Early Detection of Down Syndrome Using Image Processing and Artificial Neural Network

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***Abstract*—Down Syndrome is characterized by the absence of nasal bone during the late first trimester of pregnancy. Presently Down Syndrome is identified by visually examining the ultra sonogram of foetus of 11 to 13 weeks of gestation for the presence of nasal bone. Nasal bone is visually identified by differentiating the change in the contrast of nasal region of ultra sonogram. This method is prone to operator error as the nasal bone is a very small physical structure during the first trimester of pregnancy. Noise may also introduce errors during visual identification. This work presents a new approach for the detection of nasal bone through ultra sonogram of the foetus in the 11th to 13th week of gestation period. The proposed method is based on the extraction of image texture parameter of nasal bone region of ultra sonogram and their subsequent classification using Back Propagation Neural Network (BPNN). The features in the nasal region are extracted in the Transform domain using Discrete Cosine Transform (DCT) and Wavelet Transforms. These features are extracted from images with nasal bone and images without nasal bone. The extracted data is normalized and used to train Back Propagation Neural Network (BPNN). This work describes a new approach for identification of nasal bone based on Transform domain values and artificial neural networks. Experimental preliminary results prove that the proposed approach gives better classification rate under noisy environment. This method combined with the present detection methods can reduce operator error and overall enhance the Down syndrome detection rate by analyzing ultra sonogram.**

Keywords*— *Down Syndrome, Feature extraction, DCT, Wavelet decomposition, Back Propagation Neural Network

I. 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. Chromosome contains the genes that carry all the information necessary to develop and maintain our bodies. 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 are used for the early detection of Down Syndrome during period of gestation. In late 1980s, a new method of screening was introduced that takes into account, concentration of various fetoplacental products in the maternal circulation along with maternal age .Later in 1990s, a combination of maternal age and Nuchal thickness at 11- 14 week of gestations was introduced. This method is currently used successfully and has been shown to identify about 75% of the cases. 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.

In this work this characteristics is used for the detection of Down Syndrome. Prenatal ultrasound based detection techniques solely relay on the operator for the identification and recognition of Nasal bone structure. During the early stage of pregnancy the size of the fetus as well as size of nasal bone is very small. The fetus will be continuously changing its position and therefore the identification of nasal bone is difficult and time consuming process and is prone for operator error also.

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.

A. Prenatal Screening and Diagnosis

Prenatal screening is testing for diseases or conditions in a fetus before it is born. It is necessary to detect birth defects such as neural tube defects, chromosomal abnormalities, genetic diseases etc. In some cases, the tests are administered to determine if the fetus will be aborted, though physicians and patients also find it useful to diagnose high-risk pregnancies early so that delivery can be scheduled in a tertiary care hospital where the baby can receive appropriate care. Common testing procedures include Amniocentesis, Ultrasonography including nuchal translucency ultrasound, Serum marker testing, or genetic screening. Prenatal diagnosis is helpful for the following,

1) *Managing the remaining weeks of the pregnancy.*
2) *Determining the outcome of the pregnancy.*
3) *Planning for possible complications with the birth process.*
4) *Planning for problems that may occur in the newborn infant.*
5) *Deciding whether to continue the pregnancy.*
6) *Finding conditions that may affect future pregnancies.*

Having this information in advance of the birth means, the parents can better prepare themselves for the delivery of a child with a health problem. There are a variety of non-invasive and invasive techniques available for prenatal diagnosis. Each of them can be applied only at specific time periods during the pregnancy. Non-invasive (screening) tests estimate the risk that a fetus has Down Syndrome; Invasive (diagnosis) tests can tell whether the fetus actually has the risk condition.

B. *Invasive Diagnosis*

Invasive tests are about 90% accurate in detecting Down Syndrome and other chromosomal abnormalities. It involves probes or needle being inserted into the uterus, these are associated with significant risk and the risk includes infection of the amniotic fluid, leaking of the amniotic sac, and even miscarriage in the most serious cases. For this reason invasive methods are generally recommended for only for women age 35 or older, those with a family history of genetic defects, or those who have had abnormal results on the screening test.

- Amniocentesis: This test can be done from about 14 weeks gestation, and usually up to about 20 weeks, involves the removal of a small amount of amniotic fluid through a needle inserted in the abdomen. The cells can then be analyzed for the presence of chromosomal abnormalities. Amniocentesis carries significant risk of complications such as preternlabour and miscarriage.

- Chorionic Villus Sampling (CVS): This test involves taking a tiny sample of the placenta, either through a needle inserted in the abdomen. CVS usually takes place 10-12 weeks of gestation and this is its main advantage. It carries a slightly greater risk of miscarriage as compared with amniocentesis.

- Percutaneous Umbilical Blood Sampling (PUBS): PUBS are a diagnostic genetic test that examines blood from the fetal umbilical cord to detect the fetal abnormalities. It provides a means of rapid chromosomal analysis and is useful when the information cannot be obtained through amniocentesis, CVS. This test also carries a significant risk of complications which includes include blood loss at the puncture site, infection, and premature rupture of membranes.

C. *Non-Invasive diagnosis*

Previously Down Syndrome was detected using Invasive techniques, thought they give accuracy above 90% they carry a significant risk of having a miscarriage. Now-a days non-invasive techniques using Ultra sonogram are being used for the early detection of Down Syndrome. But such a scan is unable to detect common abnormalities. Nuchal thickness scan combined with blood test for PAPP-A and beta-hCG can yield a risk score for Down Syndrome. This is called first trimester combined test and has sensitivity (i.e. detection rate for abnormalities) of 70-78% and a false-positive rate around 5%. Alternatively a quad screen test may be taken, it's a maternal blood screening test that looks for four specific substances: AFP, hCG, Estriol, and Inhibin-A. This test is performed between 16^{th} and 18^{th} week of gestation. The false positive rate of the test is also lower.

- Ultrasonography: Ultrasonography is an ultrasound-based diagnostic imaging technique used to visualize subcutaneous body structures. The ultrasonic waves are used to image the fetus. A key benefit of ultrasound is that it does not use x-rays; therefore, it is safe for both the fetus and mother. High frequency sound waves are utilized to produce visible image from patterns of echo's made by different tissues and organs, including the fetus in the amniotic cavity. An ultrasound examination can be quite useful to determine the size and position of the fetus, size and position of the placenta, the amount of amniotic fluid and the appearance of fetal anatomy.

D. *Objective*

The basic idea behind this thesis is the early detection of down syndrome by using computer aided analysis. There are various methods to detect down syndrome. In this technique the detection of the fetal nasal bone which give accurate results.

E. *Organization*

In section II, a detailed literature survey will be provided. In section III, the details of different speckle noise reduction methods, segmentation techniques and neural network classifiers are explained. Section IV provides the details of the work done so far preliminary results that are obtained presents the conclusion.

II. LITERATURE SURVEY

In [5], the author describes Speckle as a granular noise that inherently exists in and degrades the quality of ultrasound images. It generally tends to reduce the resolution and contrast, thereby, to degrade the diagnostic accuracy of this modality. Speckle reduction is one of the most important processes to enhance the quality of ultrasound images. They proposes a statistical filter, which is a modified version of Hybrid Median Filter for speckle reduction, which computes the median of the diagonal elements and maximum of the horizontal and vertical elements in a moving window and finally the two values are compared with the central pixel and the median value of the three values will be the new pixel value. The filter is tested on phantom Ultrasound image. Effectiveness of the proposed filter is compared on the basis of Peak Signal to Noise Ratio

(PSNR), Root Mean Square Error (RMSE), Structure Similarity Index (SSI), Image Quality Index (QI) and Edge Preservation Factor (EPF) .The experimental results demonstrate that the proposed filter can reduce the speckle noise effectively without blurring the edges.

In [12], the author describes that Speckle noise is an inherent property of medical ultrasound imaging, and it generally tends to reduce the image resolution and contrast, thereby reducing the diagnostic value of this imaging modality. As a result, the speckle reduction is considered to be a prerequisite procedure to be used, whenever ultrasound images are used for tissue characterization. Among the method, which have been proposed so far to perform this task, there exits a class of approaches that employ the multiplicative model of speckled image formation and take advantage of the logarithmical transformation in order to convert the multiplicative speckle noise to an additive noise. The present study shows conceptually and experimentally that assuming the latter to be a white Gaussian noise – as it is done in a dominant number of cases – is an oversimplified and unsafe assumption that leads to inadequate performance of the filtering methods used to suppress the noise. The study introduces a simple preprocessing procedure, which modifies the acquired radio-frequency images (without altering the anatomical information they bear), so that the noise in the domain of the logarithmic transformation becomes very close in its behavior to white Gaussian noise. It allows the filtering methods based on assuming the noise to be white and Gaussian, to perform in nearly optimal conditions. The study evaluates performances of three different non-linear filters – wavelet de-noising, total variation filtering, and anisotropic diffusion – and demonstrates that in all these cases, the “modified” processing results in a dramatic improvement in the quality of resultant images.

The paper [13] reviews the application of artificial neural networks in medical image preprocessing, in medical image object detection and recognition. In the past years, artificial neural networks (ANNs) have seen an an increasingly interests in medical image processing. The intention of this article is to cover those approaches introduced and to make a map for ANN techniques used for medical image processing. Image preprocessing with neural networks generally falls into one of the following two categories: image reconstruction and image restoration. The Hopfield neural network is one of the most used neural works for image reconstruction .The feed forward neural network is the most used neural network for medical image segmentation. Compared with the traditional Maximum Likelihood Classifier (MLC) based image segmentation method, it has been observed that the feed forward neural networks based segmented images appear less noisy, and the feed forward neural networks classifier is also less sensitive to the selection of the training sets than the MLC. However, most feed forward neural network based methods have a very slow convergence rate and require a priori learning parameters. These drawbacks limited the application of feed forward neural networks in medical image segmentation. For using neural networks for medical image detection and recognition, the back propagation neural network poses most places. Neural network model employed for medical image processing, compared with conventional image processing methods, the time for applying a trained neural network to solve a medical image processing problem was negligibly small, though the training of a neural network is a time cost work and also medical image processing tasks often require quite complex computation . This may be the major contribution of using neural network for solving medical image processing tasks.

In [3], the authors describes that Down Syndrome is characterized by the absence of nasal bone during the late first trimester of pregnancy. This method is based on the extraction of image texture parameter of nasal bone region of ultra sonogram and their subsequent classification using Back Propagation Neural Network (BPNN). The features in the nasal region are extracted in the spatial domain and Transform domain using Discrete Cosine Transform (DCT) and Daubechies D4 Wavelet transform. These features are extracted from images with nasal bone and images which don't have nasal bone. The extracted data is normalized and used to train Back Propagation Neural Network (BPNN).

In [15], the back-propagation algorithm calculates the weight changes of an artificial neural network, and a two-term algorithm with a dynamically optimal learning rate and a momentum factor is commonly used. Recently the addition of an extra term, called a proportional factor (PF), to the two-term BP algorithm was proposed. The third term increases the speed of the BP algorithm. However,the PF term also reduces the convergence of the BP algorithm, and optimization approaches for evaluating the learning parameters are required to facilitate the application of the three terms BP algorithm.This paper considers the optimization of the new back propagationalgorithm by using derivative information. A family of approaches exploiting the derivatives with respect to the learning rate, momentum factor and proportional factor is presented. These autonomously compute the derivatives in the weight space, by using information gathered from the forward and backward procedures. The three-term BP algorithm and the optimization approaches are evaluated using the benchmark XOR problem.

III. PROPOSED METHOD

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 Fig.1.

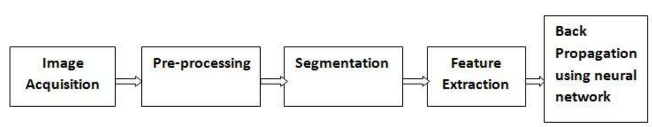

Fig. 1. Block diagram.

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 Ultrasonogram. 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. The last section is a neural network classifier which is used to distinguish an image with nasal bone from one which does not have nasal bone.

A. 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. One or more frames of the moving pictures are typically captured as still images. The image should be magnified so that the head and the upper thorax are only included in the screen. Ultrasound image of a fetus having Nasal bone is shown in Fig.2.

Fig. 2. Ultra sonogram of a foetus.

B. Image pre-processing

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. Several linear and non-linear techniques can be used for noise reduction, but for the proposed method Median filtering is used because of its simplicity and it preserve edges.

1) Median Filter: Median filtering is a nonlinear filtering method, which is used to remove the 'speckle' noise from an Ultrasound image. It assigns to each pixel the median value of its neighbourhood. The median is calculated by first sorting all the pixel values from the surrounding neighbourhood into numerical order and then replacing the pixel being considered with the middle pixel value. This filter is relatively slow, evenwith fast sorting algorithms such as quick sort. The median filter does not blur the contour of the objects.

2) Hybrid Despeckling Filter: 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. 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 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 bilateral filtering is applied before wavelet decomposition using DWT and after reconstruction of the image using IDWT. The parameters of the bilateral filter used are, $\rho_d = 1.6$, $\rho_r = 0.5$ and the window size is 3×3 with one level wavelet decomposition.

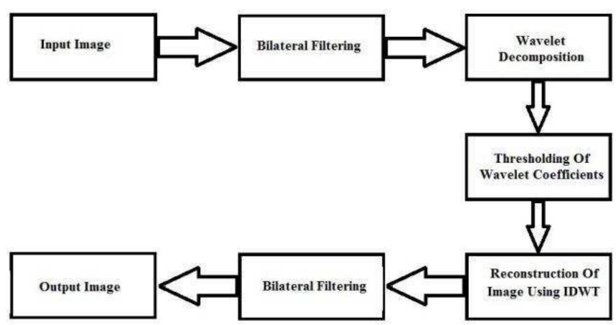

Fig. 3. Hybrid Despeckling method-Block diagram.

C. Segmentation of region of interest

Segmentation of an image entails the division or separation of the image into regions of similar attribute. The most basic attribute for segmentation is image luminance amplitude for a monochrome image and colour components for a colour image. Image edges and texture are also useful attributes for segmentation. Segmentation subdivides an image into its constituent regions or objects. Segmentation accuracy determines the eventual success or failure of the computerized analyzed procedure. Image segmentation algorithms are generally based on two basic properties of intensity values: discontinuity and similarity. In the first category the approach is to partition an image based on abrupt changes in the intensity, such as edges in an image and the second approach are based on partitioning an image into region that are similar according to a predefined criteria. There are so many methods available for the Ultrasound image segmentation that includes threshold method, clustering method, statistical model based methods etc. In the proposed work marker controlled watershed algorithm is used for segmentation of nasal bone.

1) Watershed Segmentation Algorithm: Idea underlying the watershed notion comes from the field of topography: a drop of water falling on a relief follows a descending path and eventually reaches a minimum. Marker controlled watershed algorithm 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 smoothened 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.

D. 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 ultrasonogram 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 skewness, kurtosis, fifth order moment and sixth order moment are taken here for detection purposes.The calculation of these parameters can be done in spatial domain and transform domain.

1) Time Domain Analysis:

*a) Skewness:*The skewness of a random variable ‘x’ is the third standardized moment and it is represented in equation

$$skewness=1/(M\times N)\sum[(x_{i,j}-\dot{x})/\sigma]^3 \qquad (1)$$

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. Qualitatively, a negative skew indicates that the tail on the left side of the probability density function is longer than the right side and the bulk of the values (possibly including the median) lie to the right of the mean. A positive skew indicates that the tail on the right side is longer than the left side and the bulk of the values lie to the left of the mean. A zero value indicates that the values are relatively evenly distributed on both sides of the mean.

b) Kurtosis: In probability theory and statistics, kurtosis is any measure of the "peakedness" of the probability distribution of a real-valued random variable.

$$kurtosis=1/(M\times N)\sum[(x_{i,j}-\dot{x})/\sigma]^4 - 3 \qquad (2)$$

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

2) 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 are Discrete Cosine Transform, Sine transform, Wavelet transform etc. In this work , multiresolution transform and DCT has been used for the analysis.

a) 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. DCTs are important to numerous applications in science and engineering . The discrete cosine transform of an N × N image, f(x,y)is defined by

$$C(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) \cos\left[\frac{\pi(2x-1)u}{2N}\right] \cos\left[\frac{\pi(2x-1)v}{2N}\right] \quad (3)$$

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.

3) Multiresolution Analysis: Multiresolution theory is concerned with representation and analysis of signals at more than one resolution. Features that might go undetected at one resolution may be easy to spot at another. If the objects are small in size and low in contrast, examine them at high resolution. The fundamental concept involved in multiresolution analysis is to find the average features and the details of the signal via scalar products with scaling signals and wavelets. Employing a wavelet transform we are representing an arbitrary function as a superposition of wavelets. By applying Discrete Wavelet Trans-form, the data is actually divided i.e. decomposed into four sub bands corresponding to different resolution levels.

a) 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. 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. These filter banks may contain either finite impulse response (FIR) or infinite impulse response (IIR) filters.

- Under Random Cropping: Random cropping means that a portion of the audio is lost in the time domain, but in the frequency domain, it only introduces tiny fluctuations. To resist random cropping, the watermarking strategy must be global. As the length of audio clip varies after random cropping, the frequency index must be normalised after Fourier transform. Geometric distortion by random cropping can be described by the equation (6). A powerful tool to deal with the scaling factor β is log coordinate transform. A logarithm could convert the scaling into shifting (7) in the logarithm axis.

- Under Pitch Shifting: Pitch shifting is a very common form of processing used to change the base frequency without changing the tempo. Pitch shifting may be implemented as follows: resample an audio signal for shifting the pitch, then remove and/or insert some samples of the resampled audio signal in the time domain in order to keep the tempo invariant. Removing and inserting some samples cause only a small fluctuation in the frequency domain. Theoretically there exists a statistically positive linear correlation between pitch shifted and original audio (6)

- Under Pitch-Invariant TSM: Pitch-invariant TSM can be considered to be removing and/or inserting some samples of audio signals while preserving the pitch. It causes only a small fluctuation to the LCM feature in the frequency domain.

E. 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, computer vision and control systems.

Advantages of neural networks are

- A neural network can analyse non linear problems.
- When an element in neural network fails, it can continue without any problem by their parallel nature.

1) Simple Neurons: A neuron with a single scalar input and no bias appears on the left below. The scalar input p is transmitted through a connection that multiplies its strength by the scalar weight 'w' to form the product 'wp', again a scalar. Here the weighted input 'wp' is the only argument of the transfer function 'f', which produces the scalar output 'a'. The neuron on the right has a scalar bias, 'b' . The bias is simply being added to the product wp as shown by the summing junction or as shifting the function f to the left by an amount b. The bias is much like a weight, except that it has a constant input of 1.

The transfer function net input n, again a scalar, is the sum of the weighted input wp and the bias b. This sum is the argument of the transfer function f, where f is transfer function, typically a step function or a sigmoid function, that takes the argument n and produces the output a. w and b are both adjustable scalar parameters of the neuron. The central idea of neural networks is that such parameters can be adjusted so that the network exhibits some desired or interesting behaviour. Thus, you can train the network to do a particular job by adjusting the weight or bias parameters, or perhaps the network itself will adjust these parameters to achieve some desired end.

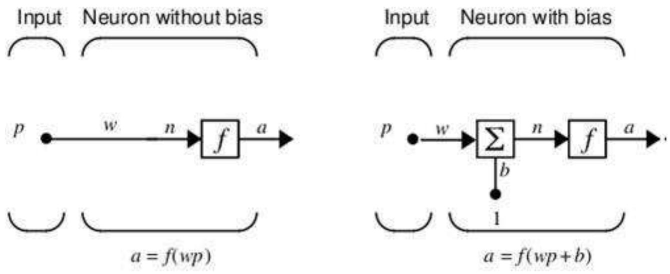

Fig. 4. Simple neuron models.

2) Transfer Functions: Most commonly used transfer functions are,

a) Hard-Limit Transfer Function: The hard-limit transfer function shown above limits the output of the neuron to either 0, if the net input argument n is less than 0, or 1, if n is greater than or equal to 0.

b) Linear Transfer Function: The output activity is proportional to the total weighted output.

c) Log-Sigmoid Transfer Function: The output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurones than do linear or threshold units.Step-like functions have discontinuous derivatives, preventing the use of gradient-based error minimization training procedures. Sigmoid output functions allow to define popular continuous graded response neurons.

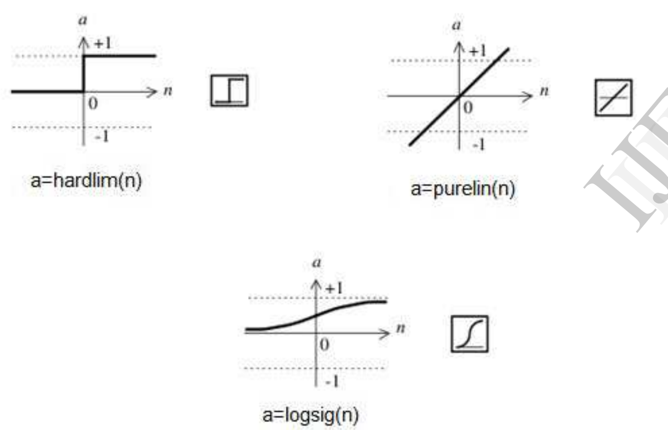

Fig. 5. Common transfer functions.

3) Working of a Neural Network: A neural network consists of a collection of neurons. The complete network can have any number of inputs and outputs. Each element typically has its own local memory, which stores the values of some previous computations along with adaptive coefficients basic to neural network learning. Often neural networks are divided into layers. Every connection entering the processing element has an adaptive coefficient called a weight assigned to it. The weight which is stored in the local memory of the processing element is generally used to amplify, attenuate and change the sign of the signal in the incoming connection. The weights are not fixed but may change. Most transfer functions include a learning law - an equation that modifies all or some of the weights in the local memory in response to the input signals and the values applied by the transfer function. In effect the learning law allows the processing elements response to change with time, depending on the nature of input signals. It is the means by which the network adapts itself to the answers desired and so organizes the information within itself.

A neural network learns how to process information either by supervised or unsupervised learning. In supervised training a set of inputs having known results are applied to the neural network repeatedly till the difference between the target output and the actual output reaches a certain predetermined value. During the training process the difference between the actual outputs and target outputs are compared. The difference is then used to adjust the connection weights of neurons in such a way that the output of the network matches closely to the target output corresponding to each input. The weights are adjusted such that error is minimized. In unsupervised training output pattern for a given input pattern is not required. The input patterns are taken and compared with existing patterns and if a new pattern is found it is trained automatically by adjusting weights corresponding to the new pattern. Hence the neural network constructs internal models that capture regularities in input pattern. The neural network model has many neurons linked through adaptive weights arranged in a parallel structure. Because of its high parallelism failures of a few neurons do not cause significant effect on the overall system performance. This characteristic is known as fault tolerance. The ability to adapt and learn that neural network models can deal with imprecise data and ill defined situations. A suitably trained network has the ability to generalize when presented with inputs that were not fed during the training process. They have the ability to approximate any non linear continuous function to the desired degree of accuracy.

4) Back Propagation Neural Network: Back Propagation (BP) algorithm is used for training artificial neural networks. Training is usually carried out by iterative updating of weights based on the error signal. The negative gradient of a mean-squared error function is commonly used. In the output layer, the error signal is the difference between the desired and actual output values, multiplied by the slope of a sigmoid activation function. Then the error signal is back-propagated to the lower layers. BP is a descent algorithm, which attempts to minimize the error at each iteration. The weights of the network are adjusted by the algorithm such that the error is decreased along a descent direction.

Traditionally, two parameters, called learning rate (LR) and momentum factor (MF), are used for controlling the weight adjustment along the descent direction and for dampening oscillations. The Back Propagation algorithm is used for many applications. However, its convergence rate is relatively slow, especially for networks with more than one hidden layer. The reason for this is the saturation behavior of the activation function used for the hidden and output layers. Since the output of a unit exists in the saturation area, the corresponding descent gradient takes a very small value, even if the output error is large, leading to very little progress in the weight adjustment. The selection of the LR and MF is arbitrary, because the error surface usually consists of many flat and steep regions and behaves differently from application to application. Large values of the LR and MF are helpful to accelerate learning.

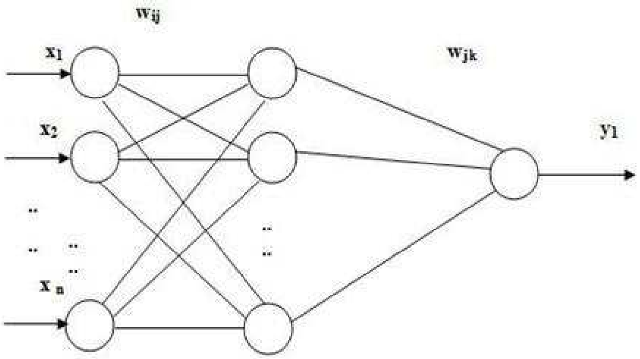

Fig. 6. Back Propagation Neural Network.

5) Training of the 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 and kurtosis. 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 and kurtosis are taken for all the three levels. These constitute 40 parameters for a three level decomposition for each image .The coefficient parameters are stored in separate files and are normalized separately. These 40 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 DownSyndrome and "1"is used to represent images having normal anatomical features.

The process of creating the training vector space from the set of training images is described by the following steps.

- Generate the greyscale representation of the image.
- Do MultiResolution transform on the greyscale image.
- Compute the statistical parameters mean variance skewness and kurtosis of each.

a) Level of decomposition and append to the coefficient statistics file.

b) Append numeral value "0" to the extracted vector if the image is having Down Syndrome.

c) Append numeral value "1" to the extracted vector if the image having normal anatomical features.

- Repeat steps 1 to 3 for N number of images.
- Normalize coefficient statistics file. Save the maximum values of each column.
- Use the above coefficients as training vector to train the neural network.
- Training of the artificial neural network can be stopped when the optimi error value is reached.

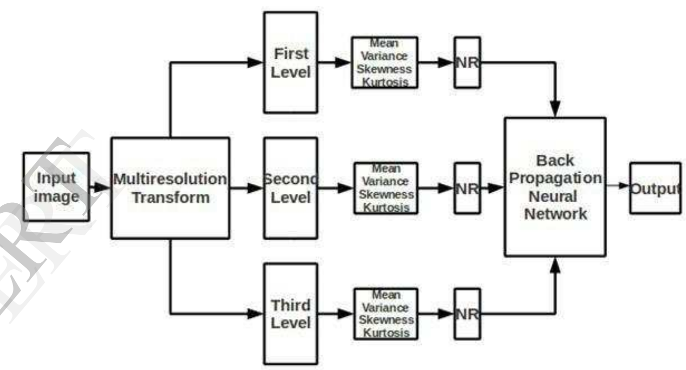

Fig. 7. Block diagram for detection tool.

The process of detection is by the following steps:

- Generate the gray scale representation of the image
- Do three level MultiResolution Transform on the gray scale image
- Compute the statistical parameters mean variance skewness and kurtosis of each level decomposition.
- Normalize (NR) coefficient statistics file using the maximum value file generated during training.
- Use the above coefficient statistics element as a test vector file.
- Propagate the generated test vector file through the back propagation neural network

If the output of the neural network is between 1 and 0.5 distinguish the image as a normal image and give the test result as "Normal image". If the output of the neural network is between 0 and 0.5 distinguish the image as, with Down syndrome and give the test result as "Abnormal image".

IV. Results and Conclusion

The images generated using Ultrasound Technique is strongly affected by Speckle noise, which degrades the quality of the image. This is reduced by using meadian filtering techniques. It is necessary to define a Region of Interest(ROI) which can compensate for changes in the fetal movement during the scanning process. Our main objective is to measure the presence or absence of Nasal bone region. So first we crop the Nasal bone region. The cropped image is then subjected to edge detection technique(Sobel,Prewitt). Then applying the marker controlled watershed segmentation algorithm to separate the exact nasal bone region.

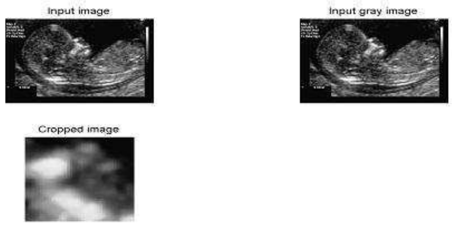

Fig. 8. Image with nasal bone region cropped.

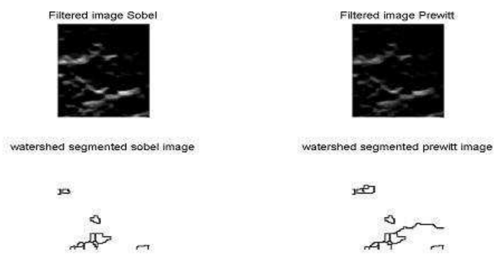

Fig. 9. Filtered and Segmented image.

In this work, presented a new approach to the use of computer aided analysis to enhance the detection rate of Down syndrome. The task of developing a process for accurate and reliable detection of the fetal nasal bone, which is the foundation for this whole idea of detection of Down syndrome. The algorithms and the procedures proposed have been subjected to training and rigorous tests. The statistical data obtained from these tests have been of prime importance in conclusions we made.

REFERENCES

[1] X Nicolaides K. H, Azar G, Byrne D, Mansur C, Marks K. "Fetal nuchaltranslucency: ultrasound screening for chromosomal defects in firsttrimester of pregnancy," BMJ 1992; 302: pp 867-889.

[2] C. Larose, P. Massoc, Y. Hillion, J. P. Bernard, Y. Ville,, "Comparison of fetal nasal bone assessment by ultrasound at ll-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.

[3] S Anjit.T.A and Rishidas.S, "Identification of nasal bone for the early detection of down syndrome using back propagation neural network," 2011 IEEE Int. conference.

[4] Nirmala.S and Palanisamy.V, "Measurement of nuchal translucency thickness in first trimester ultrasound fetal images for detection of chromosomal abnormalities," IEEE Trans. Circuits Syst. Video Technol., vol. 11, pp. 536-545, Apr. 2001.

[5] R.Vanithamani, G.Umamaheswari, A.AjayKrishnan, C.Ilaiyarasan, K. Iswariya and C.G.Kritika, "Modified Hybrid Median Filter for Effective Speckle Reduction in Ultrasound Images" Journal of computing, Volume 3, Issue 9, ISSN2151-9617, September 2011.

[6] 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.

[7] Prof.S.Suresh Dr.Sujatha Jagadeesh Dr. Uma Ram & The MediScan, "First trimester screening for Down syndrome fundamental concept," Team Fetal Care Research Foundation, Chennai.

[8] S.Jayaraman, S.Esakkirajan,T.Veerakumar," Digital Image Processing," TataMcGraw Hill Education Private Limited, Newdelhi , 2009.

[9] Carol m. Rumak, Stephanic.R.Wilson, J.William Charboneni, "Diagnostic Ultrasound,"

[10] Geoff Dougherty, "Digital Image Processing for Medical Applications," California state university, Channel Islands.

[11] "HD 15 Ultrasound system", User Manual 4535 613 83101 RevA,May 2009.

[12] A. Achim, P. Tsakalides, and A. Bezerianos, "SAR image de-noising via Bayesian shrinkage based on heavy-tailed modeling," IEEE Transactions on Geoscience and Remote Sensing, vo.41, No.8, pp.1773-1783, Aug. 2003.

[13] Zhenghao Shi and Lifeng He, "Applications of neural networks in medical image processing," Proceedings of the Second International Symposium on Networking and Network Security (ISNNS '10) Jinggangshan, P. R. China, 2-4, April. 2010, pp. 023-026

[14] Deepti Mittal , Vinod Kumar, Suresh Chandra Saxena, Niranjan Khandelwal, Naveen Kalra, "Enhancement of the ultrasound images by modified anisotropic diffusion method," Med Biol Eng Comput (2010) 48:1281-1291, Springer.

[15] Yahya H. Zweiri, "Optimization of a Three-Term Backpropagation Algorithm Used for Neural Network Learning," International Journal of Computational Intelligence 3;4 2007 pp 322-327.

[16] A.K. Jain, "Fundamental of Digital Image Processing," Englewood Cliffs, NJ: Prentice-Hall, 1989.

[17] I. Daubechies, "Ten lectures on Wavelets," Philadelphia, PA: SIAM, 1992.

[18] S. G. Mallat, "A Wavelet Tour of Signal Processing," New York: Academic, 1998

[19] R.Gonzalez and R.Woods, "Digital image processing," 2nd edition, prentice hall, 2002.