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REVIEW ARTICLE

Computer-Aided Monitoring of Fetus Health From Ultrasound Images: A Review

Ultrason Görüntülerinden Fetus Sağlığının Bilgisayar Destekli Takibi: Bir İnceleme

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ABSTRACT

Computer aided diagnostic methods have been helping medical experts for monitoring fetus health for many years. The use of new methods has made a positive effect in monitoring the health of fetus as well as the diagnosis of anomalies. This study first introduces the indicators for identifying anomalies in fetus and gives basic information about computer-based methods such as traditional image processing, machine learning and deep learning. Then an overview of existing studies which use novel techniques on monitoring fetus health and anomaly detection from ultrasound images is given. Finally, the main challenges of novel techniques and future directions of research on computer-aided monitoring of fetus health are summarized.

Keywords: Computer-Aided Diagnosis, Fetus Health, Deep Learning, Machine Learning, Image Processing

ÖZ

Bilgisayar destekli tanı yöntemleri, tıp uzmanlarına yıllardır fetüs sağlığını izlemek için yardımcı olmaktadır. Yeni yöntemlerin kullanılması, fetüsün sağlığının izlenmesinin yanı sıra anomalilerin tanısında da olumlu bir etki yaratmıştır. Bu çalışma ilk olarak fetüste anomalileri tanımlamak için kullanılan göstergeleri tanıtır ve geleneksel görüntü işleme, makine öğrenimi ve derin öğrenme gibi bilgisayar tabanlı yöntemler hakkında temel bilgiler verir. Daha sonra, ultrason görüntülerinden fetüs sağlığının izlenmesi ve anomali tespitinde yeni teknikler kullanan mevcut çalışmalara genel bir bakış verilmiştir. Son olarak, fetüs sağlığının bilgisayar destekli izlenmesi üzerine güncel tekniklerle ilgili ana zorluklar ve araştırmaların gelecekteki yönü özetlenmiştir.

Anahtar Kelimeler: Bilgisayar Destekli Tanı, Fetüs Sağlığı, Derin Öğrenme, Makine Öğrenmesi, Görüntü İşleme

1. INTRODUCTION

New devices and techniques, developed as a result of technological advances, have become widespread in almost every area of life as supporting or replacing traditional business methods, as well as in the field of medicine. Ultrasonography is an imaging method which is used in the follow-up of pregnancy and fetus health safely for more than 50 years, as it does not contain X-rays, also known as radiation (Aydoğdu, 2017; Serhatlıoğlu, 2016).

Computer Aided Diagnosis is one of the supporting technologies that have taken place in the field of medical imaging for years and novel approaches attracted the attention of researchers recently. Through computer aided diagnosis, it is aimed to quickly capture details that may be avoided the attention of humans or cannot be detected by the human eye on medical images by using methods such as image processing, computer vision, machine learning, deep learning and artificial neural networks. There are studies showing the contribution of computer-aided diagnostic techniques to the diagnosis of diseases by helping physicians (Serhatlıoğlu,2016) and using computer-aided diagnostic methods in addition to traditional methods increases the efficiency of the diagnostic process and enables a healthier progression of the pregnancy and delivery (Ergün, 2017).

With the introduction of the term machine learning by Arthur Samuel (1959) significant progress has been made in many areas such as computer vision, image processing, financial data analysis (Brattain et al., 2018). Machine learning approaches, which have shown great success especially in image processing, have shown much better success with the emergence of deep learning, which is a sub-branch of machine learning.

Krizhevesky et al. (2012) winning the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) with Alex Krizhevsky Convolutional Neural Network (AlexNet), has significantly contributed to the rapid increase in interest in deep learning. In the following years, Russakovsky et al. (2015) has led to further progress with a deeper learning architecture. With technological developments and research, the high performance of deep learning in image processing has made it to be seen as a promising method for applications in the health sector.

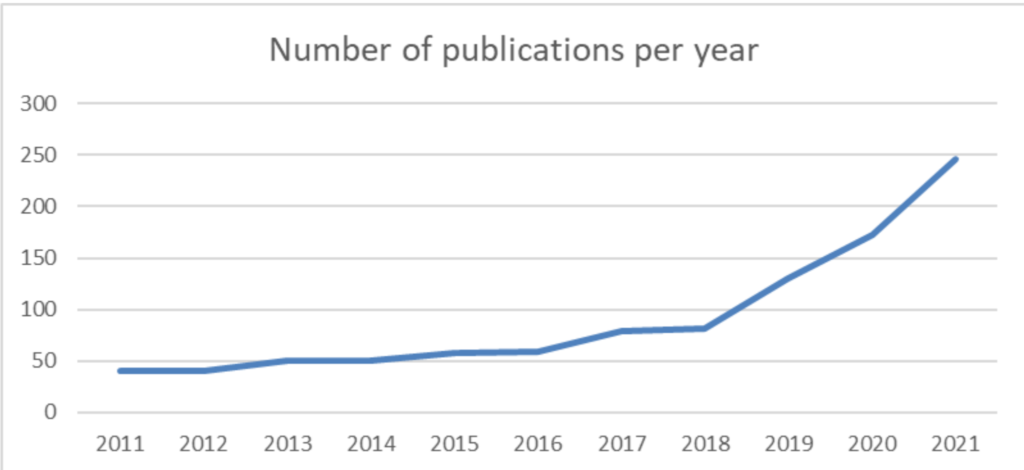

Figure 1. Number of publications about learning methods used in fetal health monitoring, within last decade by year. Numbers are obtained from ScienceDirect (https://www.sciencedirect.com).

According to the data obtained from ScienceDirect, the change of the number of publications within the last decade about learning methods used for fetal health monitoring from ultrasound images are given in Fig. 1. It can be seen from the figure that research interest in this area, increased rapidly for the last few years.

The aim of this study is to provide a comprehensive review of the studies on computer technologies used for monitoring fetal health and development recently, to evaluate the future direction of these technologies. The rest of this paper is organized as follows. In Section 2, medical terms, which are vital to be examined for monitoring of fetal development and health, are introduced. Computer-aided diagnostic methods, which are used in the follow-up of fetus health, are given in Section 3. Section 4 is where the existing studies are presented.

2. INDICATORS FOR MONITORING FETAL DEVELOPMENT AND HEALTH: BIOMETRIC PARAMETERS AND SOFT MARKERS

Ultrasonography, which is one of the non-invasive methods, is inexpensive compared to other methods such as CT and MRI, it works in real time and does not require ionizing radiation, making its use widespread by physicians (Contreras-Ortiz, Chiua & Fox, 2012). Although the image quality and technical features of the device vary depending on factors such as gestational week, fetal position and the experience of the practitioner, it is possible to recognize major structural and chromosomal anomalies with detailed ultrasonography (Paladini & Volpe, 2014).

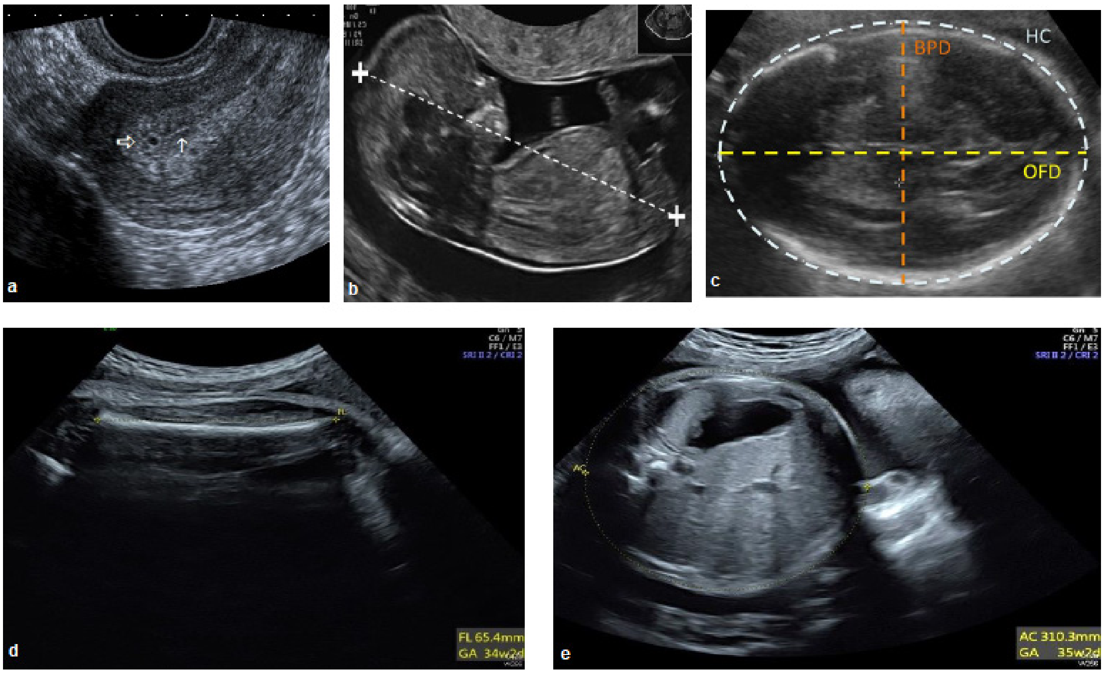

Figure 2. Sample Fetal Biometric Parameters:(a) GS (Ergün, 2017); (b) CRL (Salomon et al., 2019); (c) HC/BPD/OFD (Rueda et al., 2014); (d) FL (Johnson, 2018) (e) AC (Johnson, 2018)

Fetal biometric parameters such as gestational sac (GS), biparietal diameter (BPD), head circumference (HC), occipitofrontal diameter (OFD), abdominal circumference (AC) and femur length (FL) are used during ultrasonographic examination to determine the health and growth and development status of the fetus, and to diagnose some anomalies (Snijders & Nicolaides, 1994). In Fig. 2, samples of biometric parameters are shown on ultrasound images.

GS is the first ultrasonographic sign of pregnancy. Confirming fetal viability is an important indicator for determining gestational position (Abdallah et al., 2012). BPD is the measurement of the distance between the parietal bones on the lateral sides of the fetal head. OFD is the measure of the distance between the occipital bone and anterior bone. HC is the measurement of the fetal head circumference. BPD and HC are the most frequently measured fetal biometric parameters in the second and third trimesters to determine the gestational age (Salomon et al., 2019).

FL is the measurement of the femoral bone of fetus. Femur length shorter than a certain value, is an important soft marker for chromosomal anomaly detection (Mathiesen et al., 2014). AC is one of the biometric parameters used alone or with other parameters to calculate gestational age and fetal weight. The crown rump length (CRL) measurement of the embryo or fetus in the first 14 weeks is the most suitable parameter in calculating the gestational age (Salomon et al., 2019).

Figure 3. Sample Soft Markers: (a) NT (pink line), IT (green line), NB (part shown by arrow) (Paladini & Volpe, 2014); (b) FMF angle measurement (Lachmann et al., 2010); (c) Mild ventriculomegaly (D'Addario, 2015)

In the determination of fetal chromosomal anomalies (although some structural anomalies also indicate chromosomal anomalies), fetal chromosomal anomaly markers are used such as nuchal translucency (NT), intracranial translucency (IT), frontomaxillary facial (FMF), nasal bone (NB), ventriculomegaly and femur length (FL). These markers are called as "soft markers" (Chaoui et al., 2009; D'Addario, 2015). Sample soft markers are given in Fig.3.

NT is formed by the accumulation of fluid behind the fetal neck and can be seen on the ultrasound image in the first trimester. NT measurement varies according to fetal crown-rump length (CRL) measurement. Higher NT measurement indicates Turner syndrome, trisomy 13, 18, 21, and many more chromosomal abnormalities (Snijders & Nicolaides, 1994). IT compression in fetuses with open spina bifida was observed to be evident at 11–13 weeks (Chaoui et al., 2009). FMF angle is a measurement for detecting trisomy 21 and open spina bifida anomalies. Although the FMF angle increases in fetuses with trisomy 21 according to normal measurements, this angle decreases in fetuses with open spina bifida compared to normal measurements (Lachmann et al., 2010). Absence or hypoplasia of NB is an important marker of trisomy 21, trisomy 18, trisomy 13, or Turner syndrome (Paladini & Volpe, 2014). Ventriculomegaly can be identified by measuring the lateral ventricles (LVs) on an ultrasound scan. It occurs when the atrial diameter is more than 10 mm in the second or third trimester. It is associated with chromosomal abnormalities, most commonly trisomy 21, and congenital infections (D'Addario, 2015). Although medical experts are experienced, during the specified examinations and inspections, human errors are always possible. In addition, in the measurement of fetal biometric parameters and in the diagnosis of structural and chromosomal anomalies, studies that will make it possible to make a diagnosis with a higher percentage by using computer-assisted artificial intelligence programs, are promising.

3. COMPUTER AIDED DIAGNOSTIC METHODS USED IN THE FOLLOW-UP OF FETUS HEALTH

Factors such as gestational age, fetal position, body fat, tissue structure, mother's breathing motion, noise from the environment, or technical characteristics of the device limit the diagnostic efficiency in ultrasound scanning (Hiremath, Prema & Badiger, 2013). Speckle noise, which is a natural feature of ultrasound imaging, also reduces image contrast and resolution. The insufficient quality of the images may cause the measurements to be interpreted differently among the observers and even the anomaly detections to be overlooked. For this reason, automatic measurements are used today to get higher diagnostic value (Serhatlıoğlu, 2016).

Many different automatic measurement methods have been used in existing studies. In this section, traditional machine learning techniques together with traditional image processing techniques used for computer aided anomaly detection, and deep learning, which is also a sub-branch of machine learning, which have shown great success in image processing recently, will be emphasized.

Traditional Image Processing

Image processing is a method for obtaining images with improved quality or extracting useful information from images recorded by various mediums using computers (Vincet & Sahyun, 2003). Basically, image processing techniques are image enhancement, image detection and estimation, image restoration, image compression, image segmentation and image classification (Da Silva & Mendoça, 2005).

The insufficient quality of ultrasound images increases the necessity of pre-processing step before automatic diagnosis. This step has a key role in reducing speckle noise and increasing image quality. Although varying according to the characteristics of the image obtained in the pre-processing step, processes such as improvement, restoration, sizing, compression, filtering, and colour conversion can be performed. With these processes, the raw image becomes more processable and of higher quality. The most common pre-processing methods used to improve ultrasound images are Median filter, Gaussian filter, Lee filter, Wiener filter, Fourier transform, Wavelet filter etc. (Hiremath et al., 2013; Mounica et al. 2019).

One of the most used image processing methods in automatic diagnosis studies on ultrasound images is the segmentation method. This method is used to divide the image into meaningful parts with similar properties due to the inefficiency of processing the entire image. Traditional segmentation methods can be listed as follows: Threshold Method, Edge Based Segmentation, Region Based Segmentation, Clustering Based Segmentation, Watershed Based Method. However, with the latest developments, Artificial Neural Network Based Segmentation has gained a prominent place today (Gonzalez & Woods, 2018).

Machine Learning

Machine learning is a sub-branch of artificial intelligence that learns from data and focuses on making predictions from data. In the following, a brief description of selected machine learning methods such as Supervised Learning, Unsupervised Learning, Reinforcement Learning, Ensemble Learning, Semi- supervised Learning and Deep Learning is given. In supervised learning, the machine is trained with labelled data and learns to have specified output values. Samples of the most widely used supervised learning algorithms are Support Vector Machine (SVM), Linear regression, Naive Bayes, K-Nearest Neighbor (kNN) and Decision Trees (DT) (Hurwitz & Kirsch, 2018; Nasteski, 2017). Unsupervised learning is a method of learning by analysing existing data without having labelled data or a specific output value. An example of unsupervised learning algorithms is the k-means clustering algorithm (Ghahramani, 2003). In reinforcement learning, the model receives feedback from the cause-effect analysis among the data without training data and is directed to the best result. It is based on the Markov Decision Process (MDP) model. Monte Carlo, Q-learning algorithms can be given as examples of reinforcement learning algorithms (Kaelbling, Littman & Moore, 1996). Ensemble Learning is a method in which multiple models are trained to solve a problem. Random Forest and AdaBoost algorithms can be given as examples of Ensemble learning algorithms (Zhou, 2009). Semi-Supervised Learning trains using large amounts of unlabelled data along with labelled data. There is great interest in this approach because obtaining labelled data requires a lot of human effort. Generative models and Graph-based method are examples of semi-supervised learning methods (Zhu, 2007).

Deep Learning

Today, conventional image processing methods are insufficient for automatic diagnosis processes. With the widespread use of high-performance computers, deep learning and image processing find solutions to more complex problems. Deep learning is a sub-branch of the field of machine learning, which includes one or more hidden layers that use artificial neural networks algorithms. With deep learning, you can create models consisting of many processing layers to learn the properties of the data and then make predictions with new data (Alom et al., 2019; LeCun et al., 2015). Some of the commonly used deep learning algorithms can be listed as follows: Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory Networks (LSTM), Deep Boltzmann Machine (DBM) and Deep Belief Networks (DBN) (Razzak, Naz & Zaib, 2017).

CNN architecture, which is the most effective deep learning algorithm in image processing, shows promising performances especially in segmentation. The most used CNN models developed for different purposes can be listed as follows: Yann LeCun Convolutional Neural Network (LeNet), AlexNet, Regional Convolutional Neural Network (Mask-R CNN), Fully Convolutional Network (FCN), Convolutional Networks for Biomedical Image Segmentation (U-Net), GoogleNet, Visual Geometry Group Convolutional Network (VGGNet), Region Based Convolutional Neural Networks (R-CNN), You Only

Look Once (YOLO) , Residual Neural Network (ResNet), Dense Convolutional Network (DenseNet) (Razzak et al., 2017; Jiao & Zhao, 2019).

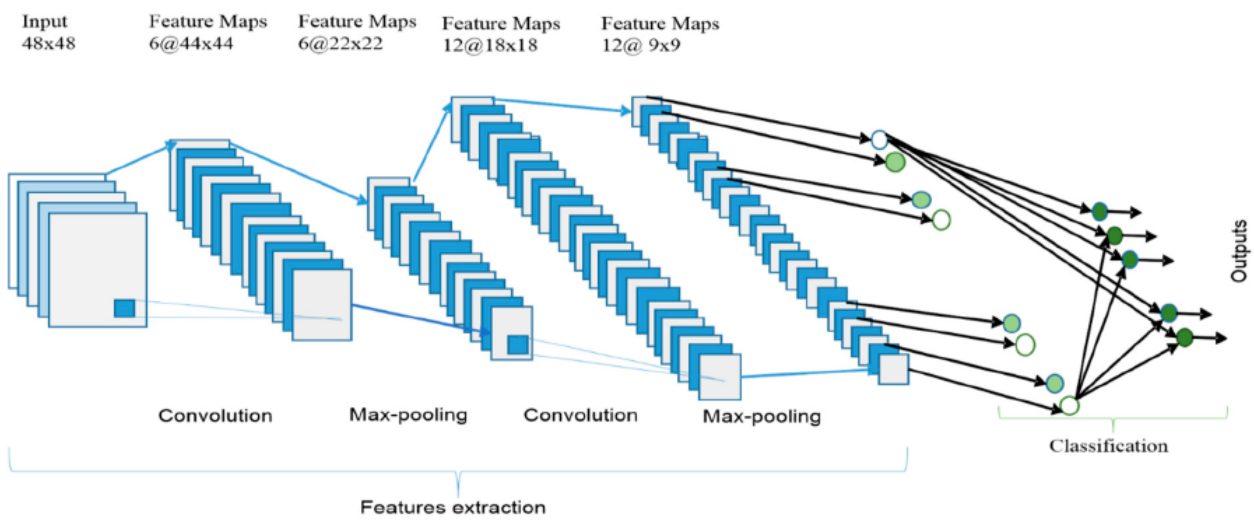

Figure 4. Convolutional Neural Network (CNN) General Architecture (Alom et al., 2019)

In Figure 4, general architecture of CNN is given.

By means of high-performance computers and software techniques that are developing day by day, deep learning models are constantly developing, and higher performance algorithms appear. In this study, traditional image processing methods machine learning and deep learning models, which have been used for medical image segmentation and classification from past to present, have been reviewed.

Table I

Classification of existing studies according to the technique used

Used Technique	Related Work
Traditional Image Processing methods	(Chakkarwar, Joshi & Revankar, 2010; Wee et al., 2010; Rawat et al., 2013; Ibrahim et al.,2017; Lu et al., 2005; Satwika et al., 2013; Mathews et al., 2014; Foi et al., 2014; Sahili et al., 2019; Rasheed et al., 2021; Thomas, Peters & Jeanty, 1991; Mukherjee et al., 2010; Wang, 2014; Methews & Deepa, 2014; Khan et al., 2015; Yu, Wang & Chen, 2015; Amoah, Anto & Crimi, 2015; Ravishankar, Prabhu & Vaidya, 2016; Hermawati et al., 2019; Yu et al., 2008; Wang et al., 2014; Jang et al., 2018; Kim et al., 2018; Nirmala & Palanisami, 2010; Lakshmi et al., 2008; Karl, Kagan & Chaoui, 2012; Sonia & Shanti, 2015; Deng et al., 2012; Anzalone et al., 2013; Sonia & Shanti, 2016; Nie et al., 2017)
Supervised Learning methods	(Khazendar et al., 2014; Ibrahim et al., 2017; Lu et al., 2005; Mathews & Deepa, 2014; Sahli et al., 2019; Carneiro et al., 2008; Anjit & Rishidas, 2011; Rafeek & Gunasundari, 2013; Deng et al., 2012; Park et al., 2013; Sciortino, Tegolo & Valenti, 2017)
Unsupervised Learning methods	(Zhang et al., 2017; Yu et al., 2008; Anzalone et al., 2013)
Semi-Supervised Learning methods	(Park et al., 2013)
Ensemble Learning methods	(Zhang, Chen & Li, 2011; Zhang et al., 2012; Zhang et al., 2017; Van den Heuvel et al., 2018; Li et al., 2018)
Reinforcement Learning methods	(Sofka et al.,2014)
Deep Learning methods	(Yang et al., 2019; Sinclair et al., 2018; Kim et al., 2019; Li et al., 2020; Rasheed et al., 2021; Sobhaninia et al., 2019; Thirusittampalam & Thangavel, 2020; Zhang et al., 2020; Fiorentino et al., 2020; Zhang, Petitjean & Ainouz, 2022; Wang et al., 2019; Ravishankar, Prabhu & Vaidya, 2016; Jang et al., 2018; Kim et al., 2018; Yang, Yang & Zhang, 2020; Oghli et al., 2021; Chen et al., 2020; Liu et al., 2019; Chaudhari et al., 2021; Zhu et al., 2021; Thomas & Arjunan, 2022)

4. EXISTING STUDIES

In this section, selected existing studies are reviewed. Some of them focus on prenatal biometric parameters and the rest focus on soft markers. For a clear presentation, existing work is organized in two subsections and three categories in each subsection as Traditional Image Processing, Machine Learning and Deep Learning. Additionally, studies which belongs in more than one category are classified as Hybrid. In Table I, as a summary, reviewed publications in this article are classified according to the used methods.

4. 1. Studies Focused on Measurement of Biometric Parameters

4.1.1. Traditional Image Processing

In the study on automatic segmentation of FL, Thomas et al. (1991) used morphological operators and made use of preliminary information on overall size and shape range for measurements. In the study, the background was first subtracted from the original image to make the femur bone more prominent, then contrast was enhanced to improve the shape of the femur bone, and then the threshold was applied to create a dual image. Next, an algorithm that searches in the femur region and designed to combine regions with general curvature was used. The obtained femur bone was used to create a single pixel-wide skeleton and finally FL measurement was made. Chakkarwar et al. (2010) worked on automatic measurement of GS size. In the study, segmentation was made with thresholding technique using Gaussian and Wiener filters for speckle noise, respectively, and the diameter of the GS was measured. It was noted by the authors that automatic measurement of the gestational sac was successfully performed with the presented method. Mukherjee et al. (2010) used polynomial curve fitting technique for automatic FL detection and measurement. Otsu threshold and curvature-based thresholding procedures were used to differentiate the femur, from other regions. In the next step, a five-parameter separator is used for the segmentation of the relevant region. After automatic segmentation, the Least Trim Square (LTS) regression method was used for polynomial curve fitting and automatic measurement was performed. It is stated that the presented method can be adapted for automatic measurement of other fetal limbs. Rawat et al. (2013) used Gradient Vector Force (GVF) snake-based segmentation algorithm for automatic segmentation of GS in their study. Satwika et al. (2013) proposed automatic BPD and HC measurement with the Hough transform method with one-dimensional parameter space developed in their study. It was emphasized that the proposed method is better than both the single parameter space Hough Transform (HT) method and the Random Hough Transform (RHT) method. Foi et al. (2014) developed the Difference of Gaussians revolved along Elliptical paths (DoGEll) method on fully automatic skull segmentation to calculate biometric measurements of BPD, OFD and HC. Using the DoGEll method, the inner, middle, and outer contour estimates of the skull were found by minimizing the cost function using the Nelder-Mead algorithm. The authors stated that the segmentation accuracy of their method was superior to other methods participating in the challenge of "Challenge US: Biometric Measurements from Fetal Ultrasound Images held in conjunction of the ISBI 2012 conference". For automated FL segmentation and measurement, Wang (2014) presented an automated morphology-based approach. Firstly, the median filter was used to reduce noise, secondly, the entropy-based segmentation method was used to determine possible candidates. In the next step, FL segmentation was performed by selecting the best elongated object according to the density and the height-width ratio. Mathews et al. (2014) used Chamfer Matching-based ellipse sensing and HT-based ellipse sensing approaches for segmentation of the fetal head for HC, BPD, and OFD measurement and compared these approaches. It was stated that the Chamfer Matching-based ellipse sensing approach performed better than the HT-based ellipse sensing approach. Wang et al. (2014) first defined an elliptical ROI to cover only the fetal abdomen to detect abdominal contour. In the next step, local phase-based Multi-scale Feature Asymmetry (MSFA) measurement was used to determine the fetal abdomen boundaries. In the last step, IRHT was applied to determine the ellipse that fits the abdominal contour. Yu et al. (2015) used the phase symmetry method and the saliency visual attention model for femur detection. In the first stage, 2D phase symmetry method, which does not change with changes in contrast and shows significant sensitivity in bone fixation, was used to determine possible image features. In the second stage, a modified prominence based visual attention model, combined with information about the structure of the femur, was used to select the femur from the candidate objects obtained in the first stage. In the last step, polynomial regression was used to find the best curve for the actual shape of the femur. Amoah et al. (2015) studied automatic measurement of FL and accordingly the prediction of gestational age. In the first step, FL was determined through phase symmetry information obtained by using Gabor filter bank, which detects bone structures. The results of the phase symmetry image were then doubled using the grassy threshold, and then dilation and erosion processes were applied. After determining FL, gestational age was calculated using Hadlock regression formula. Hermawati et al. (2019) worked on obtaining FL automatically and determining the effect of noise cancellation on segmentation accuracy. They used the hybrid speckle noise reduction method to remove noise in the first step. In this method, anisotropic diffusion, bilateral filtering and wavelet multiresolution methods are combined. In the second step, the localized region-based active contour (LRAC) method was applied to identify and segment a local area. In the last step FL was measured for gestational age estimation. It has been stated that noise reduction has a great effect on accurately measuring the gestational age.

4.1.2. Machine Learning

Carneiro et al. (2008) studied the automatic measurement of biometric parameters (BPD, HC, AC, FL, CRL) by segmentation procedure applied to ultrasound images. In the method used, a constrained probabilistic boosting tree classifier was trained to automatically distinguish between the object of interest and the background. It has been stated that the segmentation and obstetric measurements of the proposed method are close to the accuracy of the experts. Zhang et al. (2011) made automatic diameter measurement of GS from the videos. In the first stage, speckle noise was removed, in the second stage, the AdaBoost algorithm was used to find the position of the GS. Again, Zhang et al. (2012) continued their previous work and integrated machine learning and image processing techniques for fully automated GS measurement. In this study, a two-stage AdaBoost classifier was used, a database-guided multi-scale normalized cuts algorithm was used for automatic segmentation, and automatic measurement of GS was performed with an optimized snake model. Khazendar et al. (2014) worked on segmentation of GS and classification of segmented GS whether it is a miscarriage case or a normal case. In the study, the Otsu thresholding for automatic measurement of the Mean Sac Diameter (MSD), the median filter to soften the boundaries and the erosion method from the morphological processes to extract the boundaries. For classification, different methods such as DT, SVM, Naive Bayes and kNN have been used. Sofka et al. (2014) developed a system for automatic measurement of fetal head and brain structures from 3D ultrasound images. Monte Carlo method and learning-based Integrated Detection Network (IDN) method, which are sequential estimation techniques based on visual monitoring, were used for HC, BPD, OFD and LV measurements. While object detection estimation is made with Monte Carlo method, design, modification, adjustment, and application of complex detection system are simplified with IDN. Mathews and Deepa (2014) used density-based thresholding and shape-based thresholding methods for pre-segmentation. They also used the SVM classifier to select the valid femoral object from the segmented image. In the study on automatic measurement of BPD, Khan et al. (2014) developed a portable ultrasound device and made automatic BPD measurement on the tablet by transferring the fetal head images obtained from this device to the tablet. In the study, grayscale, smoothing, dilatation, erosion and binary threshold were used respectively in the pre-processing step, and then the Canny edge detection function of the OpenCV library was used to find edge and measure BPD. Khan et al. (2015) developed an automated method that can work on a tablet device to detect and measure FL. First, ROI was used to obtain the relevant region and a binary threshold was used to transform it into a binary image. Then, progressive probability Hough transform (PPHT) was applied to find a straight line with the highest number of votes to be used in FL measurement. Zhang et al. (2017) used a Texton-based method for fetal head segmentation. A random forest (RF) classifier was used to determine whether the segmented head region was obtained from an accurate imaging plane. BPD, OFD and HC measurements were then calculated with an ellipse placed on the skull border. One of the first systems for automatic measurement of HC from ultrasound images in all trimesters of pregnancy was created by Van den Heuvel et al. (2018). In the study, Haar-like features were first calculated from ultrasound images to find the fetal skull, and these features were used to train the random forest classifier. In the next step, HC was measured using HT, dynamic programming, and ellipse fitting. Parallelly with Van den Heuvel et al. (2018), Li et al. (2018) studied automatic HC measurement. They first integrated the image information into the random forest classifier to automatically determine the location of the fetal head with ROI. A non-iterative ellipse fitting method (ElliFit) was then used to correctly fit the HC ellipse. It was stated that the detection accuracy performed better than the existing methods. Sahli et al. (2019) studied automatic calculation of HC, BPD and OFD measurements and classification of normal-abnormal fetus. Wavelet transform filter was used to remove speckle noise in the first step. In the second step, region of interest (ROI) detection method, based on HT method, was used for localization accuracy. In the classification stage, support vector machine (SVM) classifier was used.

4.1.3. Deep Learning

To automatically calculate HC and BPD measurements, Sinclair et al. (2018) used VGG-16 model, which is a fully convolutional network (FCN) architecture. It was stated that the model performed at a level similar with the expert and learned to produce correct predictions. Wang et al. (2019) used an end-to-end deep neural network model to simultaneously address FL segmentation and endpoint localization in ultrasound volumes. First, the basic U-Net model (Unet-ROI) was used to localize the ROI of the FL to reduce the search area. In the next step, the ROI for segmentation and milestone localization was taken as input and trained in the U-Net model. Yang et al. (2019) studied semantic segmentation of the fetus, GS, and placenta with 3D ultrasound images. In their study, 3D fully convolutional network (3D FCN), popular in semantic segmentation, is used for semantic tagging. Then RNN was used to improve semantic tagging. Kim et al. (2019) developed a method for automatic measurement of HC and BPD based on deep learning. In the study, a CNN architecture, U-net, is used to divide the images into segments. In addition, bounding-box regression is used to remove incorrectly classified pixels. It was stated that the method used showed a good performance in determining the head limit based on learning. In the study, conducted by Sobhaninia et al. (2019), for automatic HC segmentation and prediction, multi-task CNN model used as a base and then a modified version of the Link-Net structure with multi-scale inputs (MTLN) is used. Li et al. (2020) used fully convolutional neural networks (FCNN) to automatically measure HC, BPD and OFD, as well as a regression branch to predict OFD and BPD. Ellipse fitting and ROI were used for accurate estimation of OFD and BPD length in the regression branch. The designed neural network SAPNet also eliminates speckle noise and unclear skull boundaries. It was stated that the methods used could perform better than the existing fetal head measurement methods. In another study, Thirusittampalam and Thangavel (2020) used deep learning, based on U-Net architecture, for localization of the fetal head region; afterwards, HC measurement was made by using ellipse fitting on the extracted contour. It was stated that successful segmentation was achieved with almost 100% localization accuracy and 88.96% sensitivity. Zhang et al. (2020) aimed to predict HC's automatic measurement without the need for traditional ellipse fitting and segmentation methods and a large data set of manually segmented ultrasound images. Based on this, CNN architectures and three loss functions have been studied and compared. Four models were tested, namely CNN 263K, CNN 1M, Reg-VGG16 and Reg-ResNet50. Mean Absolute Error (MAE), Mean Squared Error (MSE) and Huber Loss (HL) loss functions are used to measure the error and success rates of the models. It was stated that Reg-ResNet50 performed better with MSE loss function. Fiorentino et al. (2020) used the tinyYOLOv2 model, which is a CNN architecture, to localize and center the fetal head in automatic measurement of HC. After learning the position of the fetal head, the U-Net architecture was used for the segmentation process and HC measurement was made by applying ellipse fitting to the CNN regression output. It has been stated that the proposed method has a great potential to support physicians. Yang et al. (2020) used Residual U-Net and ASPP U-net models for automatic segmentation of biometric parameters AC, FL and CRL. Residual U-Net was used for the gradient problem and ASPP U-Net was used to increase the accuracy of the segmentation without increasing the depth of the model.

Oghli et al. (2021) developed a convolutional neural network architecture called Attention MFP-Unet for automatic segmentation and measurement of AC, BPD, FL and HC biometric parameters. It was stated that the developed approach showed superior performance compared to the latest technology studies. In the study of Zhu et al. (2021), Segnet, which is a deep learning method, and random forest regression model, which is a machine learning method, were used for automatic analysis of FL. The Segnet method shows better performance compared to the random forest regression model. Zhang et al. (2022) tried and compared various convolutional neural network models including segmentation and regression methods for automated measurement of HC. It has been stated that although the regression models do not require segmentation and ellipse fitting, they are less costly, but segmentation methods give better results and regression-based methods are promising for the future.

4.1.4. Hybrid Studies

In the study conducted by Lu et al. (2005), for the automatic measurement of HC and BPD, each image was pre-processed with a low-pass filter. The K-mean algorithm was used to classify each pixel according to its intensity value. BPD and HC were calculated from the ellipse determined by iterative randomized Hough transform (IRHT). For automatic measurement of AC, one of the fetal biometric measurements, Yu et al. (2008) developed a four-step method. In the first stage, an advanced instantaneous coefficient of variation (ICOV) method was developed to detect the edges of the abdominal contour and to reduce the effects of speckle noise. In the second step, Fuzzy C-Means clustering (FCM) is used to separate protruding edges from weak edges. Then IRHT was applied to determine an elliptical contour on AC. In the final stage, the GVF snake method was used to adapt the ellipse to the actual edges of the abdominal contour. Ravishankar et al. (2016) presented a hybrid approach by combining traditional tissue analysis methods and deep learning methods in their automated method to detect and measure abdominal contour. It was stated that CNNs performed better than traditional tissue analysis methods for better ROI localization. However, it has been also stated that the hybrid approach gives better results than both approaches. Better segmentation results were obtained in determining the best ROI when the predictions from CNN using HOG were combined with those from the Gradient Boosting Machine (GBM). In the study reported by Ibrahim et al. (2017), a trainable segmentation technique based on the Histogram of Oriented Gradients (HOG) was used to segment the GS and estimate its size. Jang et al. (2018) used the CNN method to classify ultrasound images, then Hough transform to measure AC. It has been noted that the method used performed well in most cases, despite few training data, but could not accurately predict AC in cases of extremely large fetuses or abdominal disturbances. At the same time with Jang et al. (2018), Kim et al. (2018) used CNN, U-Net and Hough transforms for automatic AC estimation in their study. After determining CNN to classify the images, Hough transform and AC to obtain an initial estimate of AC, a U-Net and a classification CNN were also used to check whether the image was suitable for AC measurement. It was stated that the proposed method is open for development. Rasheed et al. (2021) trained ultrasound videos on Alexnet and U-net architectures in their study on automatic measurement of BPD and HC parameters to determine gestational age and plotted ellipses on the resulting segmented images. They achieved 96% accuracy in the developed method.

Table II

Overview of existing studies which focus on one prenatal "biometric parameter"

Biometric Parameter	Authors	Used Techniques	Deep/Machine Learning/Hybrid*	Results/ Observations
GS	Chakkarwar et al., 2010	Thresholding operator		Automatic measurement of the GS was successful
	Zhang et al., 2011	AdaBoost algorithm	ML	Average measurement error is 0.059
	Zhang et al., 2012	AdaBoost algorithm	ML	Is practical, reproducible, and reliable approach
	Rawat et al., 2013	GVF snake-based segmentation		Not suitable for twin pregnancy
	Khazendar et al., 2014	Otsu Thresholding, morphological operators, kNN	ML	Accurately identifies miscarriage
	Ibrahim et al., 2017	HOG, neural networks	H	Producing accurate measurements
	Yang et al., 2019	3D FCN, RNN	DL	Decides miscarriage or normal case
HC	Van den Heuvel et al, 2018	Haar-like Feature, Random Forest classifier, HT, Ellipse Fitting	ML	Performs comparable to an experienced sonographer
	Li et al., 2018	ROI, Random Forest, ElliFit	ML	Detection accuracy better than the existing methods
	Sobhaninia et al., 2019	CNN based link set model	DL	Results match well with the radiologist annotations
	Thirusittampalam &Thangavel, 2020	U-Net, Ellipse Fitting	DL	100% localization accuracy, 88.96% sensitivity
	Zhang et al., 2020	CNN (CNN 263K, CNN 1M, Reg-VGG16 and Reg-ResNet50)	DL	Reg-ResNet50 performed better
	Fiorentino et al., 2020	tinyYOLOv2 and U-Net model, Ellipse Fitting	DL	Great potential to support physicians
	Zhang et al., 2022	Various CNN models compared	DL	Segmentation methods give better results and regression-based methods are promising
BPD	Khan et al., 2014	Canny Edge Detection		Reference measurements are comparable to the interobserver agreement for BPD

FL	Thomas et al., 1991	Morphological operators, threshold		The proposed algorithm has potential for reliable ultrasound measurements
	Mukherjee et al., 2010	Polynomial curve fitting, curvature-based thresholding, LTS		Method can be adapted for other fetal limbs
	Wang, 2014	Entropy based segmentation		Effective for the purpose of FL measurement
	Mathews and Deepa, 2014	Density-based and shape-based thresholding, SVM	ML	Accuracy 86.67% for BMP, 91.11 for JPEG
	Khan et al., 2015	ROI, binary threshold, PPHT	ML	The automatic method demonstrated comparable error range between the automatic and manual FL measurements.
	Yu et al., 2015	Phase symmetry, saliency visual attention model		Measurement accuracy 94.5% ± 1.6%
	Amoah et al., 2015	Phase symmetry from Gabor filter bank, Otsu threshold		Fully automatic and can replace the manual approach
	Hermawati et al., 2019	Localized region-based active contour (LRAC)		Noise reduction has a great effect on accurately measuring the gestational age
	Wang, 2019	U-Net	DL	Has potentials to be extended to similar tasks in volumetric ultrasound
	Zhu et al., 2021	Segnet	DL	Better performance compared to the random forest regression model
AC	Yu et al., 2008	Instantaneous coefficient of variation (ICOV), Fuzzy C-Means clustering, IRHT, GVF snake	H	Segmentation accuracy 98.78%+/-0.16%
	Wang et al., 2014	ROI, MSFA, IRHT	H	Can be used as a reliable and accurate tool
	Ravishankar et al., 2016	CNN, HOG, GBM	H	CNNs performed better than traditional tissue analysis
	Jang et al., 2018	CNN, HT	H	Could not accurately predict AC in cases of extremely large fetuses
	Kim et al., 2018	Classification CNN, U-Net and HT	H	Open for development

** DL stands for Deep Learning, ML stands for Machine Learning, H stands for Hybrid*

Table III

Overview of existing studies which focus on multiple prenatal "biometric parameters"

Biometric Parameters	**Authors**	**Used Techniques**	**Deep/Machine Learning/Hybrid**	**Results/ Observations**
HC, BPD	Lu et al., 2005	K-mean algorithm, IRHT	H	Results are consistent and accurate
	Satwika et al., 2013	Hough Transform with one dimensional parameter space		Can improve the speed of previous research
	Sinclair et al., 2018	VGG-16 model of FCN architecture	DL	Performed at a level similar with the expert
	Kim et al., 2019	U-net	DL	Good at determining the head limit
	Rasheed et al., 2021	U-net, Alexnet, Ellipse Fitting	H	96% accuracy
HC, BPD, OFD	Mathews et al., 2014	Chamfer Matching based Ellipse Fitting, HT based Ellipse Fitting		Superior to HT-based ellipse sensing
	Sofka et al., 2014	Monte Carlo method, IDN	ML	meets the requirements for clinical use
	Foi et al., 2014	DoGEll		Segmentation accuracy was superior to other methods
	Zhang et al., 2017	Texton-based method, RF classifier	ML	Accuracy 95%
	Sahli et al., 2019	HT method-based ROI, SVM	ML	SVM is rapid and accurate
	Li et al., 2020	SAPNet of FCNN architecture, Ellipse Fitting, ROI	DL	Better than the existing fetal head measurement methods

AC, FL, CRL	Yang et al., 2020	Residual U-net and ASPP U-net	DL	Can improve segmentation accuracy
HC, BPD, AC, FL, HC	Oghli et al., 2021	Attention MFP-Unet	DL	Superior performance compared to the latest technology studies
HC, BPD, AC, FL, CRL	Carneiro et al., 2008	Constrained probabilistic boosting tree classifier	ML	Measurements are close to the accuracy of the experts

In Table II and Table III, overview of existing studies which focus on one prenatal "Biometric Parameter" and multiple "Biometric Parameters" are given respectively.

4.2. Studies Focused on Measurement of Soft Markers

4.2.1. Traditional Image Processing

Lakshmi et al. (2008) studied automatic NT and FMF angle measurement for the diagnosis of Down syndrome. ROI, threshold, dilation, and erosion methods were used for FMF segmentation, respectively, and FMF angle was measured using the best fit line method for angle measurement. ROI and Otsu threshold were used for NT segmentation. NT thickness was estimated by finding the coordinates of the pixels and calculating the maximum vertical distance. Nirmala and Palanisamy (2010) presented a semiautomatic method measuring NB length and FMF angle for the prediction of Down syndrome anomaly. The median filter was used in the first step to remove speckle noise and the relevant areas were clipped. In the next step, the NB, anterior bone and palate were divided into sections by applying mean shift cluster analysis and the Canny operator was used to improve the visibility of the edges. In the last step, NB was measured using Blob analysis and FMF was measured using least square line fitting. Wee et al. (2010) used the normalized grayscale cross correlation technique for automatic detection of the presence or absence of NB. The threshold was set at 0.35 to classify the nasal bone according to its absence or presence. It has been stated that the method developed is an effective method for automatic diagnosis. Anjit and Rishidas (2011) developed a method for detecting NB using ultrasound images of the fetus at 11-13 weeks for early detection of Down syndrome. First, a median filter is used to remove speckle noise. In the next step, the watershed transform algorithm was used for the segmentation process and the features in the nasal region were extracted using Discrete Cosine Transform (DCT) and Daubechies D4 Wavelet transform. The extracted features were trained in the Back Propagation Neural Network (BPNN) for the classification process. It has been stated that the proposed method shows high accuracy performance in the diagnosis of Down syndrome and can reduce operator error when combined with certain detection methods. Karl et al. (2012) and Zhen et al. (2013) performed and compared the IT measurement both manually and semi-automatically with a software, which was integrated into the ultrasound machine one year apart. It was stated that the software can be used safely for IT evaluation, although it is open for development. Sonia and Shanthi (2015) have developed a method to detect NB length, which is one of the important soft markers for early detection of Down syndrome. In the first step, ROI was used to subtract the region of interest in the image and reduce the calculation time. In the second step, morphological operators (erosion and dilation), herbaceous thresholding and logical procedures were used for segmentation. In the last step, the NB length is calculated with the Euclidean distance. It has been stated that the proposed technique can be helpful in the early detection of Down syndrome. Sonia & Shanthi (2016) developed a method for measuring NT thickness for early detection of Down syndrome. In the first stage, Lee filter was used to remove speckle noise and ROI was used to extract the relevant region in the image. In the second step, morphological operators (erosion and dilation), Otsu thresholding and logical operations were used for segmentation. In the last step, NT thickness was measured based on the maximum height. Nie et al. (2017) developed an automated method based on dynamic programming to determine the area and the thickness of NT. A new cost function has been proposed for dynamic programming and it is stated that this method provides higher accuracy in NT limit detection.

4.2.2. Machine Learning

Rafeek and Gunasundari (2013) studied NB detection using the BPNN model. In the pre-processing step, hybrid method was used to remove speckle noise and ROI was used to extract the area of interest. Then the normalized dataset was used to train the BPNN and then this network was used to classify the images. It is stated that the proposed method can reduce operator error and increase detection rate when combined with detection methods. Park et al. (2013) firstly used the Hierarchical Detection Network (HDN) network to detect the NT region in their study of automatic NT measurement. Then, the approximate edges of the NT region were found using Dijkstra's shortest path algorithm and Graph Cut segmentation was used for the correct segmentation process. Finally, NT measurement was calculated based on the maximum thickness of the segmentation result. Sciortino et al. (2017) presented an uncontrolled methodology for determining NT thickness. First, a variation of anisotropic filter was used to remove speckle noise. Wavelet analysis and neural networks are used to find NT effectively. Finally, NT thickness was measured from the edges obtained with standard mathematical morphology.

4.2.3. Deep Learning

Liu et al. (2019) first designed a CNN to directly detect the NT region. In the next step, they used a customized architecture and U-Net model with loss functionality for precise NT segmentation. In the last step, NT measurement was calculated using Principal Component Analysis (PCA). Although there are not many studies on the automatic diagnosis of ventriculomegaly, which is one of the most common abnormal findings in prenatal diagnosis, Chen et al. (2020) worked on automatic measurement of LV from ultrasound images. In the first step, they used Mask-RCNN, one of the deep convolutional neural network models, for pixel-based segmentation. In the next step, the number of pixels per centimeter (PPC) was obtained by morphological processes. In the last step, the pixel length of the LV was obtained by the minimum circumscribing rectangle (MER) method and the LV width was measured by converting the pixel length to a physical length using PPC. Chaudharia and Oza (2021) developed a method for automatic NT detection based on Scale-invariant feature transform (SIFT) and General Regression Neural Network (GRNN). It is stated that this developed method has less errors than SVM, Artificial Neural Network (ANN), Naive Bayes and kNN. Thomas and Arjunan (2022) used VGG-16 based SegNet architecture for segmentation of NT region and AlexNet architecture for classification in their study. It has been stated that the study will increase the diagnosis rate of clinicians.

4.2.4. Hybrid Studies

On the measurement of NT, Deng et al. (2012) have developed an automatic method. In the study in which a hierarchical model is presented, SVM classifier was trained to classify the areas in the image as body, head and NT, and the HOG feature was used to remove speckle noise during training. The built-in Gaussian pyramid is used so that the detection window corresponding to each object can find the object in a suitable scale. In the next step, a spatial model is used to define spatial constraints. Finally, NT determination was obtained by applying a generalized distance transformation. It was stated that the method suggested was an effective method for automatic detection. Anzalone et al. (2013) The first stage is the pre-processing stage, and the following steps are applied in order: anisotropic filtering, thresholding, and mathematical morphology. In the next step, HT was used to identify the fetal head and NT. ROI was found with the template matching approach. K-means clustering is used to estimate the best template and number to use.

Table IV
Overview of existing studies which focus on "soft markers"

Soft Markers	Authors	Used Techniques	Deep/Machine Learning/Hybrid	Results/ Observations
Ventriculomegaly	Chen et al., 2020	Mask-RCNN, morphological operators	DL	Superior performance over manual measurement
NB, FMF angle	Nirmala & Palanisamy, 2010	ROI, mean shift cluster analysis, Canny operator, Blob analysis		May help the physician for better clinical diagnosis
NT, FMF angle	Lakshmi et al., 2018	Best fit line method, ROI, Otsu threshold		Good accuracy of measurement of both NT and FMF
IT	Karl et al., 2012 Zhen et al., 2013	SonoNT software SonoNT software		The software can be used safely for IT evaluation

NB	Wee et al., 2010	Normalized grayscale cross correlation		Effective for automatic diagnosis
	Angit & Rishidas, 2011	Watershed transform algorithm, DCT, Daubechies D4 Wavelet transform, BPNN		High accuracy in diagnosis of Down syndrome
	Rafeek & Gunasundari, 2013	ROI, Prewitt, Sobel and Laplacian methods, Watershed algorithm, DCT, Wavelet transform, BPNN	ML	Can reduce operator error
	Sonia & Shanthi, 2015	ROI, erosion and dilation, Otsu thresholding		Maximum NB of 5.24 ± 0.12 mm for 19-week normal fetus
NT	Deng et al., 2012	SVM classifier, HOG, Gaussian pyramid, spatial model	H	Effective for automatic detection
	Park et al., 2013	HDN, Dijkstra's shortest path algorithm, Graph Cut segmentation	ML	Suitable for clinical use
	Anzalone et al., 2013	HT, ROI, K-means clustering	H	Reliable system that can be used by physicians
	Sonia & Shanthi, 2016	Mutual thresholding, logical operations		Provides accurate NT, helps for DS detection
	Nie et al., 2017	ROI, erosion and dilation, Otsu thresholding, logical operations		Provides high accuracy in NT limit detection
	Sciortino et al., 2017	Dynamic programming-based method	ML	Average error of at most 0.3 mm in 97.4% of the cases
	Liu et al., 2019	Wavelet analysis, neural network, mathematical morphology	DL	Automatically detects and measures NT with promising performance
	Chaudharia & Oza, 2021	Customized CNN and U-Net, PCA SIFT, GRNN	DL	Has less errors than SVM, ANN, Naive Bayes and kNN
	Thomas & Arjunan (2022)	Segnet	DL	Will increase the diagnosis rate of clinicians

In Table IV, an overview of existing studies which focus on “Soft Markers” is given.

Table V

Existing studies grouped by algorithms/methods used.

Algorithm/Method	**Biometric Parameters/Soft Markers**	**Authors**
Ada Boost algorithm	GS	Zhang et al., 2011
	GS	Zhang et al., 2012
GVF Snake method	AC	Yu et al., 2008
	GS	Rawat et al., 2013
Otsu Thresholding	GS	Khazendar et al., 2014
	FL	Amoah et al., 2015
	NB	Sonia & Shanthi, 2015
	NT	Nie et al., 2017
	NT, FMF Angle	Lakshmi et al., 2018
Morphological operators	FL	Thomas et al., 1991
	GS	Khazendar et al., 2014
	Ventriculomegaly	Chen et al., 2020
kNN algorithm	GS	Khazendar et al., 2014
	NT	Chaudharia & Oza, 2021
HOG algorithm	NT	Deng et al., 2012
	AC	Ravishankar et al., 2016
	GS	Ibrahim et al., 2017
Random Forest	HC, BPD, OFD	Zhang et al., 2017
	HC	Van den Heuvel et al, 2018
	HC	Li et al., 2018

Hough Transform	NT	Anzalone et al., 2013
	HC, BPD, OFD	Mathews et al., 2014
	HC	Van den Heuvel et al, 2018
	AC	Jang et al., 2018
	AC	Kim et al., 2018
	HC, BPD, OFD	Sahli et al., 2019
Ellipse Fitting	HC, BPD, OFD	Mathews et al., 2014
	HC	Van den Heuvel et al, 2018
	HC	Thirusittampalam &Thangavel, 2020
	HC, BPD, OFD	Li et al., 2020
	HC	Fiorentino et al., 2020
	HC, BPD	Rasheed et al., 2021
ROI	NB, FMF angle	Nirmala & Palanisamy, 2010
	NB	Rafeek & Gunasundari, 2013
	NT	Anzalone et al., 2013
	AC	Wang et al., 2014
	FL	Khan et al., 2015
	NB	Sonia & Shanthi, 2015
	NT	Nie et al., 2017
	HC	Li et al., 2018
	NT, FMF angle	Lakshmi et al., 2018
	HC, BPD, OFD	Sahli et al., 2019
	HC, BPD, OFD	Li et al., 2020
Canny operator	NB, FMF angle	Nirmala & Palanisamy, 2010
	BPD	Khan et al., 2014
Support Vector Machine	NT	Deng et al., 2012
	FL	Mathews and Deepa, 2014
	HC, BPD, OFD	Sahli et al., 2019
Neural networks	GS	Ibrahim et al., 2017
	NT	Liu et al., 2019
CNN	AC	Ravishankar et al., 2016
	AC	Jang et al., 2018
	AC	Kim et al., 2018
	HC	Sobhaninia et al., 2019
	HC	Zhang et al., 2020
	NT	Chaudharia & Oza, 2021
	HC	Zhang et al., 2022
U-net	AC	Kim et al., 2018
	FL	Wang, 2019
	HC, BPD	Kim et al., 2019
	HC	Thirusittampalam &Thangavel, 2020
	HC	Fiorentino et al., 2020
	NT	Chaudharia & Oza, 2021
	HC, BPD	Rasheed et al., 2021
Phase symmetry	FL	Yu et al., 2015
	FL	Amoah et al., 2015
Segnet	FL	Zhu et al., 2021
	NT	Thomas & Arjunan, 2022
IRHT	HC, BPD	Lu et al., 2005
	AC	Yu et al., 2008
	AC	Wang et al., 2014
K-means clustering	HC, BPD	Lu et al., 2005
	NT	Anzalone et al., 2013
VGG-16	HC, BPD	Sinclair et al., 2018
	HC	Zhang et al., 2020
SonoNT	IT	Karl et al., 2012
	IT	Zhen et al., 2013
Watershed algorithm	NB	Angit & Rishidas, 2011
	NB	Rafeek & Gunasundari, 2013
Wavelet transform	NB	Angit & Rishidas, 2011
	NB	Rafeek & Gunasundari, 2013
	NT	Liu et al., 2019
DCT	NB	Angit & Rishidas, 2011
	NB	Rafeek & Gunasundari, 2013

BPNN	NB NB	Angit & Rishidas, 2011 Rafeek & Gunasundari, 2013
Erosion and dilation	NB NT	Sonia & Shanthi, 2015 Nie et al., 2017
Logical operations	NT NT	Sonia & Shanthi, 2015 Nie et al., 2017

Table V is a summary of common algorithms and methods for complete existing work reviewed in this paper.

5. CONCLUSION

Detailed examination and measurement of biometric parameters and soft markers to determine anomalies or growth-development status has an important place in monitoring pregnancy. However, measurement errors are possible due to many factors. Therefore, computer-aided diagnosis has started to occupy an important place in the field of medicine.

In this review, computer-based studies on the most commonly used biometric parameters and soft markers for prenatal diagnosis were examined. Studies are grouped according to the indicators as biometric parameters and soft markers, which are checked for monitoring fetal health and development. These two groups are then categorized as traditional image processing, machine learning, deep learning, and hybrid according to the techniques used. Hybrid studies are the ones that use traditional image processing and learning techniques together.

The computer-based diagnostic methods used in these studies gave better results than expected and showed a level of accuracy to support experts. However, results show that not any method gives accurate and precise results, and the methods are open for development. Recently, studies started to focus on deep learning methods, rather than traditional methods. One of the deep learning architecture, CNN, shows little dependence on pre-processing and shows high performance especially in image processing. Also, CNNs are the most powerful technique for image segmentation. With these features, CNNs seem as they are going to be the leading technology for monitoring fetus health for near future.

However, it should not be forgotten that considering deep learning methods give better results than other techniques, they are still open for improvement. According to the working principle of machine learning and deep learning, the more training data, the higher the success. The scarcity of available ultrasound images and the very costly and time-consuming nature of expert explanations are two of the major challenges. Training the learning model with little data and achieving success is among the future goals. In addition, the poor quality of ultrasound images reduces the success rate compared to other medical images. With the development of imaging techniques, the increase in the quality of ultrasound images and the development of 3D imaging will overcome this problem. Another challenge is that deep learning models require high-performance computers. Many hardware architectures are being studied to overcome this challenge, such as Google's Tensor Processing Unit (TPU) which is a hardware accelerator specialized in deep learning tasks.

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