

Reliable Non invasive First Trimester Screening Test Using Image processing and Artificial Neural Network

Rafeek T*, A Gunasundari**

(*PG Scholar , ** Assistant Professor)

(Department of Electrical & Electronics Engineering, PSG College of Technology, Coimbatore-641 004)

ABSTRACT

Down Syndrome is a chromosomal abnormality caused by the presence of all or part of a third copy of chromosome 21. Any woman can have a baby with Down Syndrome. Physical growth of affected babies are delayed especially the facial characteristics. Recent study proves that Down Syndrome can be detected in early stage by identifying the absence of fetal nasal bone. During the first trimester of pregnancy, visual identification of nasal bone by examining the ultrasonogram is very difficult. Speckle noise is also introducing errors in ultrasonic images. This work presents a new approach for the detection of nasal bone by using different image processing algorithms and Back propagation neural network (BPNN). A high performance hybrid Despeckling method is used in this system which can dramatically increase the accuracy of the whole system. The features in the nasal region are extracted in spatial domain as well as transform domain using Discrete Cosine Transform (DCT) and wavelet transforms. Features extracted from images with nasal bone and images which don't have nasal bone. The normalized data set is used to train Back Propagation Neural Network (BPNN). This trained artificial feed forward network is used to classify different ultra sonogram. Experimentally prove that the proposed method gives better classification rate than any other non invasive screening method. This method combined with the present detection methods can reduce operator error and enhance overall detection rate.

Keywords: Back Propagation Neural Network (BPNN), DCT, Despeckling, First Trimester, Non Invasive Screening.

1. Introduction

Down Syndrome is a genetic disorder that was named after John Langdon Down, who first recognized it as a distinct condition in 1866. It affects very small percent of world's population, approximately 1 of 800 live births. Individuals with Down syndrome tend to have a lower-than-average cognitive ability, often ranging from mild to moderate disabilities. It is difficult for a person affected by Down Syndrome to lead a normal

independent life. Several studies show that main cause for this Syndrome is the presence of an extra chromosome in the 21st pair. Routine screening (Prenatal screening) for Down Syndrome is carried out during pregnancy in order to identify women who are at high risk of giving birth to a child with Down Syndrome. Previously Down Syndrome was detected using invasive techniques, though they give accuracy of 90% or above, they carry a significant risk of miscarriage. Recently Non invasive techniques using Ultra sonogram are being used for the early detection of Down Syndrome during period of gestation. It is an established fact that, during first trimester period of gestation the absence of nasal bone is reliable indicator for the presence of Down syndrome. Prenatal ultrasound studies in 11th-14th week fetus have shown that nasal bone is not visible for the case of a Trisomy 21[1].

In this work, a process for non invasive, accurate, and reliable method to enhance the detection rate of Nasal bone from ultrasound images has been proposed. On an ultrasound scan image nasal bone appears as a very small white patch. The texture of this white patch is significantly different from that of surrounding tissues. These statistical features are extracted from image on both spatial domain and Transform domain and are fed to neural network classifier. A three layer Back Propagation Neural Network is created and these extracted parameters are used to train the neural network. After the network has been trained sufficiently, it will be able to distinguish images having nasal bone [3].

2. Proposed Methodology

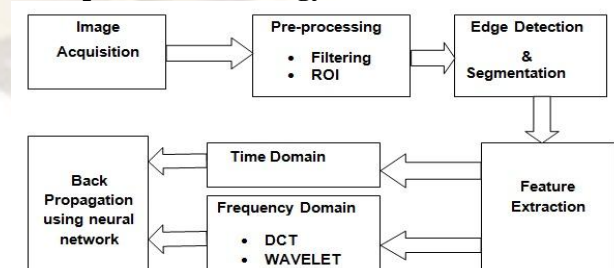


Fig. 1. block diagram

The proposed work, presents a new method for the identification of Down Syndrome through the detection of nasal bone. The block diagram for the proposed system is shown in figure. We can classify

the proposed system into four different sections. First one is image acquisition. Set of sample images are collected from an ultrasound imaging system. Second one is image pre-processing section, apply some pre-processing techniques for the removal of inherent noises, and certain characteristics of nasal bone can be easily detected. Next is to segment the region of interest. Next section is feature extraction, nasal usually appears as very small white patch in Ultra sonogram. The textures of white patches are significantly different from that of surrounding tissues. As the textures are different, statistical parameters extracted from image segment containing nasal bone will be different from region without nasal bone. This statistical difference can be used for the identification of nasal bone. Extracted features are sending to ANN network in both spatial domain and converted to transform domain data. The last section is a neural network classifier which is used to distinguish an image with nasal bone from one which doesn't have nasal bone.

2.1 Image acquisition

The first stage of any vision system is the image acquisition stage. Ultrasonography is able to detect many fetal structural and functional abnormalities. Ultrasound works by using sound to generate an image of the fetus. A special gel is applied on the mother's abdomen and a transducer is used to transmit the sound waves into the abdomen, it directs small pulses of inaudible, high-frequency sound waves into the body. As the sound waves bounce off of internal organs, fluids and tissues, the sensitive microphone in the transducer records tiny changes in the sound's pitch and direction. These signature waves are instantly measured and displayed by a computer, which in turn creates a real-time picture on the monitor.

2.1.1 Ultrasonography

Ultra sonic imaging uses high frequency sound waves and their echoes to produce images that can demonstrate organ movement in real time. Unlike electromagnetic waves, such as X-rays and gamma rays, ultrasound is non ionizing and as such is considered safe at the intensities used in clinical imaging systems. The transducer probe makes the sound waves and receives the echoes. It is considered as the mouth and ears of the ultrasound machine. In the probe, there is one or more quartz crystals called piezoelectric crystals. When an electric current is applied to these crystals, they change shape rapidly. The rapid shape changes, or vibrations, of the crystals produce sound waves that travel outward. Conversely, when sound or pressure waves hit the crystals, they emit electrical currents. Therefore, the same crystals can be used to send and receive sound waves. The probe also has a sound absorbing substance to eliminate back reflections from the probe itself, and an acoustic lens to help

focus the emitted sound waves. Ultrasonography has emerged as a useful technique for imaging internal organs and soft tissue structures in the human body. It is non invasive, portable, versatile, relatively low cost. The fetal images are obtained from ultrasound machine (model HD-15 PHILIPS) [12].

2.2 Image pre-processing:

The objective of image enhancement is to improve the interpretability of the information present in images for human viewers. Enhancement yields a better-quality image for the purpose of some particular application which can be done by either suppressing the noise or increasing the image contrast. Images are often corrupted by impulse noise due to noisy sensor or channel transmission error. This appears as discrete isolated pixel variations that are not spatially correlated. The goal of removing impulse noise is to suppress the noise while preserving the integrity of the edges and detail information associated with the original image. Speckle reduction is usually used as a critical pre-processing step for clinical diagnosis by ultrasound and ultrasound image processing. Image variance or speckle noise is a granular noise that inherently exists and degrades the quality of the active images. The first step is to reduce the effect of speckle noise.

2.2.1 Hybrid Despeckling Filter

Ultrasound imaging system is an important imaging method in medical field. One of the major drawbacks of ultrasound images is the poor image quality due to speckle noise. Only skilled radiologists can make an effective diagnosis and hence limiting its use in a wide medical network. Speckle is a multiplicative noise which creates difficulty for extracting fine details from an image. Speckle suppression by means of a digital image processing is one of the techniques to improve the image quality and possible the diagnostic potential of medical ultrasound imaging. Despeckling is the method to reduce speckle noise and to improve the visual quality for better diagnosis. Many denoising methods have been proposed over the years, such as wavelet thresholding and bilateral filtering, anisotropic methods, median filtering etc. Among these, wavelet thresholding has been reported as a highly successful method.

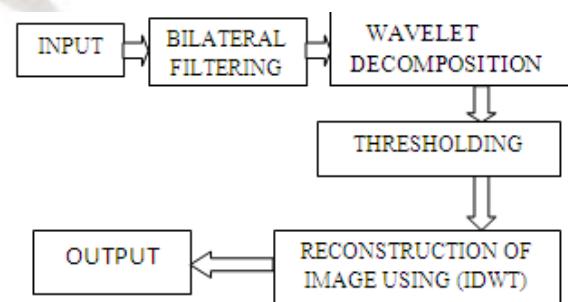


Fig.2 .hybrid despeckling method-block diagram

In wavelet thresholding, a signal is decomposed into approximation and detail sub bands and the coefficients in the detail sub bands are processed via hard or soft thresholding. The hard thresholding eliminates coefficients that are smaller than a threshold; the soft thresholding shrinks the coefficients that are larger than the threshold as well. The main task of wavelet thresholding is the selection of threshold value and the effect of denoising depends on the selected threshold. A bigger threshold value suppresses the useful information and noise components, while a smaller threshold cannot eliminate the noise effectively.

The bilateral filter is an alternative to wavelet thresholding. It applies spatially weighted averaging without smoothing edges. This is achieved by combining two Gaussian filters. One filter works in spatial domain and the other in the intensity domain. Therefore, not only the spatial distance but also the intensity distance is important for the determination of weights. Hence, these types of filters can remove noise in an image while retaining edges. The main objective of this work is to design a filter for effective Despeckling of medical ultrasound images without smoothing edges. The parameters of the bilateral filter used are, $\sigma_d = 1.6$, $\sigma_r = 0.5$ and the window size is 3×3 with one level wavelet decomposition. The main advantage of hybrid despeckling technique is, retaining edges or preserves edge when denoising. That means get a better performance of standard quality matrices like signal to noise ratio (SNR), in the case of hybrid despeckling [2].



Fig.3. original & despeckled image

2.2.2 Selection of ROI:

It is sometimes of interest to process a single sub region of an image, leaving other regions unchanged. This is commonly known as region-of-interest (ROI) processing. Image sub regions may be specified by using Mathematics or Graphics primitives, such as Point, Line, Circle, Polygon, or simply as a list of vertex positions. Region of interest (ROI) usually means the meaningful and important regions in the images. The use of ROI can avoid the processing of irrelevant image points and accelerate the processing. Extraction of regions of interest from images is an important topic in the image processing area, especially in biomedical image processing area.

2.3 Edge Detection

In an image, between two regions, a set of connected pixels are seen. Such pixel group is called as an edge. The detection of edge (boundary) is the most common method for detecting meaningful discontinuities, especially in medical imaging field. The purpose of edge detection is to identify areas of an image where a large change in intensity. Typically, edge detection is useful for segmentation, identification and registration of objects in a scene. Mathematically, first and second order derivatives are used for edge detection. Prewitt, Sobel and Laplacian operator methods are more common in edge detection. These operators work well for images with sharp edges and low amount of noise. Edge detection algorithm should look for a neighborhood with strong signs of change. Most of the edge detectors work on measuring the intensity gradient at a point in the image [15].

2.4 Watershed Segmentation Algorithm

The watershed transformation is a powerful tool for image segmentation. In a watershed transformation, the image is considered as a topographic surface. The gray level of the image represents the altitudes. Marker controlled watershed algorithm is the direct application of watershed algorithm generally leads to over segmentation due to noise and other local irregularities of the gradient, i.e. large number of segmented regions. This can be a serious enough to render the result of algorithm virtually useless. An approach used to control over segmentation is based on the concept of markers. A marker is a connected component belonging to an image. These markers can be of two types: internal marker associated with object of interest and external markers associated with the background. A procedure for marker selection typically consist of two principle steps Pre-processing and definition of a set of criteria that a marker must satisfy Marker selection can range from simple procedure based on the gray level values and connectivity, to more complex description involving size, shape, location, texture content and so on. For the proposed system external markers shows effective partition of the nasal bone region from its background. Watershed algorithm has been applied to each individual region. In other words we simply take the gradient of the smoothed image and then restrict the algorithm to operate on a single watershed that contains the marker in that particular region. Using markers bring a priori knowledge to bear on the segmentation problem [6].

2.5 Image Feature Extraction

An image feature is a distinguishing primitive characteristic or attribute of an image. Some features are natural in the sense that such features are defined by the visual appearance of an

image, while other, artificial features result from specific manipulations of an image. Natural features include the luminance of a region of pixels and gray scale textural regions. Image amplitude histograms and spatial frequency spectra are examples of artificial features. Image features are of major importance in the isolation of regions of common property within an image (image segmentation) and subsequent identification or labelling of such regions (image classification). There are two quantitative approaches to the evaluation of image features: prototype performance and figure of merit. In the prototype performance approach for image classification, a prototype image with regions (segments) that have been independently categorized is classified by a classification procedure using various image features to be evaluated. The classification error is then measured for each feature set. The best set of features is, of course, that which results in the least classification error. The figure-of-merit approach to feature evaluation involves the establishment of some functional distance measurements between sets of image features such that a large distance implies a low classification error. The most basic of all image features is some measure of image amplitude in terms of luminance, spectral value or other units. There are many degrees of freedom in establishing image amplitude features. Image variables such as luminance values may be utilized directly, or alternatively, some linear, nonlinear, or perhaps non-invertible transformation can be performed to generate variables in a new amplitude space. On an ultra sonogram nasal bone appears as a very small white patch. The texture of this white patch is significantly different from that of surrounding tissues. This characteristic of the image is extracted for the detection purpose. Statistical parameters such as mean, variance, skewness, kurtosis, fifth order moment and sixth order moment are taken here for detection purposes.

2.5.1 Mean

The simple mathematical average of set of two or more numbers. In a data set, the arithmetic mean is equal to the sum of the values divided by the number of values. The arithmetic mean of a set of numbers $x_{11}, x_{12}, \dots, x_{m_n}$ is typically denoted by \bar{x} . The mean of the values:

$$\text{Mean } \bar{x} = \frac{1}{M * N} \sum_{i=1}^n \sum_{j=1}^m (x_{ij}) \quad (1)$$

Mean indicates the tendency to cluster around some particular value.

2.5.2 Variance

In probability theory and statistics, the variance is a measure of how far a set of numbers is spread out. It is one of several descriptors of a probability distribution, describing how far the numbers lie from the mean (expected value). In particular, the variance is one of

the moments of a distribution. In that context, it forms part of a systematic approach to distinguishing between probability distributions. While other such approaches have been developed, those based on moments are advantageous in terms of mathematical and computational simplicity. The value, which characterizes its "width" or "variability" around the mean value, is the variance:

$$\text{Variance} = \frac{1}{(M-1)*(N-1)} \sum_{i=1}^n \sum_{j=1}^m (x_{ij} - \bar{x}) \quad (2)$$

2.5.3 Skewness

The skewness of a random variable 'x' is the third standardized moment and it is represented as:

$$\text{Skewness} = 1/(M * N) \sum \left[\frac{x_{ij} - \bar{x}}{\sigma} \right]^3 \quad (3)$$

Where M, N represents the image size, x is the mean and σ is the standard deviation. In probability theory and statistics, skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable. The skewness value can be positive or negative, or even undefined.

2.5.4 Kurtosis

In probability theory and statistics, the kurtosis is also a non-dimensional quantity. It measures the relative flatness of a distribution to a normal distribution. The conventional definition of the kurtosis is:

$$\text{Kurtosis} = [1/(M * N) \sum [x_{ij} - \bar{x}/\sigma]^4 - 3] \quad (4)$$

Where the -3 term makes the value zero for a normal distribution, σ is the standard deviation.

2.5.5 Fifth order features:

$$[1/(M * N) \sum [x_{i,j} - \bar{x}/\sigma]^5] \quad (5)$$

2.5.6 Sixth order features:

$$\text{Sixth Order} = [1/(M * N) \sum [x_{i,j} - \bar{x}/\sigma]^6] \quad (6)$$

2.6 Transform domain Analysis

It represents the analysis and representation of image in Transform domain. By using transforms, signals can be represented with less number of coefficients with minimum distortion. The commonly used transform domain analysis is Discrete Cosine Transform, Sine transform, Wavelet transform etc. In this work, multiresolution transform and DCT has been used for the analysis.

2.6.1 Discrete Cosine Transform

A discrete cosine transform (DCT) expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies. Like other transforms, the DCT attempts to decorrelate the image data. Discrete-Cosine Transform (DCT) has found popularity due to its comparative concentration of information in a small number of coefficients, and increased tolerance to variation of illumination. The DCT has been proved successful at de-correlating

and concentrating the energy of image data. DCTs are important to numerous applications in science and engineering. The DCT packs energy in the low frequency regions. Therefore, some of the high frequency components can be discarded without significant quality degradation. Note that the transform image has zeros or low level intensities except at the top left corner where the intensities are very high. These low frequencies, high intensity coefficients, are therefore, the most important coefficients in the frequency matrix and carry most of the information about the original image. The discrete cosine transform of an NxN image(x, y) is defined by:

$$C(u, v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x, y) \cos\left[\frac{\pi(2x+1)u}{2N}\right] \cos\left[\frac{\pi(2y+1)v}{2N}\right] \quad (7)$$

For u, v = 0, 1, 2N -1

$$\text{and } \alpha(u), \alpha(v) = \sqrt{\frac{1}{N}} \quad \text{for } u = 0$$

$$\sqrt{\frac{2}{N}} \quad \text{for } u \neq 0$$

The proposed technique calculates the 2D-DCT for each cropped region. A subset of these coefficient values is taken to construct the feature vector. Empirically, the upper left corner of the 2D-DCT matrix contains the most important values because they correspond to low-frequency components within the processed image block. The extracted coefficients/features are then used for training purpose. There is no redundant information because the wavelet functions are orthogonal. The computation is efficient due to the existence of a pyramidal algorithm based on convolutions with quadrature mirror filters. The original signal can be reconstructed from the wavelet decomposition with a similar algorithm.

2.6.2 Wavelet Transform

A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. Wavelet theory is applicable to several subjects. All wavelet transforms may be considered forms of time-frequency representation for continuous-time (analog) signals and so are related to harmonic analysis. Wavelets are mathematical function which decomposes data into different frequency components, each component with a resolution matched to its state. It has more advantage when we analyzing physical situation with discontinuities and sharp edges. The wavelet transform is identical to hierarchical subband filtering system

Almost all practically useful discrete wavelet transforms use discrete-time filter banks. These filter banks are called the wavelet and scaling coefficients in wavelets nomenclature. The wavelet transform (WT) is a relatively new type of transform. One of the main strength that characterizes this transform is its ability to provide information about the time-frequency representation of the signal. For most practical applications there are two kinds of wavelets available which are the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT). Wavelet coefficient at every scale generating a huge amount of data. Due to the huge amount of data generated through CWT, training classifiers based on its coefficients at different scales can often become difficult. The family of Daubechies wavelets was chosen as the basis functions for the decomposition. Daubechies wavelets are classified according to the number of vanishing moments, N. The smoothness of the wavelets increases with the number of vanishing moments. For the case when N = 1, the Daubechies scaling function and wavelet function resembles that of the Haar and are discontinuous. It is desirable to have smooth wavelets and therefore N is increased. Although the Daubechies2 wavelet is continuous, its derivative is discontinuous. For N greater than 2, the wavelet and its derivative are both continuous.[8]

By applying DWT, the data is actually divided i.e. decomposed into four subbands corresponding to different resolution levels. The Transform function used for the analysis is Daubechies D4 wavelet transform; it has four wavelet and scaling function coefficients. The scaling function coefficients are:

$$h_0 = \frac{1+\sqrt{3}}{4\sqrt{2}}$$

$$h_1 = \frac{3+\sqrt{3}}{4\sqrt{2}}$$

$$h_2 = \frac{3-\sqrt{3}}{4\sqrt{2}}$$

$$h_3 = \frac{1-\sqrt{3}}{4\sqrt{2}}$$

The wavelet function coefficient values are:

$$A_1 = h_3$$

$$H_1 = -h_2$$

$$V_1 = h_1$$

$$D_1 = -h_0$$

The sublevels labeled H1, V1 and D1 represent the finest scale wavelet coefficients i.e. image details, while A1 represents coarse level coefficients (approximation of image). The image is analyzed in three resolutions. The mean, variance, skewness kurtosis, fifth order and sixth order are taken for all the three levels. These constitute 6 parameters in a single resolution and hence 72 coefficient parameters (3 resolutions) for each image. The coefficients were stored in separate files in the form of a vector and later these were used for training of artificial neural network .

3. Artificial Neural Network

This section focuses on the neural network approach for the detection of nasal bone. Neural networks are introduced with an emphasis on multilayer Back propagation feed forward neural networks. An artificial neural network is a system based on the operation of biological neural networks and it is called as an emulation of biological neural system. Artificial neural networks are adaptive models. They can learn from the data and generalized things which they have learned. They can find good solution, were traditional models have failed. Artificial neural network learns by updating its network parameters according to a predefined rule called learning rules. Neural network are trained, so that a particular input leads to specific target output. The network is trained in such a way that it minimizes the deviation between output and the specified target. Neural network has been used in pattern recognition, identification, classification, and computer vision and control systems

3.1 Training using Back Propagation Neural Network

A tool for the detection of Nasal bone was designed and was implemented in MATLAB. The image is analyzed in the transform domain. The various parameters, which are used for the analysis, are mean, variance, skewness, kurtosis, fifth order and sixth order. These parameters are extracted from the transform domain. This analysis helps in finding out some statistical difference that can be used for the detection of the presence of nasal bone. To predict whether a new image contain Down Syndrome or not, need to have a training set from which the details of the new image can be predicted. Use a neural network, which will take in the inputs and train the network according to the image characteristics and creates two well-defined boundaries for images with and without Nasal bone. Images are converted to gray scale using utilities available in MATLAB before they are fed to the tool designed. Because of large fetal movement during the scanning process it is necessary to define region of interest which can compensate for changes in the fetal head position. The image is analyzed in three resolutions. The mean, variance, skewness, kurtosis, fifth order and sixth order are taken for all the three levels. These constitute 72 parameters for a three level decomposition for each image .The coefficient parameters are stored in separate files and are normalized separately. These 72 parameters are used in the training phase. Parameters are extracted from a large number of images and are then normalized. The normalized patterns are used in the training of Back propagation neural network. Training is continued till the error converges to a reasonably minimum value. During the training process the numeral "0" is used to

represent images with Down Syndrome and "1" is used to represent images having normal anatomical features.

4. Results and Conclusion

Ultrasonography is the most popular technique used in the field of imaging of soft tissue structures in the human body especially fetal images. In this work, offered a new approach to the use of computer aided examination to enhance the detection rate of Down Syndrome. Initially selected the nasal bone portion with the help of ROI, then applied different image processing algorithms including a new type of despeckling method, then used a feed forward ANN network for training the data base and detected the existence of nasal bone accurately. Here, used a latest denoising method, that is hybrid despeckle filter instead of common median filter. Performance of this filter is superior as compared to median because of the use of bilateral as well as wavelet denoising methods. Results show that the proposed system can easily detected the presence of nasal bone.

Table1: Detection using DWT

Images	No of images tested	True detection	False Detection
With NB	78	70	8
Without NB	25	21	4

Table 2:Despeckled image parameters

SI NO	METHOD	MEDIAN	BILATERAL
1.	MSE	1.0442	1.0178
2.	PSNR	17.9431	21.4011
3.	STRUCTURAL CONTENT	0.9222	0.9904
4	NORMALIZED ABSOLUTE ERROR	0.1696	0.1655
5.	NORMALIZED CROSS-CORRELATION	0.9840	0.9737

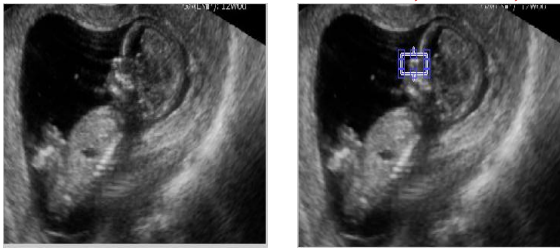


Fig.4. Selection of ROI



Fig.5. Sobel and Prewitt edge detected Results



Fig.6. Watershed results

REFERENCES

- [1] Nicolaidis K. H, Azar G, Byrne D, Mansur C, Marks K. "Fetal nuchal translucency: ultrasound screening for chromosomal defects in first trimester of pregnancy". *BMJ* 1992; 304: pp 867-889.
- [2]. R. Vanithamani, G. Umamaheswari, A. Ajaykrishnan, C. Ilaiyarsan, K. Iswariya and C. G. Kritika, "A Hybrid Despeckling Model for Medical Ultrasound Images", *Journal of computing*, Volume 3, Issue 9, ISSN 2151-9617, September 2011.
- [3]. Anjit, T.A., Rishidas, S., "Identification of Nasal Bone for the Early Detection of Down Syndrome using Back Propagation Neural Network," *IEEE Conference on Communications and Signal Processing (ICCSP)*, 2011.
- [4]. Nirmala.S and Palanisamy.V, "Measurement of nuchal translucency thickness in first trimester ultrasound fetal images for detection of chromosomal abnormalities", *International conference on control, automation, communication and energy conservation-2009*.
- [5]. B. Priestley shan and M. Madheswaran, "Revised estimates of ultrasonographic markers for gestational age assessment of singleton pregnancies among Indian population." *International journal of advanced science and technology* vol.17, april, 2010.
- [6]. Rafael C. Gonzalez, "Digital image processing," Prentice Hall, 2005.
- [7]. C. Larose, P. Massoc, Y. Hillion, J. P. Bernard, Y. Ville, "Comparison of fetal nasal bone assessment by ultrasound at 11-14 weeks and by postmortem X-ray in trisomy 21: a prospective observational study", *Ultrasound in Obstetrics and Gynecology*, John Wiley & Sons, Ltd, Volume 22, Pages 27-30, 2003.
- [8]. Stephane G. Mallat "A Theory for Multiresolution Signal Decomposition: The Wavelet Representation", *IEEE Transaction Pattern on Analysis and machine Intelligence*. Vol. II, No. 7. July 1989.
- [9]. K. O. kagan, S. Cicero, I. Staboulidou, D. Wright, K. H. Nicolaides, "Fetal nasal bone in screening for trisomies 21, 18 and 13 and turner syndrome at 11-13 weeks of gestation", *Ultrasound in Obstetrics and Gynecology*, John Wiley & Sons, Ltd, Volume 33, Pages 259-264, 2004.
- [10]. R. Vanithamani, G. Umamaheswari, "Performance Analysis of Filters for Speckle Reduction in Medical Ultrasound Images", *International Journal of Computer Application* (0975-8887), volume 12-No.6, December 2010.
- [11]. Geoff Dougherty "Digital Image processing for medical applications" California State University, Channel Islands.
- [12]. User manual 4535 613 83101 Rev A "HD-15 ultrasound System" Philips Electronics N.V, May 2009.
- [13]. B. Yegnanarayana "Artificial Neural Networks" Prentice Hall of India, New Delhi-2001.
- [14]. S N Sivanandam, S Sumathi, S N Deepa "Introduction to Neural Networks using Matlab 6.0" Tata McGraw Hill Education Private Limited, new Delhi, 2009.
- [15]. S Jayaraman, S Esakkirajan, T Veerakumar "Digital Image Processing", Tata McGraw Hill Education Private Limited, New Delhi, 2010.
- [16]. Carol M Rumack, Stephanie R. Wilson, J. William Charboneau, and Deborah Levine, "Diagnostic Ultrasound"
- [17]. ES gopi, "Digital Image Processing using MATLAB" Scitech Publications Pvt. Ltd, 2009