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Performance Analysis of a Deep Convolutional Network and a Deep Belief Network for Biometric Anomalies Detection Using fetal Ultrasound Images

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Abstract: The uterine pregnancy, the fetal heartbeat, and the general health and anatomy of the fetus are all assessed with ultrasound technology. Additionally, ultrasounds are used to determine the fetus's position, heart rate, gender, gestational age, and weight. The extremely difficult tasks of finding and evaluating fetal standard scan planes during Second trimester 2D ultrasound require years of training to master. Along with the original ultrasound images, several augmentation techniques are used to enhance the input datasets. In this procedure, fetal anomalies are identified by utilizing ultrasound (US) images. The proposed approach preprocesses the image data & then applies Convolutional neural networks with deep learning (CNNs) and Deep Belief Network (DBN) to autonomously calculate fetal biometrics which includes head circumference and femur length. The proposed approach preprocesses the image data using image processing techniques and then applies deep convolutional neural networks (CNNs) and Deep Belief Network (DBN) to autonomously estimate fetal biometrics, such as head circumference and femur length. First the images are categorized into typical cases and atypical cases. Then the atypical cases are categorized as Macrocephaly, Microcephaly and achondroplasia. The input sources are trained using several CNN layer configurations and also with the help of DBN, and classification accuracy is checked during validation. The foundation of the network is built to retrieve data at various scales. Because of this architecture, the suggested approach may be expanded to whole-slide ultrasound pictures. Our solution beats the state-of-the-art significantly; the suggested study provides more accuracy for the healthcare categorization system, which will give greater precision such as 72.05, 83.95, and 95.00 using Convolutional Neural Network and DBN with prediction accuracy for three classes of 93%. We have proposed an automated diagnosis method based on biometric features and a supervised and unsupervised classification methodology.

Keywords: *fetal ultrasound images, fetal biometrics, deep learning neural network (DCNN), Deep Belief Network (DBN) accuracy, Microcephaly, Macrocephaly, Achondroplasia.*

1. Introduction

In today's world, there are more diseases that can be seen in a fetus. It could be a genetically caused disorder or due to a disease or tumour in its body parts, among many other abnormalities. Medical diagnosis is a technique that uses medical imaging technology to pinpoint the issue based on the symptoms and outcome. A significant advancement in medical image analysis has been observed recently. In the medical field, there are numerous imaging modalities. When women experience high-risk pregnancies, the probability of an anomaly in the fetus occurring is very high. The most effective way to screen a fetus throughout prenatal development is via an ultrasound. Ultrasound is a popular imaging method for fetal and maternal health monitoring throughout pregnancy, offering fascinating advantages such as low cost, free-hand scanning, real-time, and no radiation.

In a normal medical checkup called an ultrasound (US), the doctor analyses and interprets images of the fetus that were collected using the US technology. In fact, it enables the examination of the fetus's health and growth so as to identify anomalies or ascertain its characteristics. Experts claim that because it is quicker and more useful to utilise the US than other medical applications (MRI, scanner, etc.), it would have been more beneficial. The low signal to noise ratio and image imperfections like shadowing, however, limit the diagnostic accuracy. In addition, if the fetal posture is not favourable, it may be difficult to get a precise image of the intended view.

To get over these restrictions and minimise side effects in various medical imaging systems, a number of traditional image processing and artificial intelligence-based methods have been created. The fetal biometric measurements are the

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following: Femur Length (FL), Biparietal Diameter (BPD), Head Circumference (HC), and Abdominal Circumference (AC). These common biometric measurements are based on the fetus' architecture and are frequently provided during a regular second trimester. We have chosen FL and HC from these factors.

They have been discovered to be the initial biometric parameters to identify a variety of fetal disorders. The two most well-known congenital anomalies are microcephaly and macrocephaly, which refer to the size of the head. Short femurs are another well-known anomaly. One of the main reasons for physical impairments, stillbirths, and neonatal mortality is congenital anomalies.

The mentioned abnormalities may have negative neonatal effects that are severe. Unfortunately, prenatal malformation screening and diagnosis are still challenging and time-consuming. The demand for interesting supportive techniques for the radiologist's effective monitoring and diagnosis of fetal abnormalities served as the inspiration for the proposed method. The application of an artificial neural network (ANN), particularly the deep convolutional neural networks (DCNN), for fetus anomaly identification is examined.

On the basis of Femur Length and Head Circumference, the proposed deep convolutional neural network model can assist radiologists in the rapid and exact detection of fetal abnormalities. Here, we suggest how automatic image analysis techniques give us the chance to quickly and consistently diagnose the extraction of the two biometric measurements. Automated detection and classification methods actually play a significant role in making it easier to identify subjects and in offering supplementary advice that, in complex circumstances, can be crucial.

A subset of machine learning called Deep learning (DL) has been shown to be useful in processing of medical images, particularly ultrasound, by stacking a large number of simple logic approaches in an elaborate framework to get complex conclusions. [1] [2] [3] [4] [5] [6]. Approximately 80% of the work published in the area of the evaluation of medical images has employed the CNN approach as its foundation. [1].

In this chapter [7] Convolutional Neural Network (CNN) is deep learning's foundation and is used in a variety of tasks like as the classification, segmentation, and statistical regression, as well as object detection. CNN has shown promise in recognising, detecting, and localising conventional planes in fetal ultrasonography. [8] [10]. In this chapter, an RNN is a sort of supervised artificial neural network which is used in medical US image analysis to execute a variety of task. [[9]. An RNN's depth can be defined as the whole length of the sample used for input data sequence. While clinical plane detection applications have been described [11], the validation of abnormality recognition necessitates a large number of images containing fetal defects. In Chapter [12] there is a fast ellipse fitting method (ElliFit). In addition with using the To use the Random Forest classifier, find the localization of fetal head, it was also used to measure the head circumference to determine the gestational age. HC was measured using a random forest classifier after input images were localised using machine learning techniques. The skull's middle line is discovered using the symmetry of the facial features, and fitting the ellipse is used to fit the HC ellipse for measurement. Filtering and ROI selection were done as part of the pre-processing of the input image [13]. Fetal biometric measurements of the Bi-parietal Diameter (BPD), Head Circumference (HC), and Abdominal Circumference were segmented using thresholding and binarization (AC).

The fetal weight was discovered using the features that were retrieved from the segmentation. In the end, the results of the suggested approach and clinical measurements were compared. Using a convolutional network [14] they proposed a method of machine learning in this research (CNN). Likewise, fetal ultrasound images from the second trimester were employed for the pre-processing.. It includes the acquisition of the image, Preprocessing, classification with CNN and KNN, and performance evaluation based on accuracy are all part of the process.

In this chapter's [15] two-step HC distance-field regression approach for foetal head segmentation, foetal head localization is followed up with an encoder-decoder CNN for HC distance-field regression. It was revealed that conducting foetal head localisation prior to regressing measurement fields improved delineation accuracy significantly.

This suggested method achieved 85% accuracy. n this research, They measured the circumference of the head. The measurement of fetal growth heavily relies on head circumference (HC) length. in order to differentiate Head Circumference in Ultrasound images, they presented an automated technique.

The proposed study's technique depends on CNN training with distance. data in a regression model. They attained an absolute difference (AD) mean of 1.0 (1.76) mm. In this work [16], they put forth the FUVAI framework, This perform multiple tasks deep learning-based system for processing and analysing fetal ultrasound video scans.

The technique is made to analyse fetal US video scans in order to in video sequences, locate standardised planes. categorise and take fetal biometric measurements, and calculate gestational age and fetal weight all at once. Anomaly is a perfect circumstance to study the viability of utilising deep-learning models in the analysis of ultrasound images due to the particular difficulties in applying AI in foetal ultrasonography. Gestational age (GA), biparietal diameter (BPD), abdominal circumference (AC), head circumference (HC), and femur length (FL) are the characteristics taken into account to make a diagnosis of IUGR. Additionally, throughout pregnancy's second trimester, binary classification became utilised via distinguish between normal along with abnormal fetus growth [17].

This chapter [18], explains how the use of machine learning in healthcare can be applied to the Internet of Things. The i-NXGeVita can differentiate between typical and strange cardiac rhythms and classify different issues using the deep belief network (DBN) & IoMT. The precision achievable for the suggested healthcare tracking system is 97%.

In order to accurately identify cases of abnormality in comparison to normal controls in fetal ultrasound images, that aimed to create a deep-learning model and DBN classification model. Various pre-processing techniques, such as image ROI and image augmentation, are used in this work to improve performance. To aid in the identification of the fetal US images as either typical or unusual, the additional input source sent by means of a deep convolutional neural network and Deep Belief Network. 700 fetal US pictures are used to test the algorithm. Accuracy is the metric used to assess how well this classification performs.

2. PROPOSED METHODOLOGY

The data sets for this work are collected from existing works, real-time sources, and websites. The datasets consist biometrics of fetal origin such as head circumference and femur length. First step the dataset need to covert proper format, because it’s available at different directories. At the preprocessing stage, to enhance the performance, the image augmentation, image resizing and image de-noising are done. De-noising techniques are used to reduce the noise present in the image which improves the system's accuracy so that perfect results can be obtained. The pre-processed input sources are passed through Deep Convolution Neural network and Deep Belief Network. These networks are classifying the ultrasound images into normal and abnormal images. The abnormal images are then classed as three types determined by length from the femur Achondroplasia with the size of the head circumference, with microcephaly being the smallest and macrocephaly being the largest. The proposed DBN network makes use of a 75% training data set and a 25% test data set from the whole set of data. The work that is suggested is depicted in Figure 1.

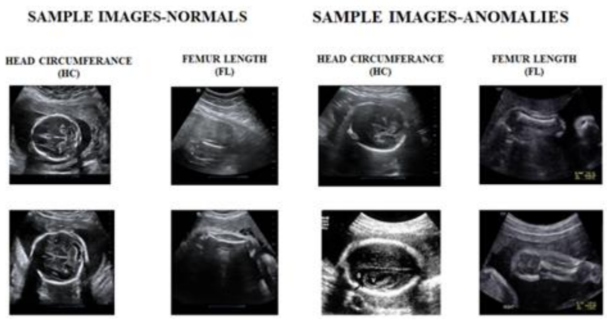


Fig. 1. Proposed Methodology

2.1. Data set description

Ultrasound Images (US):

Transvaginal and transabdominal.

In transvaginal ultrasound, in order to get a clear view of the fetus, Sound waves are bounced off organs inside the pelvis by a device placed into the vagina. And the ultrasound images are obtained. A diagnostic imaging treatment that delivers a more thorough image of your pelvic organs than a standard abdominal ultrasound.

An ultrasound transducer is firmly pushed against the skin of the belly during trans-abdominal ultrasonography. to view the fetus. This is used to show if anything of concern comes up that needs to be investigated or monitored. This is the most common type of ultrasound that is done at the first stage. If there is any abnormality found in the first trimester ultrasound, then they are advised to take another ultrasound or fetal MRI.

First trimester growth duration is (1–13 week). Second Trimester Growth duration is (14–27 week) marks a turning point for the mother and fetus. The heart beat is monitored, and all the organs will continue to mature during this stage. The movements are very much visible now. Many abnormalities in the fetus can be identified during this stage. Third trimester (28–41 weeks).

It is known as the measuring of the fetus and the numerous fetal anatomy parts. The most prevalent fetal biometrics include Bi-prenatal diameter

- head circumference
- abdominal circumference
- femur length.

Bi-prenatal diameter is a measurement of a growing fetus's skull diameter from one parietal bone to the next. Abdominal circumference is determined at the midpoint of the line between the rib and the iliac crest in the midaxillary line.Head circumference is a measurement of a fetus around its largest area. A head is typically half the size of a fetus. If the head grows too fast, it is known as macrocephaly. if it is smaller than the standard size, then it is said to be microcephaly. Abnormality in the femur length causes Achondroplasia. Here we are identifying the abnormality in head circumference and femur length.

Our data set consists of ultrasound images of the fetus biometric measures like head circumference and femur length in the second trimester. The database consists of 1519 fetal ultrasound images in total. In normal images, we have 1095 images, 280 images of femur length, and 815 images of head circumference. In abnormal, we have 424 images, which consist of 192 images of femur length and 232 images of head circumference. A detail of dataset is represented in Table 1.

Figure 2 shows a few illustrations from the collection.

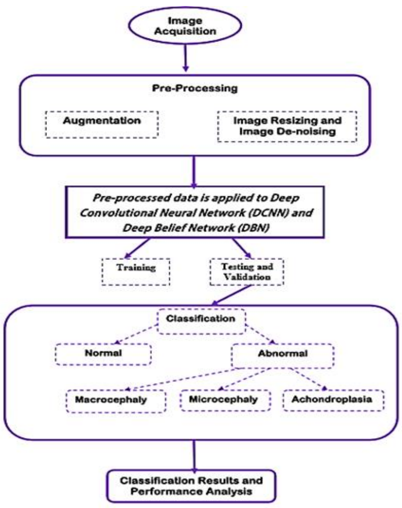


Fig 2. Sample dataset for Normal and Abnormal

2.2. Pre-processing

All the input datasets should be preprocessed so that the obtained results will be more accurate. It is mainly used to remove the clamour, stabilize the intensity of the images, and clear the artefacts. By enhancing the image quality and removing the noise, we also improve the feature present in the image. Here we have used two preprocessing techniques: augmentation and de-noising the image.

- Augmentation:

To increase model performance and reduce over fitting, data augmentation is utilised to create more data. Augmentation of images is a technique for changing existing images in order to provide more data for model training. In other words, it is a strategy for boosting the data set that can be used for deep learning model training artificially.

The techniques used for Augmentation of data are

- Lateral and diagonal rotation
- Diagonal flip
- Rotate

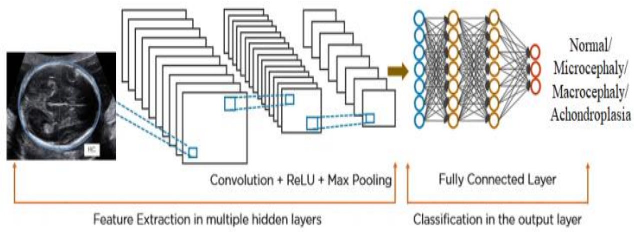
Image Resizing;

The images are resized as the CNN accepts images only within 224*224, so using matlab functions. All the images, including the training and validation data are transformed by the same dimensions. To get the appropriate input size, image resizing is done to get the image size of 224*224 to input CNN.

- Image De-noising:

An essential pre-processing step for image analysis is image de-noising.

The noise is eliminated via the filtering technique.



Speckle noise is typically visible in US images.

Table 1. Database Details

Category	*Head Circumference count*	*Total*	*Category*	*Femur Length count*	*Total*
Normal	815	1047	Normal	280	472
Microcephaly	145		Achondroplasia	192	
Macrocephaly	87				

There are two main categories of speckle reduction.

spatial filter at a single scale.

multiscale transform domain filters.

In this proposed work median filter is used for de-noising the images.

2.3. Convolutional Neural Network (CNN)

Deep Learning (DL) and its applications remarkable success in image identification tasks using Convolutional Neural Networks had been major factors within amazing rise in artificial intelligence during the past ten years [CNNs]. Convolutional neural networks' success is partly related to their ability to analyse enormous volumes of data, including text, images, and images. They are mostly useful for classifying images, locating objects, and extracting attributes from images, like edges or corners. They typically consist of one or more hidden layers, with each layer containing a set of neurons, which are programmable filters. CNN's categorization of medical pictures is more accurate than the human eye in identifying abnormalities in X-ray, MRI, or ultrasound images. Such algorithms may analyse picture sequences (for example, tests gathered over time) and detect minute differences that human analysts would miss. It also enables the use of predictive analysis. To train classifier algorithms for medical pictures, large public health datasets are employed. The created models may be applied to patient test data to identify medical diseases and offer a quick diagnosis. CNN image classifications begin with a source image and analyse it before categorising it. An input image is seen with computers like an array of pixels, the number of which depends on the image resolution. To edify and appraise deep learning CNN models, every source image will go towards a sequence of convolution layers.

 Kernel's

Convolution learns visual qualities from tiny squares of incoming data while maintaining the pixel connection. It is a mathematical approach that takes a pair of inputs: image matrices and the mask. Convolution may accomplish operations like edge recognition, blurring, & refining by adding filters to an image.

 Pooling

When the photos are too huge, pooling layers would lower the number of parameters. Spatial pooling, also known as down sampling, decreases the dimensionality of each map while retaining critical information. There are several forms of spatial pooling:

- Max pooling: The batch's highest value for pixels is chosen.
- Min pooling: The batch's least value for pixels is chosen.
- The average pooling selects the average value of all pixels in the batch.

 Fully connected layers (FC)

In the FC layer, you simply flatten a matrix into a vector and send it into an entirely connected layer, similar to a neural network.

 Apply Softmax function

In the end, an activating function likes softmax or sigmoid is used to identify the results as either typical or unusual. To categorise an item using probabilistic values ranging from 0 to 1, Deep convolutional artificial neural networks are mostly employed for object recognition, picture classifying, and systems for recommendation, but they are also utilised for natural language processing on occasion. A kind of convolutional neural network (CNN) is used for overall processing. Figure 3 depicts the procedure.

Fig 3. Overall Process using CNN

STEPS IN CNN ARCHITECTURE:

- Add images to the convolution layer, choose the parameters, and, if necessary, apply filters with stress filters and pads.
- Apply convolution on the picture after applying the activation of ReLU in the matrix.
- Scale down the size of the dimensionality by using pooling. Until satisfied, use as many convolutional layers as necessary.
- The fully connected layer (FC Layer), It outputs the categories utilizing an operator of activation, then classifies images by logistic regression coupled with cost functions, then flattens the result and feeds it through the FC Layer.

2.4. Applied to the Deep Belief Network (DBN):

This Deep Belief Network (DBN) is an effective generative model, makes advantage from a deep architecture [19]. Association of Deep Belief a DBN typically includes numerous RBM model levels. Hinton and Salakhutdinov [20] have demonstrated that RBMs are accumulated and greedily trained to produce so-called Deep Belief Networks (DBN). To create a deep hierarchical data set training a representation, graphic models referred to as DBNs are trained. The hidden neurons draw relevant data from the observations, which can subsequently be used as input for another RBM. By layering RBMs, learn with a higher level representation. Deep neural networks & deep belief networks do not constitute the same thing. Connections between levels in a DBN are undirected. Restrictive Boltzmann machines are what are used for DBN's undirected layers. An unsupervised learning approach that is very quick can be used to train these layers. Deep Belief Networks feature numerous layers for problems involving image categorization, and each layer is trained using a greedy layer-wise method.

Architecture of DBN:

A DBN's fundamental structure is made up of numerous RBM layers. Each RBM, a model with generative algorithms is one that learns a probability dispersion from incoming data.. The first layer of the DBN learns the underlying structure of the data while the subsequent levels learn higher-level features. The DBN's last layer is utilised for supervised learning tasks like classification and regression.

An unsupervised learning technique called contrastive divergence is used to separately train each RBM in a DBN. This technique can be used to estimate a gradient of the data set's log-likelihood for the RBM’s parameters. Then, by stacking the trained RBMs stacked on above one another, the output with one trained RBM’s is used as the input for the next RBM.

By modifying the weights of the last layer using a supervised learning technique like back propagation after the DBN has been trained, supervised learning endeavors can be carried out on it. The DBN's performance on the particular task it was trained for can be enhanced through this fine-tuning procedure.

Working of DBN:

We must train a property layer in order to directly receive pixel input signals. We then determine the properties of the features that were first acquired by treating the values of these competing interest groups as pixels. The least constraint with the log-liability for the training data set is raised by each additional subclass of parcels or characteristic we introduce into the network. The deep belief network's operational pipeline is described as follows:

- To begin, execute many rounds of Gibbs measurement in the upper two layers that are concealed.
- The upper two layers that are concealed define the RBM.
- As a consequence, this stage is effective in eliminating a sample from it.
- After that, run a single ancestral sampling pass across the remaining regions of the model to obtain a sample from the visible units.
- We will utilise a single bottom-up strategy to determine the values of the latent variables, which are the ones that exist in each layer.

An information vector is present in the lowest layer of greedy pre-training. After then, the generative weights are shifted in other way.

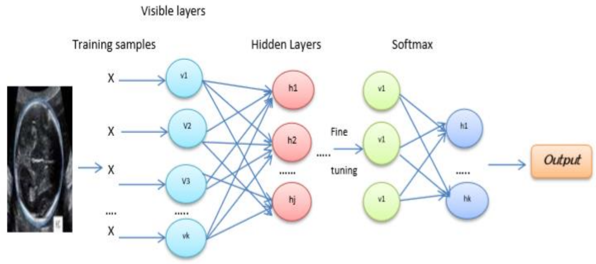


Fig 4. Overall operation using DBN

2.5. Classified Output

The deep neural networks and Deep Belief network's (DBN) categorised results are displayed in Figures 3 and 4. Learning under supervision (CNN) and unsupervised (DBN) Learning an input-output mapping function based on examples of pairs of inputs and outputs is the task at hand. The test and training images are adequately isolated from the normal and abnormal images. Microcephaly, macrocephaly & Achondroplasia in the input data. Performance is evaluated as a result of the accuracy of the categorised output. The analysis of the design is done based on accuracy.

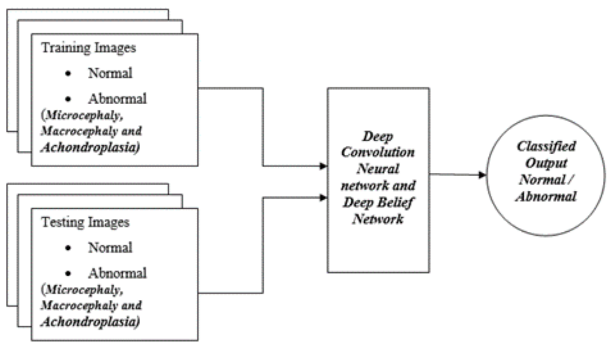


Fig 5. Classified Output.

3. Results and Discussion

Input data:

There are a total of 1519 fetal ultrasound pictures in the entire database. We have 1095 imageries in the normal set, 280 images of the femur, and 815 images of the head circumference. We have 424 images in abnormal, of which 232 are head circumference images and 192 are representations of femur length.

These assessments might be performed to assess the overall accuracy and sensitivity of linked constraints.

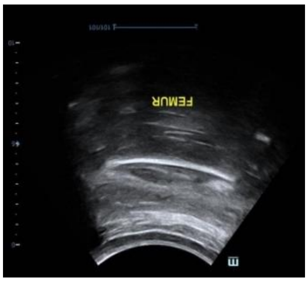
Accuracy (%) = (TP + TN/TP + TN + FP + FN) * 100

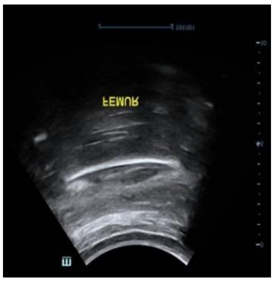
This condition is used to calculate the performance accuracy of both Convolutional Neural Network and Deep Belief Network

Pre-Processing Outputs:

On ultrasound images, image scaling enhancement and image de-noising are carried out. Figure 6 and 7 display the sample results.

Horizontal and vertical flip: Vertical flip:





Rotation:

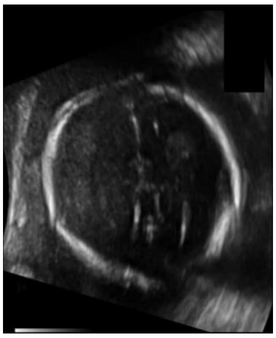


Fig 6. Pre-Processed data set Result for Image Augmentation.

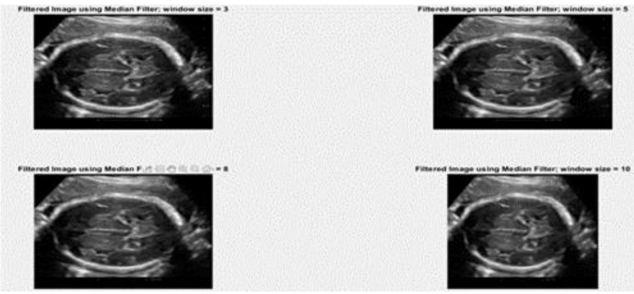


Fig 7. Pre-Processed data set Result for Image de-noising.

Performance analysis of Proposed Work:

For CNN:

These requirements include the use of 35*1 layers, normalization with an input size of 672*802*3, and an image's input size of 672*802*3. The number of connections there are at the moment in the network For the specified problem, epoch 80 in a didactic rate that is 0.01 and a 95% accuracy, a validation frequency of 200, and a maximum number of 80 iterations could be used. These are mentions in a table 2

Table 2. CNN Performance results

SI.No	Parameters	Output for Proposed Work (CNN)
1.	Acquisitions image size	672*802*3
2.	Normalization input size	672*802*3
3.	No of layers used	35*1
4.	No of connection present in network	1*1
5.	Epoch	80
6.	Maximum iteration	80
7.	Iteration per epoch	1
8.	Validation frequency	200
9.	Learning rate	0.01
10.	Accuracy	95.00%

Fig 7. The Mathwork response Convolutional Neural Network.

The fig 7 shows the classification accuracy rate using CNN.

For DBN:

The Measures of proposed study accuracy based on Training and Testing measures illustrated in below table 3.

Table 2. DBN Performance measures

Using DBN our proposed work attained a accuracy for the ratio of 75:25 is 93.05%. In this network for training purpose 821 The network is trained using regular images. In an atypical situation, 318 images are utilised to train the network. For Testing 274 normal and 106 abnormal images are used in the network.

In our proposed work of Both Convolutional Neural Network and Deep Belief Network obtain accuracy is 95%

Table 3. Database Details

Image Ratio	Normal		Abnormal			Training		Testing		Accuracy
	HEAD CIRCUMFRENCE	FEMUR LENGTH	Microcephaly	Macrocephaly	Achondroplasia	N	A	N	A	
75:25	815	280	145	87	192	821	318	274	106	93.05

and 93.05% that information's appear in the table 4.

Table 4. CNN and DBN Performance results

Proposed Networks	Accuracy
Convolutional Neural Network (CNN)	95.00%
Deep Belief Network (DBN)	93.05%

Here with we attached some comparison work done with existing work. It is appears in table 5.

TABLE 5 DBN Performance results

Author	Methodology	Parameter used	Performance analysis
Xavier p et al.	DCNN	Fetal anatomical planes	93.60%
Zhen Yu et al.	DCNN	Fetal facial recognition	96.53%
Christian F et al.	Fetal detection and localization	Fetal biometrics and parts	90.09%
R.Ramya a et al.	Image Pre-Processing	Fetal biometrics	Pre-processed results
D Selvathi et al.	DCNN, Alex net, Google net	Fetal biometrics – Bi-parietal diameter (BPD), head circumference (HC), abdominal circumference (AC), and femur length (FL).	DCNN – 81.25% Alex net – 90.43%, Google net – 88.70%
D Selvathi et al.	DCNN	Fetal biometrics – Bi-parietal diameter (BPD), head circumference (HC), abdominal circumference (AC), and femur length (FL).	DCNN – 80.01%
Proposed Work	DCNN,DBN	Fetal biometrics - head circumference (HC) and femur length (FL).	DCNN – 95.00% DBN – 93.05%

4. CONCLUSION

Our proposed approach, when implemented in real life, helps the Sonologist to identify the growth of the fetus and diagnose Abnormalities by measuring the fetus biometrics, like as head

Circumference and femur length. If there is an abnormality in the ultrasound images, it can identify the abnormality, and the doctors will get a second opinion. It will be helpful for the doctor to note even small changes. It also reduces the time than the traditional procedure. Here we use ultrasound images, which are classified as normal and abnormal, considered the source to the deep convolutional network. It classifies the result as normal If it is abnormal, Based on the qualities, it is divided into three groups. This accuracy is about 95.00% for CNN and 93.05% for DBN. According to the recommendations, more research can be done to identify more abnormality in fetal using all the biometrics in the same system. The data must be trained and tested on the current model in order to detect different types of diseases.

Conflicts of interest

The authors declare no conflicts of interest.

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