Ultrasound Medical Images Classification Based on Deep Learning Algorithms: A Review

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Abstract

With the development of technology and smart devices in the medical field, the computer system has become an essential part of this development to learn devices in the medical field. One of the learning methods is deep learning (DL), which is a branch of machine learning (ML). The deep learning approach has been used in this field because it is one of the modern methods of obtaining accurate results through its algorithms, and among these algorithms that are used in this field are convolutional neural networks (CNN) and recurrent neural networks (RNN). In this paper we reviewed what have researchers have done in their researches to solve fetal problems, then summarize and carefully discuss the applications in different tasks identified for segmentation and classification of ultrasound images. Finally, this study discussed the potential challenges and directions for applying deep learning in ultrasound image analysis.

Keyword: Fetal Brain Deformities, Deep Learning Algorithms, Ultrasonic Images, Classification.

I. Introduction

Some of the most common congenital malformations are fetal brain deformities. Intracranial anomalies can be one in every 100 births in long term follow-up studies [1, 2]. Ultrasound transabdominal is the primary option to diagnosis the fetus brain of disorders such as (comfortable, non-radioactive, non-invasive, and complex observational technique). Two axial norm neurosonography planes (SANPs), transcerebellar (TC), and trans ventricular (TV)are designed to evaluate the anatomic integrity of the brain, enabling visualization of cerebral structures [3] [4] [5] [6] Ultrasound(US) has long tradition identification of fetus brain defects. The identification rate is primarily caused by physicians lack of familiarity with pathology and complicated brain anatomy [7] [8], position of fetal head unacceptable, late or early gestational ages, maternal obesity, and the out dated appliances .To be professionals, physicians need to train for a long time. However, certain abnormalities can be difficult to detect even in specialist hands in ultrasound [9].

Deep learning is a type of machine learning that helps computers to learning from experience and understand the environment in terms of a hierarchy of concepts. The hierarchical of concepts helps the machine to learn abstract conceptions from simpler ones, certain layers of the hierarchy are profound [10] [11] [12] Deep learning (DL) is a high-tech image processing platform that encompasses remote sensing (RS) images [13].Deep learning has proven to be an efficient set of models for the learning of useful semantic knowledge. However, these are often indirectly taught as part of a classification task. Artificial intelligence is a computer's ability to do intellectual work, such as understanding reasoning and problem solving (AI). Machine Learning (ML) is an Artificial intelligence (AI) part which contains systems that can build the capability to learn from data and that has previously shown the potential to support people in various medical fields [14] [15]. Deep learning (DL), a subset of ML[16] [17] [18], simulates human thinking by stacking several simples functions to make complex choices in a deep structure and has proved to work well in the medical and medical fields [19] [20].

Ultrasound medical imaging uses high frequency waves of sound to imagine biological tissue. An ultrasound test composed of a collection of components transmits sound to a target area, moving through the body, and experiences differences of acoustic impedance, allowing the waves to return to the probe. [21] The benefits of ultrasound imaging over other modalities of medical imaging include cost-effectiveness, motion, real time imaging, and the absence of toxic ionizing radiation. [22] Deep neural networks (DNNs) have recently obtained hi-tech results in various AI activities, including image recognition. [23] photo segmentation [24] auto voice acknowledgment [25], and gaming [26]DNNs have been used in ultrasound imaging, including finding the normal plane in fetal ultrasound images. [27] [28].

In this paper, a comprehensive review is performed for the latest and most efficient approaches that have been performed by researchers in the past years about classification of ultrasound images in the area of deep learning. Also, the details of this method, such as using algorithms/architectures of deep learning, datasets, and the findings achieved are summarized. In addition, we highlighted the most commonly used approaches and the highest accuracy methods achieved.

The organization of the remaining paper is as follows: Section II contains a theory of architectures and algorithms of Deep learning mentioning its types, properties, and challenges; Section III gives a related work on deep learning algorithms; Section IV comparison and discussion on the deep learning algorithms, and the last section conclude the research work.

II.Theory Background

1. Architectures of deep learning

They begin with a brief introduction to architectures of deep learning that are commonly used in ultrasound research. As machine learning (ML) industry, profound learning basically includes computing hierarchical characteristics or representing sample data (ex. images). The abstract characteristics of higher levels are described by comparing them with lower ones. [29]In the most recent work in this area, a deep learning architecture can be divided into three key groups that are focused on the architectures of deep learning and as well as the techniques of classification, segmentation, or detection; either alone, or in combination [30] [31].

- Deep networks supervised.
- Deep networks unsupervised

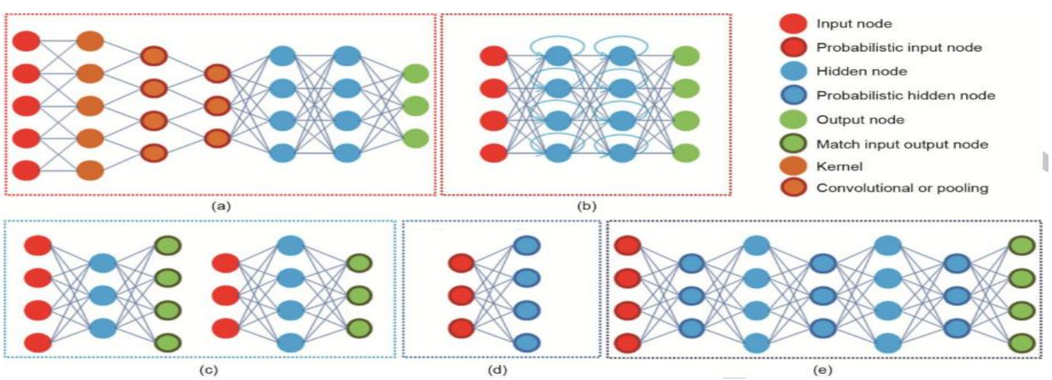

Figure 1. This figure presented neural network architectures [32]:

(a) CNN (b) RNN (c) auto-encoders/sparse auto-encoders (d) Boltzmann machines that are restricted (e) deep belief networks.

1.1. Deep Networks Supervised

Currently supervised profound models for (segmentation, recognition and identification) of the anatomical installations in Ultrasound medicinal images are typical. For these tasks, the two most common architectures are CNNs and RNNs. A description of two depth models is given as follow:

1.1.1. Recurred Neural Networks (RNN)

In fact, an RNN is commonly considered a form of a deeply controlled network used in medical research by the Ultrasound images for different tasks [33] [34] [35].

The number of hidden layers in an RNN can be as long as the length of the input data sequences (e.g., medical Ultrasound video sequences). The RNN network structural features allow for an inherent benefit in the modeling sequences data (e.g., medicinal ultrasound video sequences). However, RNNs have not been commonly used in the numerous research tasks known as sequence models until recently. This is partially because the RNN itself is hard to train in order to track long-term dependency. In the early 1990s, the RNN commonly triggered gradient explosion or gradient disappearance problems [36] [37].Several advanced memory units have therefore been developed and are the earliest and most common long-term memory (LSTM) cells. [38].Simplification and simplification of the Recurring Unit [39] [40]. To date, RNNs are often used in language or texts perception fields and are scarcely used to analyze medical images, even less in Ultrasound medical analyses. Also, RNN can be consider as a deeps paradigm to unregulated learning. RNN is typically used to model subsequent sequences in unattended learning mode using previous data samples. There is no requirement for extra class knowledge such as “goal class labels” to aid learnings; however, the labels sequences are necessary for supervised mode learning.

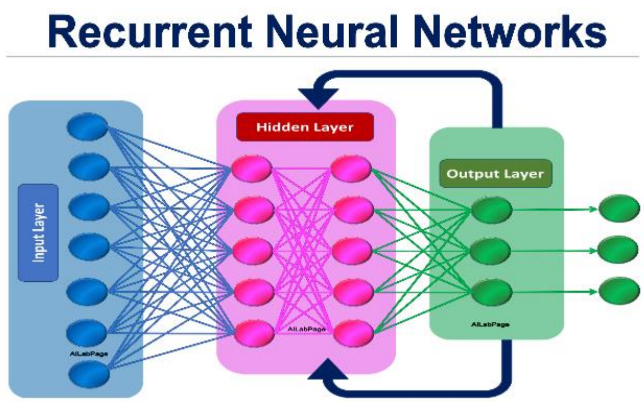

Figure 2. Recurrent Neural Networks [41].

1.1.2. Convolutional Neural Networks (CNN)

The CNN is a type of artificial neural network that is capable of extracting local data features [42].This comprises several modules, each consisting in general of a convolutional pooling layer and layers [43]. They are accompanied with other layeres, such as a rectified linear unit “ReLu”, and batch normalizations if is necessary. In the last segment of the network, completely connected layers typically form a typical neural multi-layer network. As for structure, these modules are typically stacked to form a deep model with one on top of the other, allowing spatial and layout details to be used as an input using 2D or 3D images.

In general, the CNN models, the determination of hyper parameters in a convolutional layer is important for CNN networks to resolve the convolutional phase reduction. These requires, in total, three hyper parameters of deep, padding and transit. The number of the filters corresponds to depth of the output volume, where each one of them learn to search for different something locally in a data (input). By defining a phase, it can be able to monitor how the filter converges around the input volume. In practical, small steps often works well, so the early network (i.e., the layers closest to the input data) will product large activation map, that can leading to higher output [44]. A CNN with several convolutional layers can be troublesome because some regions, particularly boundaries are wasted during every convolutional process. With a padding (generally zero-padding), input volume along the boundary is a type of the most widely employed techniques to minimize the influence of dimensionally diminished convolution. One of the key benefits of padding is that it enables the creation of deeper networks. Moreover, padding actually increases performance, as it avoids data loss at the boundaries of the input volume. This means that trade-offs between several variables have to be taken under constraints of small measurement costs and time costs. For a specific job, in practice such as (filter height, number of filters, network width, and step) [45]. In tradition, the outputs of the convolutional layer are sub-sampled via the corresponding pooling layer to minimize a data ratio from the below layer. The weight of the convolutional layer will imbue the (CNN) some a property invariant in accordance with chosen pooling schemes, including translational invariance. The number of parameters can also be reduced considerably, such as the weight number no depends solely on a scale of un input images. Note that completely linked layers typically don't share the weights that are usually applied at the end of the convolutional network stream. A spread through classes is commonly accomplished by feeding activations in the last layer of the network via a softmax feature in a traditional CNN model. However, various classical machine learning approaches use a substitute such as SVM linear or voting [46] [47].

several deep learning classic and CNN architectures have been advanced and extended to (medical) imaging processing and speech recognition. AlexNet contains models CaffeNet, which is more quickly for a Caffe DL framework, GoogLeNet , ResNet, VGGNet LeNet, R-CNN [48].

1.2. Unsupervised Deep Learning

Unsupervised deep learning implies the experience of task-based reporting. Example, “annotated target class labels” in the learning process is redundant. In reality, various deep learning models are used to produce data samples by network samples such as AE, RBM/DBNs, and generalized demobilization) AEE [49] [50]. Unregulated deep models are generally called generative models to be used in this respect in different activities.

1.2.1. Deep Networks and Restricted Boltzmann Machines (RBM)

An RBM is a specific form of random Markov consists of two-layer architecture, [51]. It is an unwrought graphical conceptual single-layer model, consists of (detectable and undetectable layers), with symmetrical communication among these layers and no connectivity between units. Consequently, it is basically an auto-encoder [52]. In practical, an RBM is used (rarely and a lonely) but is stacketed one-by-one to create a deeper network, which is typically results in the single probabilities model called a deep-belief network “DBN”. A DBN is composed of several hidden layers and a transparent layer, the upper two layers are generated by a non-directed bipartite graph such as an RBM.

1.2.2. The Auto-Encoder and the Variables Thereof

Simply speaking, the auto-encoder is a non-linear approach to function elimination, which does not require the use of goal type labels. This technique is generally used to efficiently encrypt or represent the input data in hidden layers (for example in the form of input vectors) [29]. The features extracted are not based on the execution of particular tasks (e.g., classification) but on the preservation and representation of information. The AE is usually a primary network of a minimum three Layers of information: an input layer, X, that represented one Or more input vectors or hidden data vectors such as (voice spectrum or pixels/patches in an image) [53]. Layers h, showing the features transformed, layer y that correspond with input layer x to the nonlinear AE feature for triggering the not visible layers. There are several AE variables that have been produced. For example denotative auto-encoders (DAEs) and distributed auto-encoders (SAEs) [54] in the SAE models, regularization and sparsity restrictions are adopts to enhance the training network resolution processing. Around the same time, decrease noise is used to avoid the trivial solutions from being located in the network. These models are stacked by positioning the “auto-encoder layers on top of each other”.

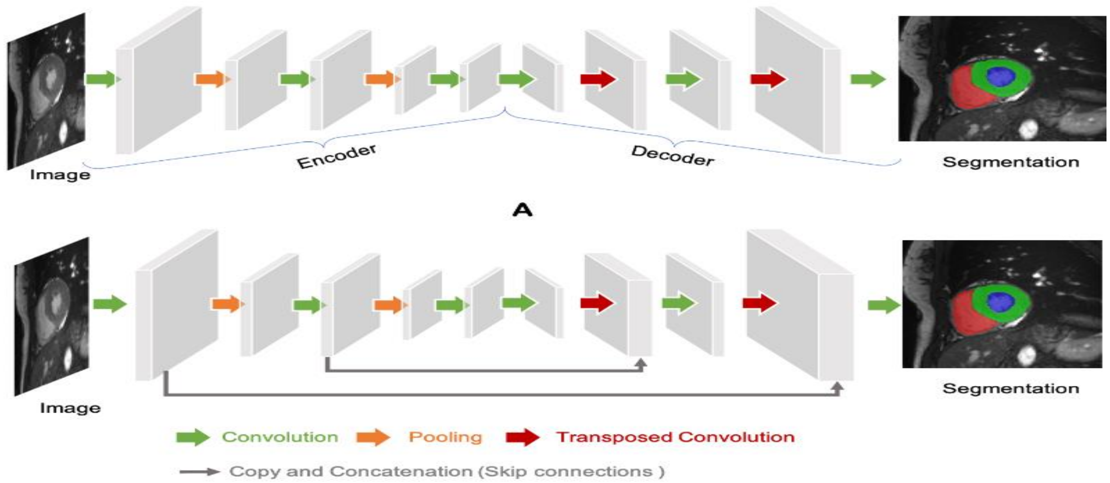

Figure 3. Encoder and Decoder segmentation [55].

2. Strategies and Challenges in Deep Models Training.

To achieve excellent learning performance, the successful of depth learning coming from a fact that a great number of unlabeled examples be required. The current medical analysis is expensive because some diseases are scarce in the studies, and it is challenging to meet this demand [56]. The challenge for US medical doctors is that to train a deep model, they will have to use a small amount of data. A significant issue with the limited training sample is that the deep model can be easily over-fitted. The choice between "Optimization of models" and "Transfer learning" is almost similar. There are a number of approaches that are successful, such as a well-designed model initialization strategy, stochastic gradient descent, and its variants [57]. In recent years, Various useful activation functions have been developed and continuously tested as such [11].

- Well-designed developed strategies for initialization/momentum [58] which require specially designed techniques and algorithms to slowly but gradually increase the fitness parameter of the training model.
- This activation function is performing a nonlinear function such as ReLu,[59] Lastly, Maxout [60]. It is one of the activation functions that is especially suitable to dropout practice.
- Drop-out [61] At each training iteration, units/neurons would have a rate (e.g., 0.5) of being successfully engaged.
- Batch-normalization [62] normalizes each mini-batch of data and then backs propagates the data before training..
- It was neutralizing the corrupted data by using the denoising feature [63] and reconstructing it by the stacking feature, it is used for AEs.

3. Classification

The classification of imaging's is a basic cognitive role in diagnostic radiology. The work is achieved by the recognition of certain anatomical. or pathological characteristics that can discriminate one anatomical arrangement of tissues from another. While computers are not capable of the complete chain of logic needed for medical image analysis, computer-aided diagnostic systems are a research priority in computer-based medical diagnosis [64]. Traditional machine learning techniques also use handcrafted features derived from the ultrasound images in conjunction with a multi-way linear classifier (e.g., SVM) to perform a particular classifying goal. But these approaches are vulnerable to potential image-distorting factors and factors impacting the imaging process. Deep neural networks (DNNs) have many benefits attributable to the direct learning of trivial characteristics (or images). Then DNN may be used to measure an individual likelihood score for each image so as to detect targets of interest.

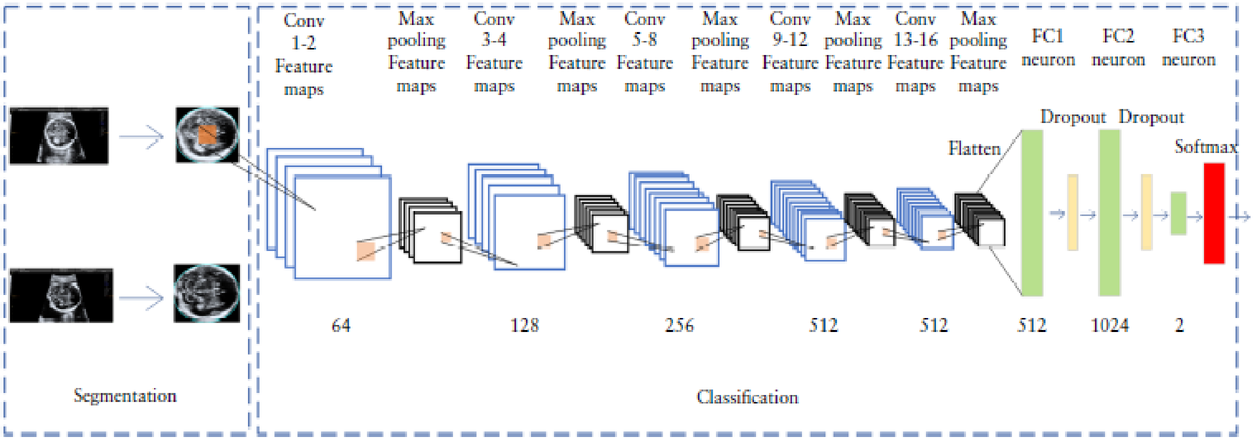

Figure 4. CNN architecture for Medical Image Processing [65]

4. Segmentation of Fetus Brain Area

Methods were tested for automated calculation of gestation age by head, neck, and spine measurement relevant to calculating gestation age [66]. An adaptive approach is used to segment the tissue, in which conventional image processing methods are used [67], or for standard machine learning methods , etc. In some experiments, it has been found that the use of CNN-based networks has contingent outcomes. Using these scans, the craniocerebral regions may be segmented with considerable ease. They actually implemented a completely convolutional network that is capable of performing the segmentation process. Using the U-net [68] task, we slowly and repetitively took corrupted copies of the map. The feature maps were processed in the down sampling direction, and this can be achieved by a double convolution operation with the ReLU and max-pooling feature to minimize the resolution due to its easy structure and suitable image processing efficiency. Analysis has shown that symmetric structures have been acquired in the extensions path. After the up sampling and deconvolutional operations have been completed, two repeated convolution operations were conducted to smooth the performance. After the max-pooling phase, the number of channels doubled and halves, following deconvolution back to its original scale. To compensate for the information loss from the skip link phase, the technique gave the function maps the same resolution.

In the procedure, randomly shuffled illumination angles within and considered the vertical or horizontal (reflections) reflections of illumination angles [23]. One way they done the study was similar to [69], which involved by using similar volumes of data for the three datasets in a batch. In this experiment, the researchers used twelve split view image and ten of both single view images and video frame per-batch. The images that were randomly chosen from the previous batch were used during testing. Both images in ultrasound were translated into grayscale and resized to 256 × 256. Then transformed into grayscale.

5. Classification of Normal Fetus Brain and Abnormal

Deep neural networks (DNNs) have good capacity to extract [70].They had a total of sixteen convolutional layers with kernel sizes of three by three, 3 FC and 5 max pooling layers. A drop-out layer has also been added to mitigate overfitting of the first two FC layers. The distribution of information has been an important means of creating a high-performance standard [71]. Although the standard and image ultrasound differ greatly, low level feature may be transmitted alternately across both fields. All parameters except the last three FCs were transferred from the pre-trained model of ImageNet after conception in [72] to convolutional layers. With the Gaussian distribution, the FC layers are uniformly initialized. Because of the inconsistencies in their data set and the ImageNet dataset, the data set for the pretrained network has been changed. Both convolutional strata were, in truth, first placed on ten echoes for preparation. Then all model parameters for a further 20 echoes have been updated. Images of fetus brain are collected via a segmentation network. The pictures were randomly rotated, taking horizontal or vertical reflection into account

(-45, 45). Owing to the variations between different populations, the procedure illustrated in the "Craniocerebral region segmentation" section has been used.

6. Detection of The Fetus Brain Deformities

Detection of objects of concern (injuries or deformities) Detection of objects of concern (injuries or deformities) is important for ultrasound images or video sequences, deformities or lesion identification in specific, it promotes the segmentation of artefacts well and differentiates between malignants and benign tumor. Anatomical entity (regular fetal plane, organs, tissue localization and/or landmarks). The localization of tissue is often considered a required phase for segmentation activities or for clinical diagnostic workflows for imaging and therapy.

III. Related Work

In this section, classification of ultrasonic images for fetal brain deformities and deep learning algorithms along with related works would be reviewed.

R. Qu et al. [73] Proposed two main methods automatically identifying six normal deep convolutional neural networks planning of the fetus brain. Deep convolutional neural networks (CNN) are one of them, and the CNN based field transfer learning is the other. They constructed two datasets to examine these algorithms' performanceDataset1 contain 30,000 2D ultrasound images from 155 participants between 16 and 34 weeks. Dataset2 was collected over 40 weeks, including 1200 images and it is all pregnancy, from a test participant. Experimental studies indicate that the strategies suggested to produce promising outcomes are typically better than those that are used in other classic, deep-learning approaches and that profoundly convolutional neural networks generally illustrate their great potential.

J. M. J. Valanarasu et al. [74] They propose to synthesize Ultrasound images from separate segmentation masks using a multi-scale, self-attention generator. They demonstrate that, with qualitative and quantitative advancements over recent state-of- the art synthesis techniques, the process will synthesize high-quality ultrasound images with each treated segmentation mark. The findings demonstrate that it is possible to use the current synthesis system to produce practical Ultrasound images to enhance the efficiency of a sectional algorithm.

E. L. Skeika et al. [75] They introduced a new approach for the segmentation by way of a fully converging VNet (VNet-c). They produced a new mix of techniques that use a 3D V-Net as a framework, such as preprocessing, batch normalisation use and falling evaluation, activation mechanism, The Network has a new method of segments of two dimensional ultrasonic image fetals based on a V-Net architecture. The calibration results show that a proposal has been possible to obtain up to 97.91 percent of the right segmentation of fetal skulls and head circumference measures exceeding state-of-the-art methods.

A. I. Namburete et al. [76] They proposed a feature-based model has been developed that relates brain formation to the use of the visual system using MRI data from the ultrasound images , they verify that the model can correctly predict the age of newborns the computer machine has an accuracy of up to 6.1 days of fetal gestational age estimation. The preliminary study of the age-discriminating brain regions found in fetal ultrasound images namely Sylvian fissure, callosal fissural sulcus, and parietooccipital fissure, both reporting major differences in gestational times.

M. Hamisa et al. [77] The researchers indicated to the study involved 23 pregnant women of a fetus with congenital brain defects for a span of 1 year with ultrasound. They conducted an appraisal of the function of MR Imaging in the diagnosis of fetal brain abnormalities versus 2D or4D Ultrasound review. Their results showed that fetal MR imaging is useful in detecting fetal central nervous system abnormalities as well as a complementary modality to 2D/4D Ultrasound in the diagnosis of fetal central nervous system anomalies. MRI was conducted within one week after 2D and 4D ultrasound examination.

Z. Lin et al. [78] They suggest a new Multi-Task Learning System for regular plane detection and quality evaluation using a faster regional convolutional neural net (MF-R-CNN) architecture. MF R-CNN will define the essential anatomic structure of the fetal head and analyze if ultrasound image magnification is acceptable and then conduct ultrasound image quality assessments based on clinical guidelines. Experimental findings on their own data set indicate that their system can correctly perform ultrasound plane quality assessments within half a second.

S. S. M. Salehi et al. [79] They indicated to a deep fully convolutional neural network depend on 2D U-net and autocontext, and evaluated and contrasted with two alternative fast methods based on a fully convolutional voxelwise network and a system depend on SIFT features random forest and conditional random field. On 250 training stages they have educated the networks using manual brain masks and checked 17 stacks of ordinary fetal brain image.

Experimental results show that in the standard, difficult test sets, their U-net approach was above the other approaches and achieved average dice metrics of 96.52 and 78.83 percent respectively.

C. F. Baumgartner et al. [80] They propose a new approach focused on convolution neural networks(CNN), that can automatically found thirteen fetal standard views from the 2D free standing data and provide a bounding box for locating fetal structures. A significant contribution is that the network learns to locate the anatomy using poor monitoring using only image labels. they present real-time annotation results, retrospective frame recovery from saved videos, and position on an extremely wide and challenging dataset of images and video recordings with complete clinical anomaly screenings.

P. Sridar et al. [81] they propose a general system in which the various planes of any particular fetal organ are immediately defined. The CNN is pre-trained to create a feature extractor that derives the best image features for discriminating fetal ultrasound pictures without relying on anatomical priourse or preprocessing. The generality of the experienced US characteristics allows the various US aircraft to be categorized independently of the fetal organs. Their system obtained a mean precision of 94.97 percent and 85.74 percent, better than state of the art baseline algorithms, in the classification of fetal head and heart planes.

G. Sanroma et al. [82] They discussed two assembly techniques that merged the abilities of both families, namely, piling and cascading. they present studies on 6-month infant brain segmentation and a fetal cohort with isolated non-severe ventriculomegaly (INSVM). INSVM is diagnosed as ventricles are slightly swollen and there are no other defects. Prediction is complicated based entirely on the degree of ventricular expansion. To identify markers for a more accurate prognosis, the resultant segmentations are used in the cortical folding of INSVM fetuses to identify anomalies. Segmentation findings show that each mixture technique beats all individual strategies and thus shows the potential to learn structures that improve overall.

L. Xu et al. [83] They suggested a new network of image segmentation with CU-net as a tool for automatic semantic segmentation with the SSIM loss function. The findings of tests demonstrate that this approach functions significantly better than other methods in terms of dice score (DSC), Hausdorff distance (HF) and pixel precision (PA). Improved the end-to-end network, CU-net, by adding branch monitoring and inter-net connectivity to specifically segment the seven fetal brain structures. They also extended the SSIM loss feature to multi-tissue segmentation of ultrasound fetal products and found that it can incorporate global information and help refine tissue borders. This illustrates the capacity and reliability of the segmenting SSIM loss function.

Al-Bander et al. [84] They introduced a way to segment the fetal head in ultrasound images focused on deep learning. The fetal headboundary was observed by integrating an R-CNN (Regional Convolutional Neural Network) mask with an FCNN by inserting an object localization scheme into the fragment. The suggested model has been educated and tested on 999 3D ultrasound pictures of 335 pictures of 551 pregnant women of 12-20 weeks' gestational age. For the least quarter fitting algorithm, the contour of the observed fetal head was gradually fitted with an ellipse.

Table 1: Comparison for Classification of Ultrasonic Images for Fetal Brain Deformities with Different Types of Deep Learning Algorithms

Ref	Years	Methods	Dataset	Result
[73]	2019	CNN	Dataset1 contains 30,000 2D ultrasound images from 155 subjects between 16 and 34 weeks Dataset2 contains 1,200 images, was acquired from a research participant throughout 40 weeks, which is the entire pregnancy	This shows that neural networks of convolution have a strong capacity to identify and segment ultrasound images.
[43]	2020	R-CNN FCNN	Applied on 999 3D ultrasounds and checked on 335 images of 551 pregnant women aged 12 to 20 weeks.	An ellipse of the observed fetal head contour was modified using the least square fitting algorithm their result appear appropriate for segmentation.
[41]	2019	K-best+ SFFS+SVM	Dataset comprises a collection of 60 pathological and therapeutic axial MRI and 3D ultrasound images.	Their findings showed the highest tissue segmentation efficiency by the combination from 10 chosen radiomic properties.

[85]	2019	FCN+ M-FCN	Based on the overlap between the automatic segmentation and the manual segmentation, brain segmentation performance was measured. On the testing dataset	method achieved an average of 0.958 Dice score, 0.950 sensitivity rate, and 0.968 accuracies, and it took an average of 6 s to process one fetal MRI stack on a TITAN X GPU and i7-6700 CPU workstation.
[86]	2020	CNN	A total of 5430 images of fetal brain from 1994 pregnant women were included.	This approach has averaged 0,958 dice, 0,950 sensitivity and 0,968 data collection, and it has taken 6 seconds on average to process a TITAN x GPU and i7-6700 CPU workstation for a fetal MRI array.
[6]	2020	RNN	Data set about the fetal brain ultrasound images	method obtained 0.942 dice score in the craniocerebral segmentation area, 0.96 dice score on average and 0,497 average IOU for lesion position.
[87]	2018	CNN 2D U-net Autocontext	The training was carried on a manual brain mask networks of 250 stacks of images and 17 stacks of regular fetal brain images were studied.	The findings suggest that the U-net strategy has been superior to other approaches in regular and difficult test sets and obtained average dice metrics of 96.52% and 78.83%.
[24]	2018	2D U-net Voxelwise 2D MRI	Dataset consists of automated segmentation of fetal brain with a test time of around 1 second per stack without a post-processing on both usual and demanding test sets	The U-net method yielded substantially better performance.
[88]	2018	CNN+ VP-Nets	Two additional simple strategies have been applied based on Random Forests ,are 3D U-Nets and VP-Nets.	VP-Nets consistently succeeded other methods of localization Their best VP-Net model was a divergence from the prediction center, height difference, and 3D Intersection Over Union (IOU), 63.2% as against the field.
[89]	2020	RNN CNN	The model has been based on three dimensional ultrasound images and tested on data of 551 pregnant women showing a gestational period between twelve and twenty weeks	the result of the algorithm was appear with a high accurate 90%.
[90]	2020	CNN DACD U-Net	dataset applied to split the brain and abdomen for fetal	From the observed findings, it is found that the accuracy of the DACD present machine learning method is 99.7 percent.
[91]	2020	CNN	dataset containing of Fetus brain images for 15372 normal cases and 14047 abnormal.	The algorithms find seams specifically in 61.6% of abnormal images, closely in 24.6% of abnormalities and irrelevant in 13.7% of abnormalities..

IV. Discussion

Throughout this review, we have discussed many different approaches of deep learning ultrasound images implementations and each have shown different performance rates. In Table 1 the most significant and comparable results are compiled from all the different types of models, aggregation methods and different loss. From the table we can see that the authors of [74] have clearly outperformed all the other model types with a rate of 96.52 percent; this result is clearly produced by their use of U-net strategy method. The authors in [57] used deep learning algorithms for a large set of ultrasound images of the fetus' brain using the important algorithm, which is the convolutional neural network (CNN), and this shows that convolutional neural networks have a strong capacity to identify and segment ultrasound images.

The Recurrent neural network (RNN) also have a strong capacity to identify and segment ultrasound images. The authors of [88] has been based on three-dimensional ultrasound images and tested on data of 551 pregnant women, showing a gestational period between twelve and twenty weeks, the result of the algorithm was appeared with a high accurate 90%.

V. Conclusion

In this paper we have reviewed the basics and clarified the progress that has been made in the past couple of years in the images classification and segmentation field for fetus brain. It is concluded that the classification of US images can be safely implemented in systems that requires its presence to function, since it is in a state that can be effectively utilized, however, there is still a space for improvements. Although most of the utilized models such as (2D U-net, Voxelwise)in [24],(CNN, DACD,U-Net)in [90],and (CNN,VP-Nets)in [88] are trained using the two most prominent algorithms (CNN and RNN), there could always be more algorithms to help and push the field forward.

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