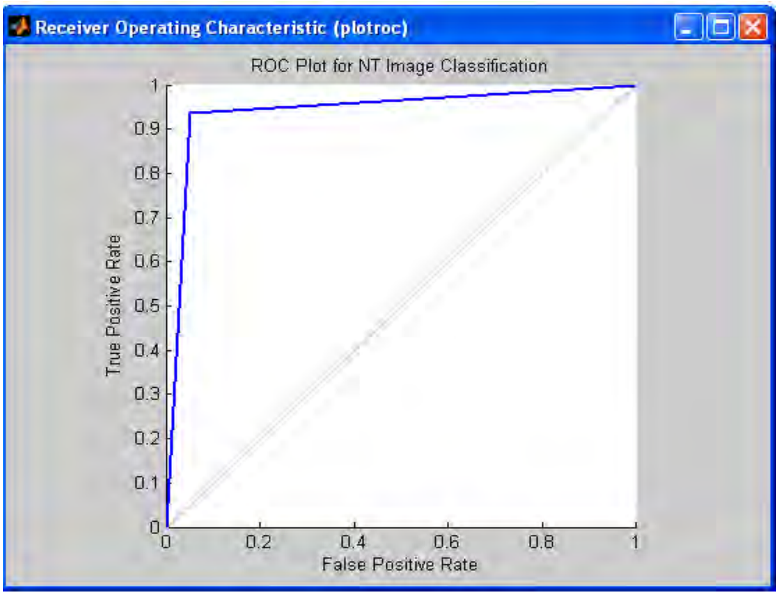

Fig. 5. ROC curve for NT classification

TABLE II. RESULT ANALYSIS OF NT IMAGE CLASSIFICATION

Feature Extraction Technique	Kernel Function	SVM Classifier - Classification Rate					
		Lee Filter			Frost Filter		
		Normal NT	Abnormal NT	Average	Normal NT	Abnormal NT	Average
GLCM	RBF	84.3	97.4	90.9	87.5	92.3	89.9
	Linear	90.6	79.4	85.05	93.75	76.92	85.3
	Polynomial	93.75	94.8	94.4	90.62	92.3	91.46
	Quadratic	96.875	94.8	95.87	87.5	89.74	88.6

It is observed from the above table that Lee filter and frost filter with RBF, Linear, and Polynomial kernel function produces different classification rate and accuracy for normal and abnormal NT images. The Lee filter with polynomial function results in the classification rate of 93.75% for normal and 94.8 % for abnormal images. The overall accuracy of both NT images is 94.4% calculated using confusion matrix. The association between sensitivity and specificity is measured using Receiver operating characteristics (ROC) curve.

V. CONCLUSION

The proposed work for Down syndrome image classification helps to classify the both normal NT and abnormal NT images more efficiently. Features are extracted using Haralick features and ultrasound images are classified using SVM classifier with four kernel function. Polynomial kernel with Lee filter is computationally very effective and produces best promising result. The proposed method produces 94.4 % of accuracy for overall NT image classification

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