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A Detection of prenatal growth using Artificial Neural Network

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Abstract

Amniotic fluid abnormalities are caused by perinatal death and morbidity. Foetal growth and development are examples of parameters that must be accessible. Ultrasound technology is used to make an image of the uterus. Main aim of this work is to reduce the mortality and morbidity. Because, every year, 30 million new-borns have growth limitation, and there is a link between oligohydramnios (lack of amniotic fluid) and perinatal death. AFI can be measured with the assistance of ultrasound images. It is divided into four equal quadrants, with the Amniotic Fluid Index being the average of these quadrants (AFI). The performance of an Adaptive Neuro-Fuzzy Inference classifier is used for classification techniques. For the implementation of this research uses convolution neural network. During the second and third trimesters of pregnancy, this method is used to detect malformations using deep learning techniques. This strategy aims to reduce diagnostic time and risk factors in earlier stages of pregnancy.
Keywords: Ultrasound images, Amniotic fluid volumes, Oligohydramnios, polyhydramnios.

1 Introduction

Deep learning is an AI function that mimics the workings of the human brain in processing data for detecting objects, recognizing speech, translating languages, and making decisions. Computational model is developed using deep learning techniques. It comprises of multi layers to learn the details of the data with multiple level. During pregnancy the images of the fetus, amniotic sac, placenta and ovaries can be exhibited using this method. Pregnancy management decisions are made by Sonographic calculation of the amniotic fluid of fetus. Amniotic fluid volume (AFV) less than 5 cm is 00 given as oligohydramnios, 8 to 20 cm is termed as normal and 24 cm is labelled as polyhydramnios. Oligohydramnios indicates that there is growth retardation in a fetus. Development rate of a fetus is given by Fetal Intrauterine Growth Retardation. By measuring the amniotic fluid pockets, the Amniotic fluid volume assessment can be made subjectively or objectively [1, 2]. Abnormal amount or appearance of the fluid may also be an indirect sign of an underlying disorder. The average amount of Amniotic fluid volume in third trimester of about 34 weeks of gestation into the pregnancy is 800 ml. But due to malformation 600 ml of amniotic fluid surrounds the baby at full term is at 40^{th} weeks which implies abnormality [4]. This can be assessed by ultrasound by using AFI and SDP method. Thus in this paper, we develop a deep learning algorithm which is able to detect and classify adverse pregnancy outcomes.

2 Framework for detecting amniotic fluid volume

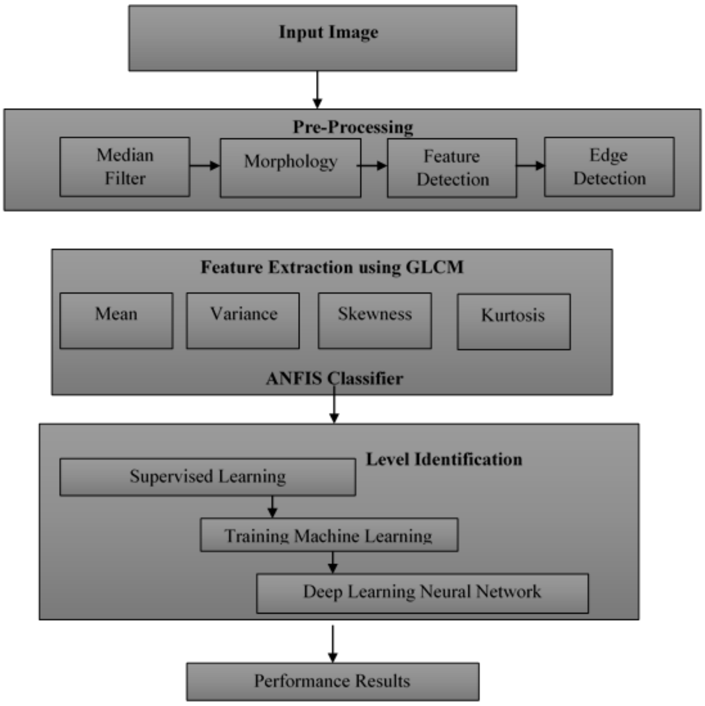


Figure 1: Proposed work of foetal image analysis.

Figure 1 illustrates the model architecture of detecting amniotic fluid volume index. The the features of the image are extracted by feature extraction process such as Intensity Histogram and GLCM. Feature extraction helps to measure the set of data intended for more information. Then the extracted feature values are trained using ANFIS [3].

3 Methodology

A. Contrast Limited Adaptive Histogram Equalization (CLAHE)

Amplification factor is limited by CLAHE. The procedure helps to enhance the contrast of the gray scale image by transforming the values of CLAHE.

Gray Level Co-occurrence Matrix features (GLCM) the texture based feature extraction process that also includes Histogram-based features[8, 9, 11]. The Histogram based features are given by:

$$Variance = \sum_{(b=0)}^{(L-1)} (b-\bar{b})^2 p(b) \tag{1}$$

$$Skewness = 1/\sigma^3 \sum_{(b=0)}^{(L-1)} (b-\bar{b})^3 p(b) \tag{2}$$

$$Kurtosis = 1/\sigma^4 \sum_{(b=0)}^{(L-1)} (b-\bar{b})^4 p(b) \tag{3}$$

Haralick exposed the mathematical texture features equation 4-7

$$Energy = \sum_{(i,j=0)}^{(n-1)} (P_{ij})^2 \tag{4}$$

$$Contrast = \sum_{(i,j=0)}^{(n-1)} P_{ij}(i-j)^2 \tag{5}$$

$$Contrast = \sum_{(i,j=0)}^{(n-1)} P_{ij} \frac{(i-\beta)(j-\beta)}{\sigma^2} \tag{6}$$

$$Homogeneity = \sum_{(i,j=0)}^{(n-1)} \frac{P_{ij}}{1+(i-j)^2} \tag{7}$$

Where,
P_{ij} = Variable *i,j* of the normalized symmetrical GLCM.
n = No: of gray levels in the image
β= The GLCM mean that contributes to the GLCM,

calculated as,

$$\beta = \sum_{(i,j=0)}^{(n-1)} iP_{ij} \tag{8}$$

σ^2 = the variance that contributed to the GLCM, calculated as,

$$\sigma^2 = \sum_{(i,j=0)}^{(n-1)} P_{ij}(1-\mu)^2 \tag{9}$$

ANFIS System Classifier

ANFIS is a data driven procedure that represents a neural network approach for the solution of function approximation problems. FIS comprises of the fuzzy model to formalize a systematic approach [5]. It generates fuzzy rules from an input output data set. IUGR is connected with a diminished volume of amniotic fluid. Critical dismalness has been found in pregnancies with an AFI estimation of < 5 cm. There is a large umbilical cord free vertical pocket in each of the four quadrants in a similarly isolated uterus [6, 7].

4 Supervised Machine Learning Approach

A. Convolution Neural Network:

Visual imagery helps to examine Convolutional Neural Networks (CNN). Functional Components include convolution, pooling and activation. The node of the input layer and output layer are connected with each other. It helps in preserving the spatial information so that its performance can be improved. equation 10 refers linear activation function.

$$Yj^l = f(\sum ikijWx^{(l-1)}i + bj) \tag{10}$$

Where, *Yj(l)* is the j^{th} layer outcomes of i^{th} layer, it is a on linear activation function. k refers to kernel filter, $x(l-1)$ refers to modern feature map with present layer AFI Results

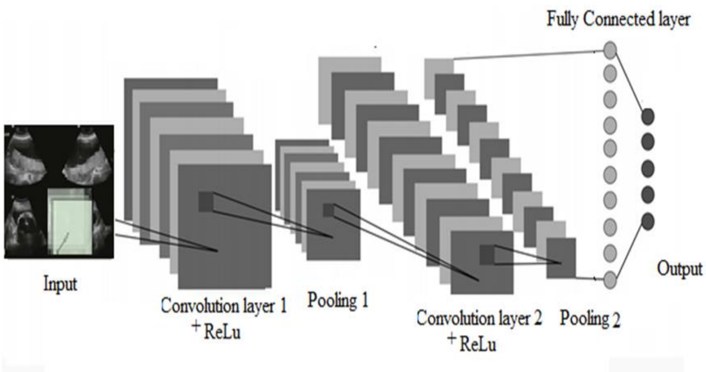


Figure 2: Building blocks of Convolution Neural Network.

B. Deep Learning Neural Network

When compared to neural network, Deep Neural Network is more accurate and level of complexity is higher. It has one hidden layer and output layer and many input layers. This technology is outperformed by machine learning techniques than other NN. Figure 2 shows the model of the deep learning neural network.

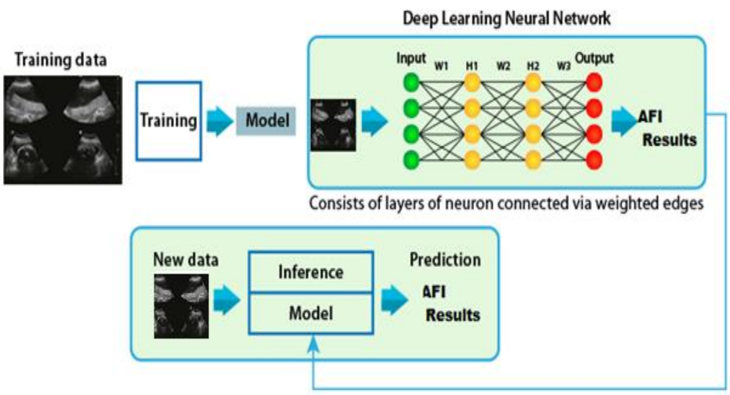


Figure 3: Model blocks of DNN.

Improper training of dataset may cause poor performance in vanishing gradient, Computational load and overfitting. Back Propagation algorithm helps to increase the performance. It is commonly used gradient descent optimization algorithm that adjusts the weight by calculating loss function of gradient.

$$W_{ij}(t+1) = W_{ij}(t) + \eta\frac{\delta C}{\delta W_{ij}} + \epsilon(t) \tag{11}$$

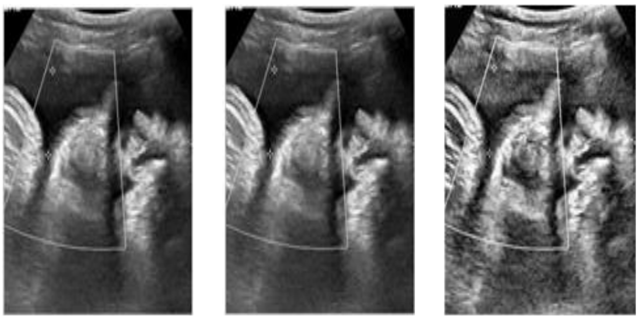
Where, η is referred as learning cost rate, C is cost function, $\xi(t)$ stochastic function. The parameter fill in a training samples is performed by Stochastic gradient descents. The equation is given by:

$$\theta = \theta - \nabla\theta j(\theta; x(i); y(i)) \tag{12}$$

The output data is pre-trained because it is a supervised learning techniques so we can achieve the better results as expected.

5 Experimental results and discussions

In the proposed work, 116 images of amniotic sac of a fetus from ultrasound scan images has been used. The proposed automatic method was capable to measure AFV. Automatic detection of AFV shows whether the fetus is affected by Oligohydramnios or Polyhydramnios.

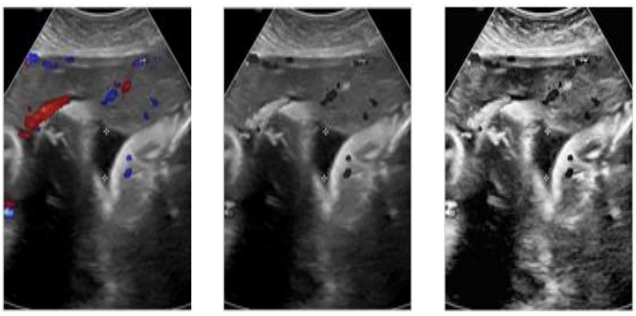


(a) (b) (c)

Figure 4: Detection of Amniotic Fluid Volume (a) Input Image (b) Pre-processed Image (c) Enhanced Image.

Figure 5 is the measurement of AFV. The input image is resized to 500 × 500 pixels and pre-processed by selecting red channel and the resultant image is enhanced by CLAHE. From the enhanced image, the feature values namely, contrast, energy, correlation and homogeneity are extracted and these values are trained in ANFIS. The image sets are tested and gives the output value of Amniotic Fluid Index [10, 12].

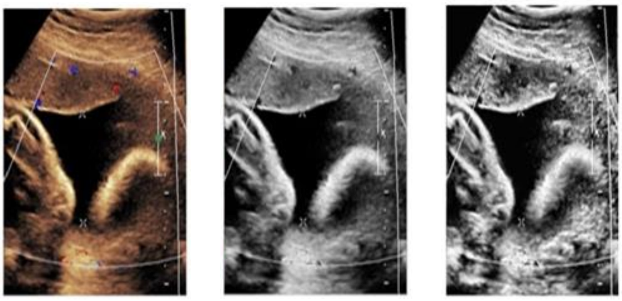
Oligohydramnios is cause a deficiency during pregnancy periods. If it is in less than 5 centimetres of about 36^{th} to 40^{th} week is diagnosed as the same. Figure 6 shows of about the processing steps for the measurement of low AFV.



(a) (b) (c)

Figure 5: Detection of Low Amniotic Fluid Volume (a) Input image (b) Pre-processed Image (c) Enhanced Image.

Polyhydramnios is described as an excessive amount of fluid in the sac. When the liquid is greater the 24 centimetres it shows abnormalities. Figure 5 shows the steps for the measurement of excess amount of AFV.



(a) (b) (c)

Figure 6: Detection of Excess AFV (a) Input image (b) Pre-processed Image (c) Enhanced Image.

Table 1: Histogram based feature values.

Images	Mean	Variance	Skewness	Kurtosis	AFI(cm)
1	0.1652	0.6542	0.1054	0.0154	0.42
2	0.0586	0.6235	0.1451	0.0246	0.55
3	0.1590	0.6845	0.1075	0.0468	0.80
4	0.1863	0.6124	0.1300	0.0369	0.66
5	0.1050	0.6080	0.1385	0.0700	0.82
6	0.1205	0.6174	0.2035	0.0824	0.89
7	0.1947	0.6395	0.0964	0.0264	3.25
8	0.1398	0.6550	0.0654	0.0344	4.80
9	0.0680	0.6932	0.0741	0.0148	5.36
10	0.0724	0.6193	0.1647	0.0214	5.40

Table 1 shows the histogram based feature values such as mean, variance, skewness and kurtosis. The feature values for 10 images are shown. The extracted features are trained in ANFIS and the resulting AFI is not comparable to manual Amniotic fluid index. The accuracy is 60%. Table 2 shows the GLCM feature values. All GLCM features for 116 images are extracted and among these, only 4 features give best results. Four features namely contrast, energy, correlation and homogeneity are extracted and these values are trained using ANFIS and gives the AFI values accurately. The image sets are tested and gives the output value of Amniotic Fluid Index [13]-[15].

The GLCM features gives better results compared to Histogram based features. The anomalies are also classified as normal AFV, Oligohydramnios and Polyhydramnios using ANFIS. The texture of the image gives more information of intensity in an image. So GLCM gives much better performance than other algorithm.

In ANFIS editor window, the input data i.e., the four feature values are loaded and generate FIS by selecting subtractive clustering. Now train the data after selecting optimization method as hybrid. The data set is used to train Fuzzy System by adjust the membership function parameters that performance the best model this data and Figure 7 illustrates the training state results of ANFIS.

Figure 8 shows the training data and FIS output of ANFIS. From the figure, it is clear that the data trained to the system and fuzzy inference output overlap each other.

Figure 9 shows the regression plot of the trained data for performance analysis. These plots give you an idea of how close the output from your model is to the actual target values.

The data set is used in this work is initially divided a part of training and testing images. Performance measures is calculated for testing images. Amniotic fluid volume images is classified as normal,

Table 2: Gray Level Co-occurance Matrix feature values.

Images	Contrast	Correlation	Energy	Homogeneity	AFI(cm)
1	0.2771	0.9643	0.1152	0.9012	0.66
2	0.1660	0.9783	0.1544	0.9383	0.97
3	0.1848	0.9727	0.1119	0.9259	1.30
4	0.2035	0.9661	0.1101	0.9150	0.94
5	0.1343	0.9784	0.1234	0.9382	0.97
6	0.1635	0.9787	0.2437	0.9379	1.11
7	0.2749	0.9688	0.0937	0.9043	5.96
8	0.1763	0.9746	0.1514	0.9373	6.13
9	0.1363	0.9813	0.1339	0.9328	7.49
10	0.1124	0.9840	0.2626	0.9536	7.56

Figure 7: Training state results of ANFIS.

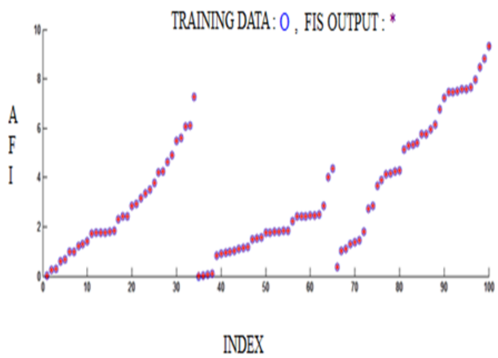


Figure 8: Training data and FIS output of ANFIS.

oligohydramnios and polyhydramnios

Table 3: Shows the Database of input image.

Category	Training Images	Testing Images
Normal	24	40
Oligohydramnios	24	36
Polyhydramnios	247	48

Performance of the accuracy is measured by using Computational Complexity, True -positive and True- Negative rate.

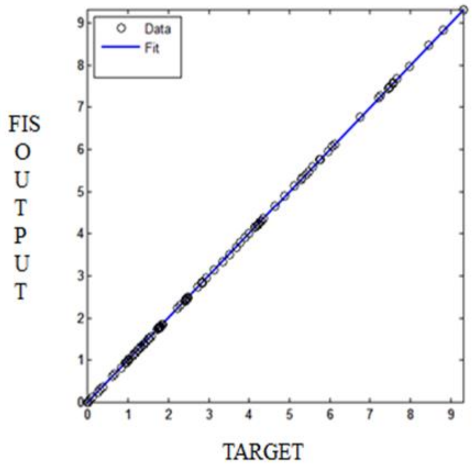


Figure 9: Regression plot of the trained data for performance analysis.

Accuracy Measures of the classifiers:

Table 4: Measurement of AFV.

Fetal Age	Manual Measurement (cm)	Proposed Method (cm)	Status
15 weeks	1.77	1.77	Normal
25 weeks	4.26	4.26	Polyhydramnios
24 weeks	3.51	3.51	Normal
17 weeks	0.94	0.94	Oligohydramnios
22 weeks	3.14	3.14	Normal
20 weeks	1.21	1.21	Oligohydramnios
24 weeks	5.80	5.80	Polyhydramnios
27 weeks	2.85	2.85	Oligohydramnios
26 weeks	6.06	6.06	Normal
25 weeks	7.58	7.58	Polyhydramnios

Table 4 refers the manual measurement and automatic measurement of AFV. Abnormality presence in volume is also shown. The 116 individual quadrant images are acquired and processed. The manual measurement done by the physician is compared to automatic measurement value.

Table 5: Confusion matrix for conventional DCNN.

Category	Normal	Polyhydramnios	Oligohydramnios
Normal	37	3	0
Polyhydramnios	33	2	1
Oligohydramnios	30	3	7

Table 5 shows the mathematical calculation performed for classification accuracy. Evaluated performance measure is using formulae equation 13-15

$$True\ positive\ rate = \frac{True\ Positive}{True\ Positive+False\ Negative} \tag{13}$$

$$True\ Negative\ Rate = \frac{True\ Negative}{True\ Negative\ +False\ Positive} \tag{14}$$

$$Computational\ Complexity = \frac{True\ Positive + True\ Negative}{True\ Positive\ + True\ Negative + False\ Posiitive + False\ Negative} \quad (15)$$

Table 6: Performance measures of DCNN approach.

Category	**TP**	**TN**	**FP**	**FN**	**TPR**	**TNR**	**Accuracy %**
Normal	52	58	3	3	0.94	0.95	94.8
Oligohydramnios	40	68	4	4	0.90	0.947	93.1
Polyhydramnios	38	72	3	3	0.92	0.967	94.8
Accuracy Results	-	-	-	-	92	95	94.2

Table 6 shows the accuracy of the performance of proposed work is about 94%. This work is helpful for gynecologist for diagnosis to reduce time and ease to use for second opinion. The outcome of this method is is enhanced the ultrasound feal image to classify the images whether it is normal or abnormal that is polygohydramnios or oligohydramnios. The perforamnce of the statistical data analysis of the image and processed image are trainied by DNN model its gives better accuracy. Convolution Neural Network considered as very high rated model response for the trained images.Overall performance of this method is well improved.

6 Conclusion and future scope

Ultrasound plays a vital role in detecting the growth and anomalies of fetus in an invasive manner. An automatic detection technique of AFV for use in obstetrics has been developed and implemented. Prediction of AFV will be helpful for the physicians to take decision regarding the development of fetus and this will lead to normal delivery. The detection of AFV is a difficult task in medical field and takes more duration to measure as the fluid is covered with fetal parts and umbilical cord. This approach can easily estimate the fluid volume with less diagnosis time. More number of images can be trained in ANFIS and this can be accomplished using Graphical Processor Unit. For optimal solution for fluid volume measurements in case of twin fetus using deep learning process as it is an emerging field in medical image processing. Convolution Neural Networks and Deep Learning Neural Network models gives the effective performance in the image processing. Accuracy also good in validation about 94%. For future enhancement, to train the images with GPU for much better performance and reduces the computation time than CPU trained model.

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Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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