Down Syndrome Fetus Detection Using Deep Learning Approaches

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Abstract —Down syndrome (DS) is the most common chromosomal aneuploidy to result in a live birth. The radiologist determines the length of the nasal bone at second trimester stage for DS detection at an earlier stage. There is the region where the fluid is segregated and accumulated, which is called as Nuchal translucency (NT). The length of the NT in fetus may ranges from 45mm to 84 mm. The thickness of NT in fetus decides the possibility of DS in fetus. Hence, the detection and segmentation of NT region in fetus is important for identifying the DS.To detect and classify the fetus images (down syndrome) into either normal or down syndrome affected images using machine learning soft computing methods To detect and segment the nasal bone in classified fetus images for down syndrome diagnosis using deep learning soft computing methods. To analyze the impact of nasal bone parameters for down syndrome diagnosis.

Keywords— Fetus, Down syndrome, Nuchal translucency, Deep neural network, convolution

I. INTRODUCTION

Down syndrome (DS) is a genetic disorder that cannot be prevented but can be detected early in pregnancy. Women of a higher maternal age are more likely to have DS. Ultrasound (US) Imaging is preferred over other modalities because of it is safe, economical, and non-invasive nature. DS is examined using screening and diagnostic tests. Amniocentesis & Chorionic Villi Sampling are the two diagnostic tests performed to detect DS. Although these tests produce a high detection rate, they also carry the risk of miscarriage and fetal injury. The screening test includes a blood test such as Beta Human Chorionic Gonadotropin (Beta-HCG) and Pregnancy Associated Plasma Protein (Papp-A) as well as a US examination. These blood tests are frequently used in conjunction with the US to look for "markers" that can indicate the presence of DS. Nuchal Translucency (NT) is the most significant marker for detecting DS early in pregnancy (11-14th weeks). NT refers to a fluid deposit beneath the fetal skin. It is a black area that lies between the two bright NT boundaries. According to research findings [4], [5], increased fetal NT thickness (>3 mm) is associated with an increased risk of DS. The mid-sagittal plane is used to calibrate NT [6], and the broadest region of the translucency is used for measurement. NT is calculated manually by the clinicians using an electronic caliper. This measurement is operator dependent and prone to error. As NT is of small size a slight variation caused in the estimation leads to an incorrect assessment of the fetus. Thus, computerized methods are proposed to overcome the problems faced in manual measurements and to provide a better detection rate. Giuseppa et al. devised an automated method for determining the thickness of NT. This method employs wavelet and multi-resolution analysis to assist clinicians in predicting DS in the early stages of gestation. Lee et al. presented a method for locating NT edges and accurately measuring their thickness. This method emphasized the semiautomatic method, in which the NT boundary is highlighted with a diffusion filter and its thickness is calibrated with dynamic programming. Using wavelet analysis and neural networks, Sciortino et al. proposed a non-supervised method for tracing and calibrating the thickness of NT. For accurate NT estimation, the fetal position should be in the mid-sagittal region. Measurement of NT is an important step in computer-aided diagnosis (CAD) for early detection of DS. Conventional segmentation methods face a lot of challenges like fuzzy edges, Intensity homogeneity, more time consumption, and high probability error in extracting the NT region. Automatic detection of DS would resolve these obstacles and provide a fast and better diagnosis of the fetus. Deep learning (DL) is a useful technique for constructing networks that can effectively mimic higher-order systems and achieve humanlike performance. DL is an effective approach for segmenting complex medical images. DL-based methods can learn efficient traits directly from the datasets. Especially, the development] of the Convolutional Neural Network (CNN) has further enhanced the state-of-the-art in semantic segmentation of medical datasets. CNN has proven to perform exceptionally well for image segmentation and classification tasks. The Semantic Segmentation model (SegNet) is the well-known CNN architecture for image segmentation and it is computationally efficient and developed for pixel-wise semantic segmentation. Image classification plays a significant task to classify the disease by learning its feature from the Segmented model. Kei Otsuka presented a transfer learning-based technique for segmenting medical images using SegNet. The SegNet algorithm classified the images of trained blood smears into three categories: background, blood parasites, and blood cells. Thus, SegNet model will significantly boost the performance of image recognition, segmentation, and categorization in the area of computer vision. This study proposes a novel methodology for semantic segmentation of NT and categorization of DS in the early stages of pregnancy using CNN architecture.

BACKGROUND AND RELATED WORK

A. Details of subjects

The US fetal image was provided by the Mediscan Fetal care Research Foundation, Chennai, India. The dataset contained images of 100 fetuses between 11-14 weeks of gestation. There were 50 healthy and 50 DS fetuses in the database. The size of the image is 1136x852. The protocol [23] for accurate measurement of NT was outlined by the Fetal Medicine Foundation (FMF)

BPerformance Analysis Parameters

Sensitivity (Se) =TP/ (TP+FN)

Specificity (Sp) = TN/ (TN +FP)

Accuracy (Acc)= (TP+TN) / (TP+FN+TN+FP)

Positive Predictive Value (PPV)= TP/ (TP+FP)

Negative Predictive Value (NPV)= TN/ (TN+FN)

B. Data pre-processing

US Images are prone to inherent noise, poor quality, and size variation. Speckle [20] is the granular noise observed in the US images which degrade the quality of the active images. Image processing is a primary step to extract useful details from the images by removing noise and distorted pixels. The US images are subjected to pre-processing techniques such as filtering and resizing. Filtering [21] reduces noise, enhances the image, and preserves fine edge features. The filtration of an image is accomplished using a wiener filter as shown in Fig.2.a). The images are then transformed to grayscale and resized before being given to the system as input. As a result, the pre-processing method aids in normalizing all images so that they are independent of their origin and the image size influence on system performance is avoided.

CONCLUSION

In this paper, we developed a novel methodology using DL for the early diagnosis of DS. Fetal US images were preprocessed to remove the speckle noise and resized for faster computation. The contours of NT were semantically segmented from US fetal images using VGG-16 based SegNet architecture and effectively classified using AlexNet Model. Thus, the CAD will certainly be a great tool for clinicians in screening for DS, enhances the detection rate, and provides a valuable second opinion for early diagnosis of DS. This technology helps to identify the individuals who are at higher risk for this condition and allows termination at the early stages of gestation.

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