Global Journal of Engineering and Technology Advances

eISSN: 2582-5003

Cross Ref DOI: 10.30574/gjeta

Journal homepage: https://gjeta.com/

(Research Article)

Down syndrome identification and classification using facial features with neural network

Vincy Devi VK [1,*] and Rajesh R [2]

[1] *Department of Computer Science, Bharathiar University, Coimbatore, India.*

[2] *Department of Computer Science, CHRIST (Deemed to be University), Bangalore, India.*

Global Journal of Engineering and Technology Advances, 2022, 12(01), 001–011

Publication history: Received on 15 May 2021; revised on 23 June 2021; accepted on 26 June 2021

Article DOI: https://doi.org/10.30574/gjeta.2022.12.1.0090

Abstract

The medical image tool named Ultrasound imaging is used for the analysis of fetus behaviour. Due to the presence of noise the quality of these images is low. Proper filtering is required to suppress this noise. Before the fatal development analysis, it is required image processing method. The processed images are then used for the analysis and it helps to take care of the health. Down syndrome is one of the crucial chromosomal disorders. It is due to the presence of a further copy of chromosome 21. The ultrasound imaging helps to point out DS in the earlier stage of pregnancy by handling the image in an efficient manner. In this work, nasal bone identification and texturing methods are used to detect the disease. Here we designed a nasal bone identification module for the image classification as normal or abnormal. Down syndrome detection utilizes a collection of facial expression images. A compact geometric descriptor is employed for extracting the facial features from the image set. There is no specific treatment for Down syndrome. Thus, early detection and screening of this disability are the best styles for Down syndrome prevention.

Keywords: Ultrasound image; Pre-processing; Down syndrome; Nasal bone identification; Classifications; Artificial neural network

1. Introduction

In recent years researchers focusing on the field of biomedical image processing. There are many kinds of imaging devices are used for medical diagnoses such as Ultrasound, X-rays, computed tomography (CT), and magnetic resonance imaging (MRI). To diagnose internal body organs Ultrasound imaging is used. It is a very safe and non-aggressive method. It is portable, low cost, and widespread when compared with other tools for imaging. The risk factor is less than the other display modes. To analyze fetal conditions ultrasound method is used because of its real-time imaging. It is a commonly used investigation technique to study fetal biometric constraints. It is also used for prenatal growth monitoring and to detect fetus anomalies. The images obtained from ultrasound scanning are incorporated with noise. This noise reduces the quality of the image and therefore it is in poor condition for further study. It is not possible to reach a good decision by using these images [1]. So, the experts start to refine the images by removing the noise. Processing these denoising images and then analyzing them. The main aim of this analysis is the progression of prenatal by denoising and enhancing the ultrasound image. The denoising of an image means eliminating the noise to improve the quality of the images and find out every single element from that image. Normally discrete wavelet transform method is used for denoising. To advance the image contrast it is needed an image enhancement method. The enhanced image has high picture quality and it is used for any other applications [2].

DS is one of the crucial chromosomal disorders. It is due to the presence of a further copy of chromosome 21. Generally, human beings have 46 chromosomes, 23 inherited from the father and 23 from the mother. In some special cases instead

*Corresponding author: Vincy Devi VK

Department of Computer Science, Bharathiar University, Coimbatore, India.

of 46 chromosomes one extra chromosome, i.e., 47 chromosomes may be present in each cell. This special case is described as DS by a British doctor J. L Down. In worldwide, the existence of DS is come close to be about 1 in 1000 births. Complete Trisomy 21, mosaicism, and translocation are the three types of Trisomy21. In this, the complete Trisomy 21 is the most common case in which every cell possesses an extra copy of chromosome 21. In mosaicism not all the cells will have an additional chromosome. Translocation occurs when a whole or extra copy of a chromosome has gotten attached to another chromosome. A nucleus is allied with each cell and it holds the genetic material. Additional genetic materials are generated when the chromosomes increase. This may cause abnormalities and other diseases [3,4].

Kruszka et al. [5] and Zhao et al. [6] presented a combined method of texture and geometric information for DS detection. Support Vector Machine classifier is used for differentiating between normal and abnormal cases. For the feature extraction, Saraydemir et al. [7] proposed the Gabor wavelet transform method. They used an SVM classifier for the distinguishing. Another method known as the Elastic bunch graph matching method is introduced by Erogul et al. [8] for DS recognition. David and Lerner [9] also used an SVM classifier for the DS classification. Loos et al. proposed a computer-based graph matching algorithm for DS analysis. Artificial Neural Network based automated methods are proposed by many authors [10,11] to recognize and detect the fetal nasal bone.

2. Proposed methodology

The presented approach has different steps for DS recognition in face images. The facial detection -segmentation - feature extraction - classification. The detailed explanations are in the following sections. Proposed system frame is shown in Fig.1.

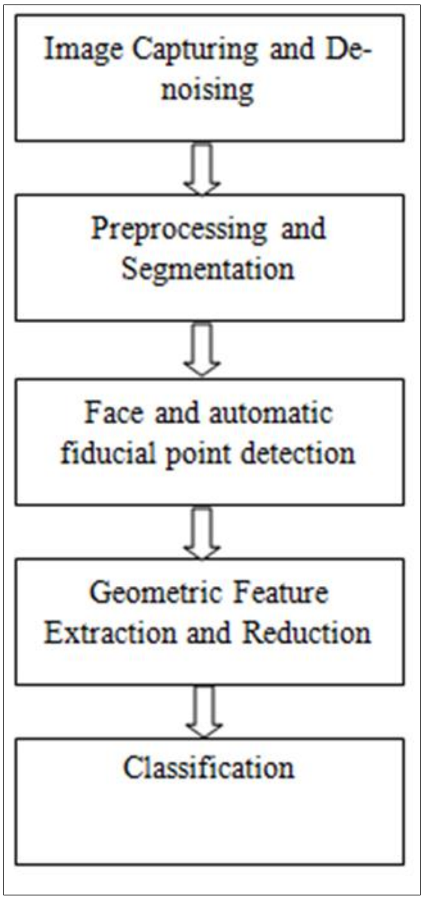

Figure 1 Proposed System Frame

Initially, the integral image method is applied for face detection. This is a machine learning algorithm. Significant features are selected through a machine learning algorithm. For the identification of face, a cascade classifier is composed of several phases. It helps to advance the probability of a face being identified [12]. Then Dlib library [13] is used to extract facial landmarks after a face is detected. The points were corresponding to two coordinates of regions neighboring each facial structure such as eyes, eyebrows; nose, etc. located in the images. The open-source library Dlib-ml is an excellent and powerful debugging tool, which offers support for developing ML software in python, R, MATLAB, etc. [14].

For the development of medical image pre-processing is done. It is a technique for the betterment of image quality by removing unwanted things. The various filters like a mean filter, median filter, etc. are used for this function. For computer-supported medical image diagnosis application segmentation is an essential step. It includes the subdividing of the medical images into different regions for the further extracting of features [15]. Different segmentation methods can be considered as threshold-based, edge-based, region-based, clustering, and matching techniques. Watershed algorithm [16, 17] and Otsu's thresholding [18] algorithms are the different algorithms used for the segmentation.

The terms sensitivity, specificity, and accuracy are used to evaluate the system performance of the algorithm. Sensitivity is the ratio of true positives to the sum of true positives and false negatives. Specificity is defined as the ratio of true negatives to the sum of false positives and true negatives. Accuracy is the ratio of the sum of true positives and true negatives to the total sum of true positives, false negatives, true negatives, and false positives [19]. From the study, it is proved that the accuracy is high in Otsu's approach.

After the processing of image features is extracted. It is the process of extracting the relevant pieces of information from images and denoted them in a lower dimensionally space. It is an important process as it helps to distinguish the features exactly. In this step, using the spotted facial landmarks the geometric features are extracted. It signifies the fundamental traces for syndrome diagnosis. The geometric illustration uses different two-dimensional facial fiducially points. The geometric features are divided into horizontal and vertical distances. The horizontal distances were normalized by the distance between eyes (distance between landmark pair (1, 4)), and the vertical distances were normalized by the distance from the middle point between eyebrows to the lower point of mouth [20, 21].

The points P1 and P2 denote the center of the eyebrows, one-point P3 for the glabella, the points P4, P5, P7, and P8 denote the inner and outer corner of the eyes, one-point P6 for the root of the nose, P10 and P11 for the alars sidewalls, one point P9 for the supratip, P12 for the columella, the mouth corners have two points P14 and P15, the point P13 for the top of the upper lip and one point for the bottom of the lower lip P16. Figure 2(a) and 2(b) show the localization of the 16 facial points. Fourteen distances are extracted from the mentioned 16 points, as shown in Fig. 2(c).

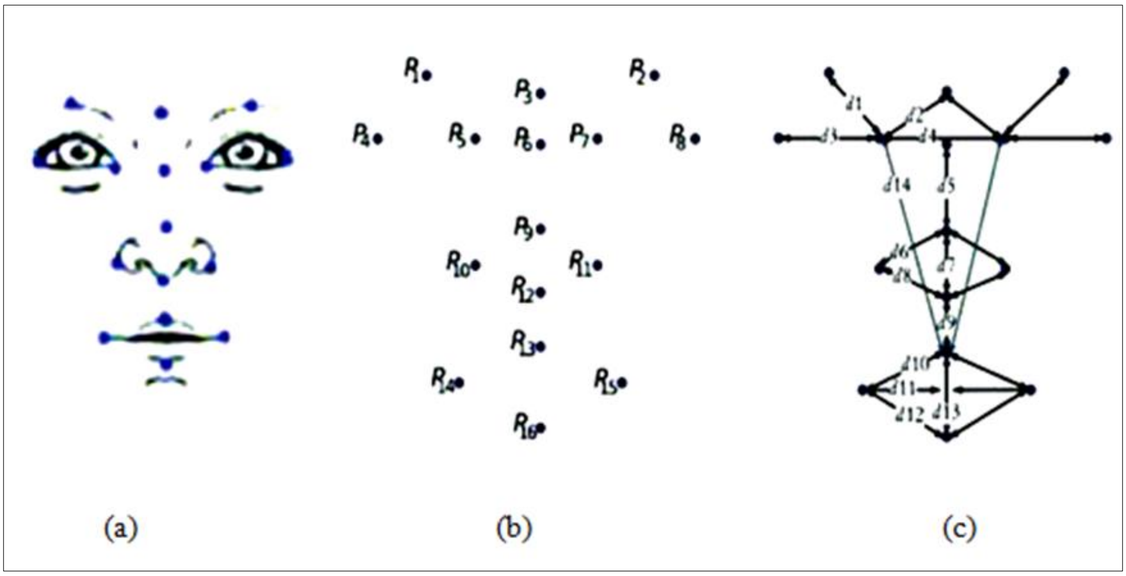

Figure 2 Localization of facial points

To make sure the features are scale-invariant all the distances are normalized to the face width. The normal values of the two imitated distances on both sides of the face are denoted using the distances d1, d2, d3, d6, d8, d10, d11, d12, and d14. The intersection point of the line between the upper and lower lips and the line between the left and right corners of the mouth is used to calculate the latter distance d11. There are only 14 dimensions in the resulting feature vector. The study of intercanthal distance d4 is so significant to recognize the DS. Where d4 is the distance between the inner corners of the eyes [22].

People with DS existing an increase in intercanthal distance. Another common characteristic is the occurrence of small space between the lateral and medial canthus of the eyes. This feature is captured by distance d3. A flattened nose is often presented in persons with Down syndrome. Distances d5 to d8 represent this characteristic. Finally, another symptom is the presence of a small mouth, whose characteristic is captured by distances d10 to d13.

In the image processing method feature extraction made a significant role. To illustrate the typical features from the input data, the feature extraction method is used. It helps to distinguish the data into different groups. This method is very helpful if the input data is very large. Features are extracted after the pre-processing of the images. Feature extraction methods are classified into two – texture-based and non-texture-based algorithms [23-25]. A Statistical based texture algorithm is used for the present work. In this, gray level Co-occurrence Matrix features are measured which is based on the orientation and distance. It gives the number of the existence of particular pair of pixels or image combinations. This type of feature extraction helps to study the NB region.

The present work is focusing on the extraction of matrix features as well as the shape from the NB region. The DS-affected fetus is categorized by the absence or very small NB. Contrast, correlation, energy, and homogeneity are the different features used for the classification of the normal and abnormal nasal bone. For object identification and classification, the shape features such as major and minor axis length, perimeter, orientation, etc. are used also [26-29].

To maintain the best vivid features during the feature reduction employed two methods like principal component analysis (PCA) and linear discriminant analysis (LDA) [30]. It helps to bypass noisy information. For every feature set, these are used consecutively and applied independently for each feature set.

3. Classification

Classification is another significant phase in image processing. The learned images are classified based on the extracted features. The processed images are classified as normal or abnormal. The widely used classification method is pattern classification along with machine learning techniques. The objective of a classifier is to generate a specified group of decision regions. The neural network approach and fuzzy and hybrid models are some of the classification methods. The figure shows a classification model. It consists of attaining data, feature selection from data, training, and optimization. If the classifier performance is inadequate then the system is retrained till the optimum result will reach. The neural network classifiers, SVM, and Bayesian classifiers are some of the classifiers used for this purpose [31, 32].

Another important task is to find out the distance between the different points (e.g.: d1-d2, d1-d3, etc.). Suppose the two points are denoted by d1(x1, y1) and d2(x2, y2). The distance between the two points is calculated by using the Euclidean distance formula as follows [33]. The Euclidean distance between two points is the length of a line segment between the two points. It can be calculated from the Cartesian coordinates of the points using the Pythagorean Theorem. Therefore, sometimes it's named Pythagorean distance.

4. Artificial neural networks

ANNs are stimulated by the functionality and edifice of the human brain. It seems like a network consists of a large number of interconnected components called neurons. For the classification of medical images, ANNs are very effective and widely used. Fast learning capacity, adaptability, parallelism, storage capacity, robustness, and generalization are some of the features of ANN. The performance of the ANN is associated with the transfer function selected for the training, weight updating, and net output calculation. The generalization and learning abilities are the attractive features of ANN. The processing elements or the artificial neurons are the basic functional units of ANN. Three different layers of neurons are used for processing. The layers are the input layer, hidden layer, and output layer. The layers are interconnected to each other by weights. Each artificial neuron takes an input from the input sources, applied an activation function to this input, and generates the net result [34].

ANNs input layer collects the information from files or devices (for real-time) and transfers data to the real world through the output layer. Any number of hidden layers can be included. The weighted sum of inputs constitutes the activation of the neuron. To calculate the response from each neuron a transfer function is applied to this element. The system continuously adjusts the weights during the training period to minimize the error between actual and target values. The system stops its iteration process when an anticipated level of accuracy is reached.

For the training purpose, three learning algorithms such as supervised, unsupervised, and reinforced are used. Supervised learning permits collecting data and creating data responses from preceding experiences. By using this data, the algorithm helps to optimize the performance criteria. Unsupervised learning is the training of a machine using information that is neither classified nor labeled and allowing the algorithm to act on that information without guidance. Reinforcement algorithms use the estimated errors as rewards or penalties. The penalty is high if the error is big, so the reward becomes low. The reward is high for an error-less response [35].

The backpropagation neural network method is used for ANN training. It is a multilayer feed-forward neural network. The important steps for the training of a NN are as follows;

- Input vectors are feed forwarded
- The computer error is then backpropagated
- Updates the weight function to minimize the error.

The neural network is very helpful in image processing. For the image reconstruction and restoration process NN is very effective. The segmentation methods using neural network training are less noisy but their convergence speed is very slow. For image recognition and detection, BPNN is widely used. To minimize the error Levenberg Marquardt algorithm is used. It produces a faster response with a minimum number of iterations. The performance function becomes reduced in each iteration. A large training dataset is required for the NN training. The system does not generalize properly if we used a small number of datasets [36, 37].

This BPNN algorithm targets reducing the root mean square error of the response. The delta rule is used for weight updation. The NN training performance depends on the initial weights, learning rate, update interval, and hidden layers.

5. Results and discussion

In this work, the different features for DS detection are described. Also, studies on the extraction of these images along with image classification by NN-based algorithms. A Nasal bone identification module is designed to identify the presence or absence of nasal bone in the image that is used for the diagnosis. The denoised image as shown in Fig. 3 is processed with the help of this system and classifies the images as normal and abnormal.

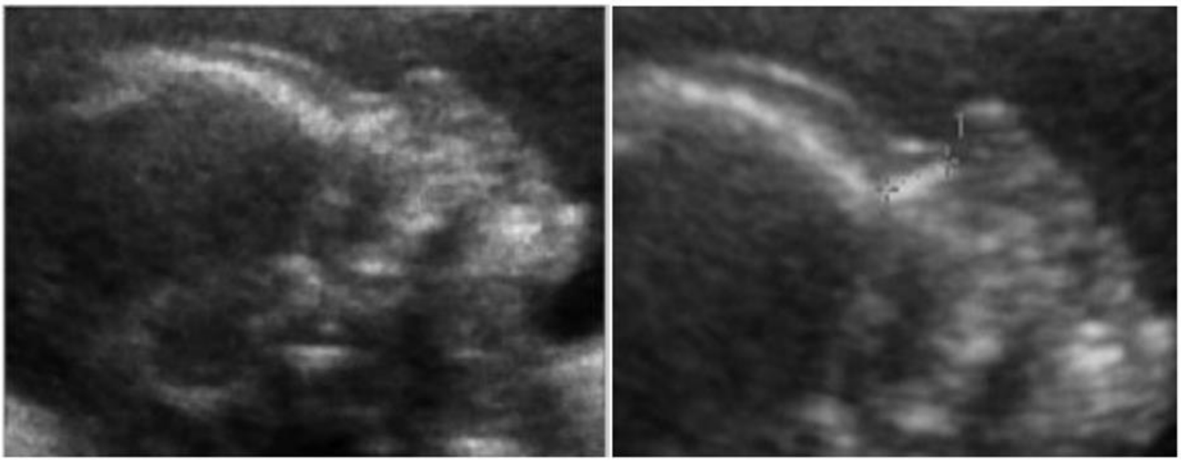

Figure 3 Denoised image

Figure 4(a), 4(b), 4(c) and 4(d) shows the graphical user interface (GUI) screenshots of the presented system. Figure 4(a) shows the GUI of the designed module when the image is loaded after the denoising. Figure 4(b) shows the segmentation stage of the image processing.

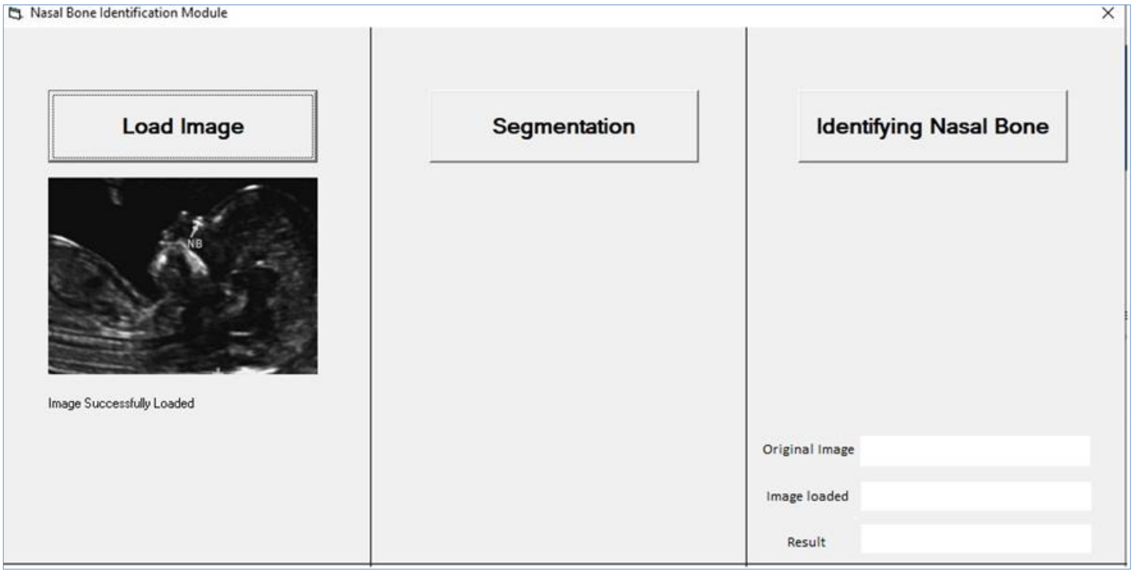

Figure 4(a) GUI Screenshot – Image Loading

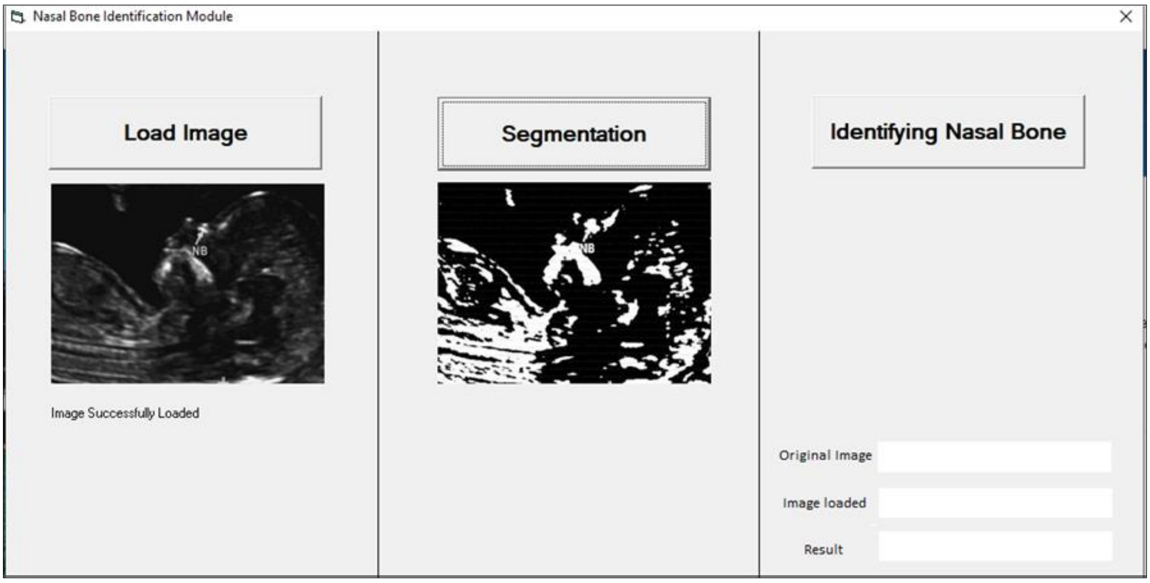

Figure 4(b) GUI Screenshot – Segmentation

Fig 4(c) shows the GUI screenshot of normal nasal bone identification and 4(d) shows the abnormal nasal bone identifying section. If any abnormalities being occurred the results shows the “abonormal”.

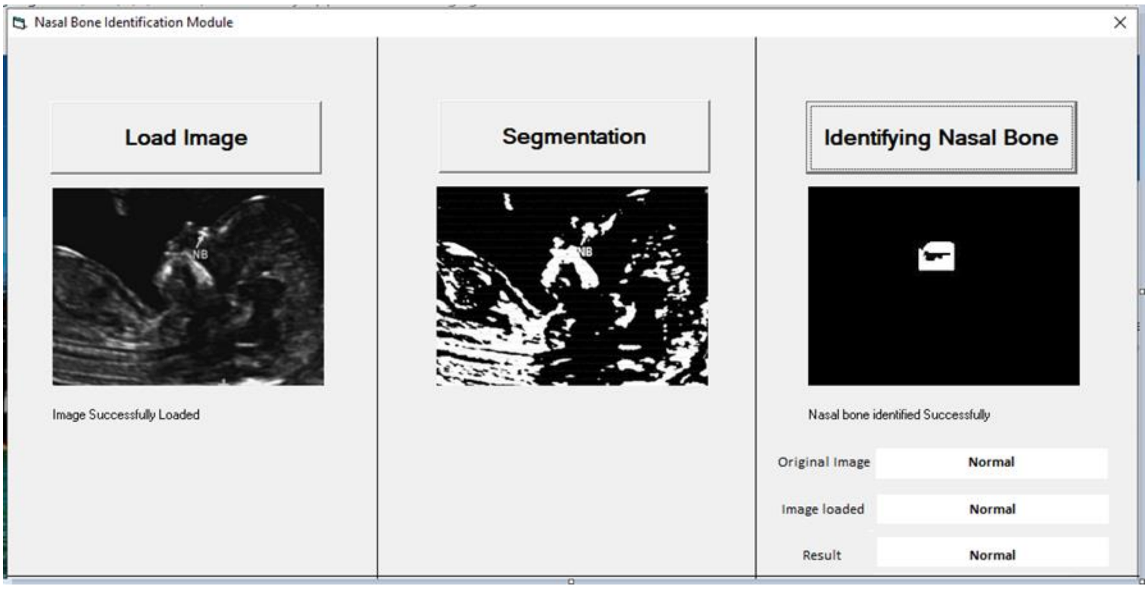

Figure 4(c) GUI screenshot - Normal nasal bone identification

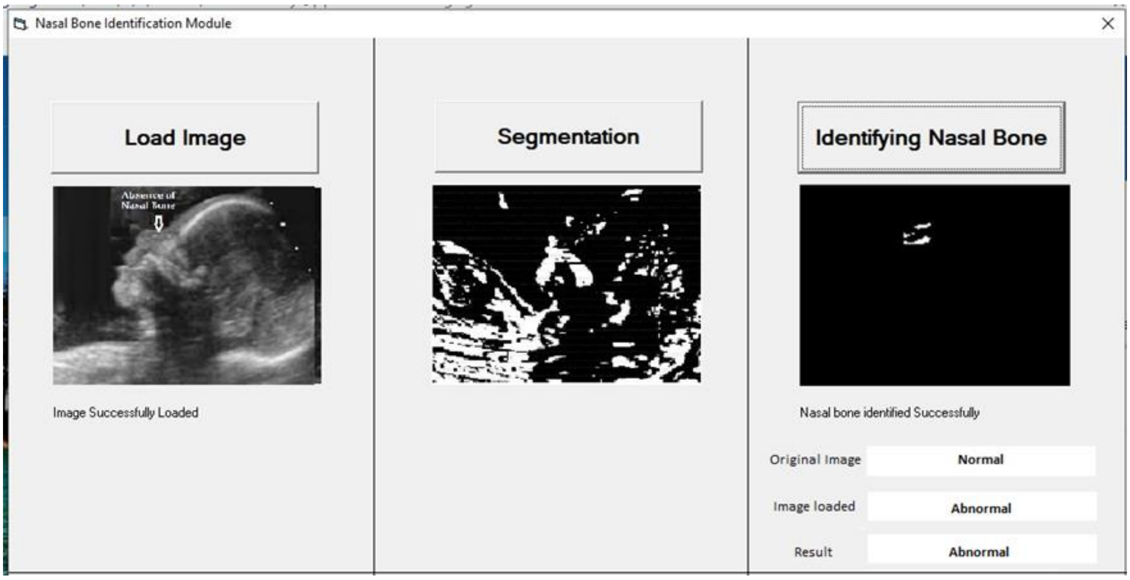

Figure 4(d) GUI screenshot – Abnormal Nasal bone identification

Studied the shape features of normal and abnormal images and from the study, it is clear that the area, major and minor axis length, etc. of both images are different. Fiducial points are points that are used as points of reference or measure. Some of the main fiducial points are the eyes, lip edges, nose, chin, etc. In this study, some images from the Dartmouth Database of Children's Faces are selected, inclusive of males and female images that were showing very distinct facial expressions. In this implemented work different features like contrast, energy, etc. are determined from the segmented outputs of the module. The nasal bones of normal and abnormal images are shown in the Fig. 5(a) and Fig. 5(b) respectively.

Figure 5 (a) Normal and (b) Abnormal Nasal Bone

The responses from the realized system and its performance investigation prove that this method provides a better detection rate and it helps in the effective diagnosis of DS. Also, the system has good accuracy. Then the system is trained using the BP algorithm. A neural network toolbox is used for the training. Figure 6 shows the NN training screenshot. The LM-based algorithm is used for the training. Here 70% of the data is used for the training, 15% of data is used for testing and the remaining 15% is used for validation. Figure 7 shows the regression analysis diagram. From the figure, it is clear that the overall efficiency of the system is 93.58%. Getting stuck in local minima is a drawback of the BP algorithm. So, the use of better optimization algorithms helps to improve the efficiency of the system.

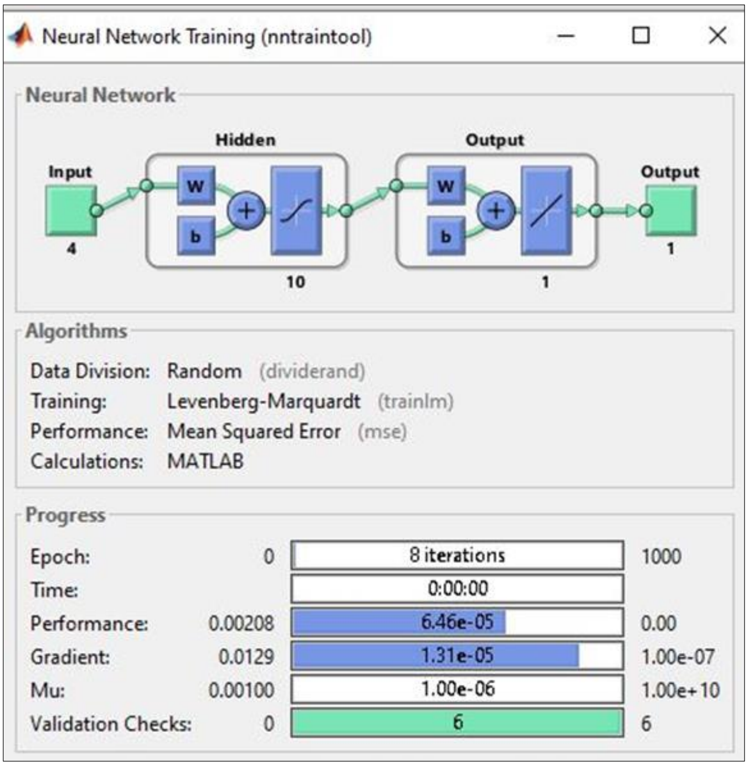

Figure 6 NN training structure

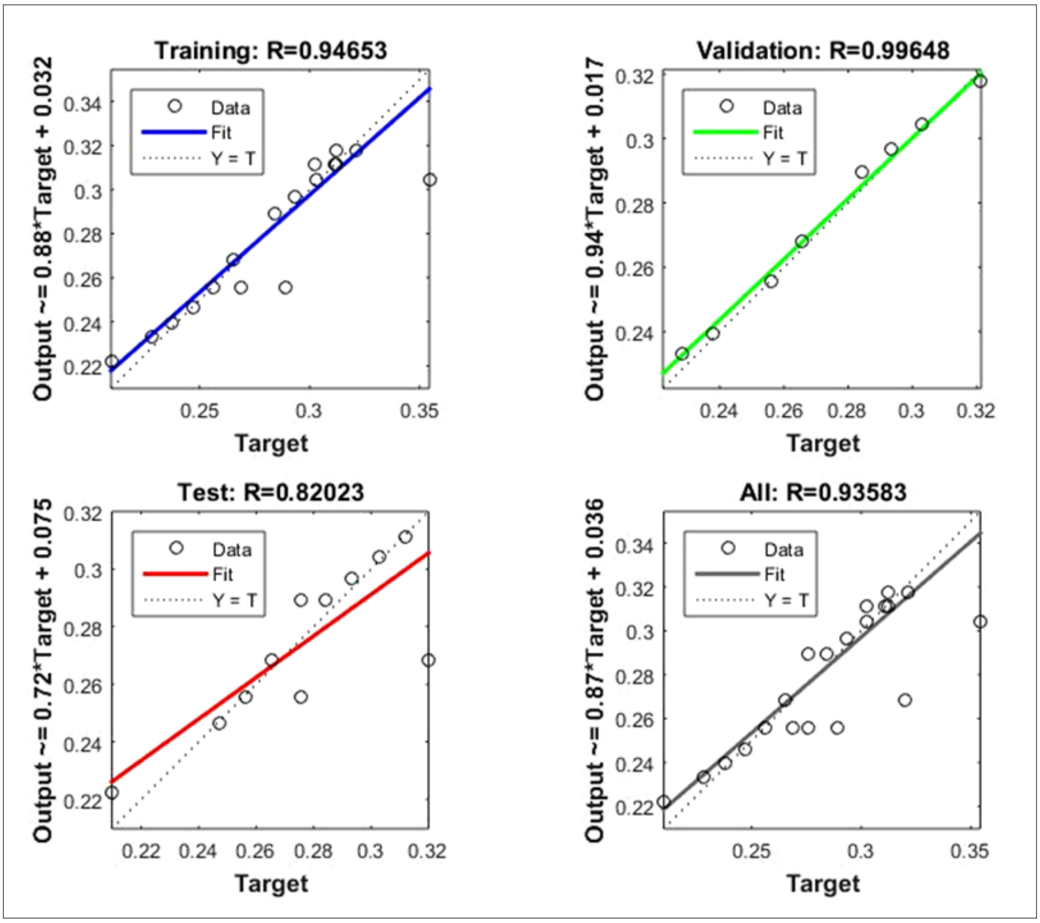

Figure 7 Regression Analysis Diagram

6. Conclusion

The ultrasound technique is used to analyze fetal conditions because of its real-time imaging. It is a commonly used investigation technique to study fetal biometric constraints. It is also used for prenatal growth monitoring and to detect fetus anomalies. Proper processing of these images helps to find out some diseases DS at the fetal development stage. The method for recognizing Down syndrome in face images was discussed which consists of facial fiducial point detection, feature extraction, feature reduction, and classification. As for directions for future work, we intend to analyze other sets of visual features and apply the developed system to different genetic disorders.

Compliance with ethical standards

Acknowledgments

Vincy Devi V K would like to express her gratitude to the research guide for the full-fledged support of the present research. Also, thanks to my family for the support during this research

Disclosure of conflict of interest

There are no conflicts of interest in this manuscript.

References

[1] JebaShiney O, Amar Pratap Singh J, Priestly Shan B. A Review on Techniques for Computer-Aided Diagnosis of Soft Markers for Detection of Down syndrome in Ultrasound Fetal Images. Biomedical Pharmacology Journal. 2017; 10(3).

[2] JadishaYarifRamírez Cornejo, HelioPedrini, Ariane Machado-Lima, Fátima de Lourdes dos Santos Nunes. Down syndrome detection based on facial features using a geometric descriptor. Journal of Medical Imaging. 2017; 4(4): 044008.

[3] F Hickey, E Hickey, KL Summar. Medical update for children with Down syndrome for pediatrician and family practitioner. Adv. Pediatr. 2012; 59(1): 137–157.

[4] SP Arjunan, MC Thomas. A Review of Ultrasound Imaging Techniques for the Detection of Down syndrome. IRBM. 2019.

[5] P Kruszka et al. Down syndrome in diverse populations. Am. J. Med. Genet. Part A. 2017; 173(1): 42–53.

[6] Q Zhao, et al. Hierarchical constrained local model using ICA and its application to Down syndrome detection," in Int. Conf. on Medical Image Computing and Computer-Assisted Intervention. Springer, New York. 2013; 222–229.

[7] S Saraydemir, et al. Down syndrome diagnosis based on Gabor wavelet transform. J. Med. Syst. 2012; 36(5): 3205–3213.

[8] O Erogul, et al. Recognition of Down syndromes using image analysis. in 14th National Biomedical Engineering Meeting. IEEE. 2009; 1–4.

[9] David B. Lerner. Support vector machine-based image classification for genetic syndrome diagnosis. Pattern Recognit. Lett. 2005; 26(8): 1029–1038.

[10] CK Neocleous, KH Nicolaides, KC Neokleous, CN Schizas. Artificial neural networks for non-invasive chromosomal abnormality screening of foetuses. The 2010 International Joint Conference on Neural Networks. 2010; 1-4.

[11] TA Anjit, S Rishidas. Identification of nasal bone for the early detection of down syndrome using Back Propagation Neural Network. 2011 International Conference on Communications and Signal Processing. IEEE. 136-140.

[12] WisnuJatmiko, IkhsanulHabibie, M. Anwar Ma'sum, RobethRahmatullah, I PutuSatwika. Automated Telehealth System for Fetal Growth Detection and Approximation of Ultrasound Images. International Journal on Smart Sensing and Intelligent Systems. 2015; 8(1).

[13] DE King. Dlib-ml: a machine learning tool kit. Journal of Machine Learning Research. 2009; 10: 1755–1758.

[14] HS Loos, et al. Computer-based recognition of dysmorphic faces. Eur. J. Hum. Genet. 2003; 11(8): 555–560.

[15] R Gonzalez, RE Woods. Digital Image Processing (Upper Saddle River, NJ, Prentice-Hall. 2002.

[16] AS Kornilov, IV Safonov. An Overview of Watershed Algorithm Implementations in Open Source Libraries. Journal of Imaging. 2018; 4: 123-138.

[17] Levner, I., Zhang, H. Classification-driven watershed segmentation. IEEE Transactions on Image Processing, 2007:16(5): 1437-1445.

[18] Goh TY, Basah SN, Yazid H, Safar MJA, Saad FSA. Performance analysis of image thresholding: Otsu technique. Measurement. 2018; 114: 298-307.

[19] Q Ferry, et al. Diagnostically relevant facial gestalt information from ordinary photos. 2014; eLife 3:e02020.

[20] Shamya Shetty, Jose Alex Mathew. Analysis of Fetal Development Using Ultrasound Images. IOSR Journal of VLSI and Signal Processing. 2016; 6(3); 01-07.

[21] JA Noble, D Boukerroui. Ultrasound image segmentation: a survey. IEEE Transactions on Medical Imaging. 2006; 25(8): 987–1010.

[22] Vincy Devi VK, Rajesh R. Down syndrome detection using modified AdaBoost algorithm. International Journal of Electrical and Computer Engineering. 2021; 11(5): 4281- 4288.

[23] J Anquez, ED Angelini, G Grangé, I Bloch. Automatic segmentation of antenatal 3-D ultrasound images. IEEE Transactions on Biomedical Engineering. 2013; 60(5): 1388–1400.

[24] SD Pathak, V Chalana, Y Kim. Interactive automatic fetal head measurements from ultrasound images using multimedia computer technology. Ultrasound in Medicine and Biology. 1997; 23(5): 665–673.

[25] SMGVB. Jardim, MAT. Figueiredo. Segmentation of fetal ultrasound images. Ultrasound in Medicine and Biology. 2005; 31(2): 243–250.

[26] FA Hermawati et al. Automatic femur length measurement for fetal ultrasound image using localizing region-based active contour method. J. Phys. 2019.

[27] Hermawati FA, Tjandrasa H, Suciati N. Hybrid Speckle Noise Reduction Method for Abdominal Circumference Segmentation of Fetal Ultrasound Images. International Journal of Electrical and Computer Engineering. 2018; 8(1): 1747–1757.

[28] L Creavin, RD Brown. Ophthalmic abnormalities in children with Down syndrome. J. Pediatr. Ophthalmol. Strabismus. 2009; 46(2): 76–82.

[29] J Epstein, et al. Protocols to establish genotype-phenotype correlations in Down syndrome. Am. J. Hum. Genet. 1991; 49(1): 207–235.

[30] JebaShiney O, Amar Pratap Singh J, Priestly Shan B. Medical Ultrasound RF Processing using Adaptive Activity-Dependent Rule-Based Wavelet De-Noising Approach. International Journal Control Theory and Applications. 2017; 10(3).

[31] Q Li, RM Nishikawa. Computer-Aided Detection and Diagnosis in Medical Imaging. Taylor and Francis, Boca Raton, Florida. 2015.

[32] JYR Cornejo, H Pedrini, F Flórez-Revuelta. Facial expression recognition with occlusions based on geometric representation. inIberoamerican Congress on Pattern Recognition, Springer, New York. 2015; 263-270.

[33] Amoah B, Anto E A, Crimi A. Automatic fetal measurements for low-cost settings by using Local Phase Bone detection. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2015;161–164.

[34] Mienye ID, Sun Y, Wang Z. Improved sparse autoencoder based artificial neural network approach for prediction of heart disease. Informatics in Medicine Unlocked. 2020; 18: 100307.

[35] VM Joy, S. Krishnakumar. Optimal Design of Power Scheduling using Artificial Neural Network in An Isolated Power System. Int. J. of Pure and Applied Mathematics. 2018; 118(8): 289–294.

[36] VM. Joy S. Krishnakumar. Optimal design of adaptive power scheduling using modified ant colony optimization algorithm. International Journal of Electrical and Computer Engineering. 2020; 10(1): 738–745.

[37] Anitescu C, Atroshchenko E, Alajlan N, Rabczuk T. Artificial neural network methods for the solution of second order boundary value problems. Computers, Materials and Continua. 2019; 59(1):345-359.